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Characterization of Texture and relation with Color diffferences

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List of abbreviations:

ASM – Angular second moment
CIE – International Commission on Illumination
CUReT – Columbia-Utrecht Reflectance and Texture Database
FT – Fourier Transform
GLCM – Gray Level Co-occurrence Matrix
HSV – Human Visual System
ICA – Independent Component Analysis
KTH-TIPS – Kungliga Tekniska Högskolan - Textures under varying Illumination, Pose, and Scale
MCD – Maximum Contrast Distance
PC – Principal Component
PCA – Principal Component Analysis
RGB – Red, Green, Blue
WT – Wavelet transform

Since our parents hear us saying our first words we are all convicted to listen to them telling us how to live and what to do with our lives. They tell us to be careful, to make good choices, to choose the right path in our life. Even though it is annoying at the moment, they become the voice in our head pushing us to do better and get further.

You see, my mother taught me some really awesome things like, for instance, making baklava. For a very long time my only concern was how to make the most tasteful baklava and I can proudly say today I mastered that craft. My mother also taught me that if I want to master any other craft I have to listen to older, more experienced people. Listen to what they can teach me but not to follow their footsteps, not to make the same mistakes they made but learn and benefit from those mistakes. She taught me how to pay attention to others and memorize information that can be useful for me in the future.

My father, on the other hand, was a typical man. He taught me how to fix my broken bicycle, how to assemble machinery and most importantly he taught me how to kick a ball. He was also one of my chess coaches and honestly he was the strictest one. From him I learned that it is not a problem if you lose a game but it is a problem if you don't learn from the mistakes you made. Only accepting that you were defeated can open your mind to see what the mistake you made was and help you remember not to make the same one ever again.

All these values that I have gained in early age helped and guided me through my life and education. They helped me absorb knowledge and be patient enough to wait for the moment when I will know enough to start researching and deepening my knowledge with practical work. With this desire I came to CIMET.

Today I can say with a lot of pride and honor that CIMET gave me a possibility to meet some amazing people. For these two years I was privileged to study, work, laugh, cry, be angry with and love so many different and unique people that gave me energy to get where I am now. Critiques and grades built me professionally, good lectures inspired me and the bad ones motivated me to build my own presentations skills to be better. I will cherish this time and use it as fuel to continue with my work because “working hard always pays off and there is never enough of knowledge”.

Thank you for your time and patience.

Abstract

Texture, along with color, is one of the most important characteristics of a material defining the appearance of its surface, and is one of the early steps towards identifying objects and understanding the scene (Bergen et al., 1991). While color had been studied for a long time and continues being a hot topic, the analysis of texture has traditionally been postponed. It is known that viewing conditions appreciably affect perceived color differences. The latest color-difference formula proposed by the International Commission on Illumination (CIE), CIEDE2000 (CIE, 2001.), contains parametric factors (kL, kC, and kH) related to illuminating and viewing conditions, whose influence on color differences is called parametric effects. The viewing conditions include, among other parameters, the sample surface structure (texture). The influence of texture on color perception is known and has far reaching industrial relevance. Nevertheless, the texture of the samples has not been yet thoroughly studied in color science. We initiated the study of this influence in a previous work (Huertas et al., 2006) for a very specific kind of simulated textures, which must be extended. On the other hand, new color difference formulas, based on Color Appearance Model as CIECAM02 (Luo et al., 2006), must be tested for this kind of samples. In the last years texture is being more and more considered, for example in image analysis and processing to detect regions of interest in images or recognize objects. Different ways to manage texture have been proposed, where almost all of them are based on the so called texture features parameters computed from the image, which include first-order statistics of local areas (Ferro et al., 2002) (mean, entropy, and variance), and second order statistical measurements based on Grey-Level Co-occurrence Matrix (GLCM) (Haralick et al., 1973). If these parameters characterize a texture, then they must be related with the perceived sensation that texture produces and the effect over color differences. Some previous work has been carried out studying how texture parameters are related to texture perception. Therefore, the objective of this work is to analyze the influence of textures on perceived color differences and the performance of the most recent color-difference formulae for samples with simulated textures, including random-dot textures and simulated textile samples. Firstly, textures must be characterized through its spatial and colorimetric properties. Secondly, we will check the performance of different color-difference formulae for experimental data, applying different approach using or not spatial characterization of the samples.

"If surfaces were smooth, friction would not exist, the Earth would be bombarded by meteorites and life would not have developed. If surfaces were smooth, pencils would not write, cars would not run and feet would not keep us upright……texture is what makes life beautiful; texture is what makes life interesting and texture is what makes life possible"

Maria Petrou and Pedro Garcia Sevilla
"Dealing with texture"

1. Introduction

1. Introduction

1.1. Subject and goal

In order to achieve the goal of characterizing texture and defining its relation with the color differences the subject of this research is to test the usability of some texture analysis procedures used in image processing in order to create texture features and relate those features to the human perception of texture. Thus, the goal of this research is to find appropriate texture features, related with its perception, that can be used for describing texture in an objective and numerical sense and use these findings to describe its effect on the perceived color differences.

1.2. Definition of the problem and a way to solve it

While color had been studied for a long time and continues being a hot topic, the analysis of texture has traditionally been postponed, mainly because of its difficulty. The influence of texture on color perception is known and has far reaching industrial relevance. Nevertheless, texture samples have not been yet thoroughly studied in color science even thou it is known that viewing conditions include, among other parameters, the sample surface structure (texture). In order to achieve the goals defined in this research it is necessary to perform a set of theoretical and experimental investigations. Firstly, texture must be characterized through its spatial and colorimetric properties. Secondly, the performance of different color-difference formulae for experimental data must be check, applying different approach using or not spatial characterization of the samples.

The theoretical part of this research emphasizes information gathering about texture in general, its relation with perception, but as well the way it is treated in image processing and the available solutions for its analysis. Detailed description of the available texture analysis methods is provided and the reasoning for selecting the method used it this research.

The experimental part of this research includes statistical calculations performed on a carefully selected set of texture images and their relation to perception of texture and color difference calculations performed on the selected set of texture images. Therefore it can be divided into three big phases. In the first phase the knowledge gained in the theoretical part of this research is used to generate algorithms for different statistical calculations that will numerically represent a set of texture images. Later this numerical data is used in the second phase to be compared with the human perception of texture. For the purpose of the second phase a set of visual experiments is performed where the observer's response to the selected set of texture images is observed. Of necessity the third phase, which includes color difference calculations in order to observe the performance of different color difference formulas when they are applied to texture images will be left as future work.

2. State of art

2. State of art

Perception of color can be influenced by many factors that affect its appearance. Materials having the same color but different surface structure can be perceived differently. Hence material's texture affects its color evaluation (Zhang et al., 1996). Many studies showed that the surface structure of a material influences the perception of its color and consequently their color difference evaluation. Since it is not easy to predict how color will be changed with the uniformity of a surface, evaluating color difference of non-uniform samples is a quite demanding task (Tomic et al., 2011). In these cases standard color difference formula cannot be used with a satisfactory and reliable precision (Zhang et al.,1997; Johnson et al., 2003; Huertas et al., 2004).

Even though texture is an important characteristic of materials, so far there is not a single, precise definition of what it is but a lot of different definitions that look at it from different perspectives. From one perspective real texture found in nature can be defined as a tactile quality of a surface that explains how a surface feels like when it is touched – e.g. smooth, rough, soft etc. On the other hand simulated texture could be thought of as what our eyes tell us about how objects should feel like if it would be possible to touch them. However, it is desired to characterize texture through numbers that tell about the nature of a certain texture, its behavior is and its appearance. In order to be able to obtain these numbers digitalize texture is needed. Therefore the focus in this work will be on definitions of texture in computer science and image processing.

According to the definition in computer science texture can be thought of as a two dimensional array of variation or basically a frequency of change and arrangement of tones on an image (Julesz, 1962). It can be also thought of as set of patterns with some kind of repetitive structure, or composite of elementary objects (Mirmehdi, 2008). However, to be able to compare the mathematical characterization of texture with the actual human perception it is advisable to turn to the definitions that treat texture in a manner that is close to the observed sensation. In 1973 Robert Haralick (Haralick et al., 1973) stated that to find features for describing texture it is necessary to follow the way the human visual system (HSV) treats it. The HVS, when observing a scene, is actually looking for spectral (average tone variation in various bands), textural (spatial distribution of tonal variations) and contextual (information from the surround) features. He states that textural features contain information about the spatial distribution of tonal variations within a scene. Therefore it can be assumed that texture information in a digitalized image is contained in the overall or "average" spatial relationship which the gray tones in an image have to one another. This relationship can be represented by a gray tone spatial-dependence probability matrix also called as gray-level co-occurrence matrix (GLCM). The GLCM contains information about how many times a combination of two neighboring pixels occurs in an image which can be also thought of as a probability of the occurrence of such pixel gray level combination. Therefore it represents the joint probability of certain sets of pixels having certain values. This function is defined over pairs of discreet gray values and it is a 2D matrix whose size depends on the number of gray levels present in an image. This provides a possibility of getting both spatial and tonal information at the same time as the co-occurrence matrix conveys information concerning the simultaneous occurrence of two values in a certain relative position (Petrou et al., 2006).

From 1973 until present the GLCM approach to texture analysis has been widely used in computer vision for texture segmentation and classification. The reason why, probably lies in the fact that this is a relatively simple, statistical approach that follows the principles of human perception of textures. As mentioned in two of Julesz's perceptual studies based on psychology it was proven that GLCM matches the level of human perception of textures the best (Julesz 1962; Julesz et al., 1973). However, many papers (Augusteijn et al. 1995; Unser, 1995; Lu et al., 1991; Livens et al., 1997; Feaugers et al., 1978; Julesz, 1975; Pollen et al., 1983; Daugman, 1990; Milic et al., 2011; Zhang et al., 2007) suggest that texture analysis can be performed also in a different manner. For example in the frequency domain by using Fourier transform (FT), Gabor functions (Augusteijn et al., 1995; Livens et al., 1997) or even by performing calculations based on multiresolution decomposition which implies the usage of the Wavelet transform (WT) (Unser, 1995; Livens et al., 1997).

When talking about using Fourier domain information about a certain texture sample it is necessary to focus all the computation on the Fourier spectrum, especially on the real part of it. The information contained in the spectrum can be used to compute a set of features that can give information about the direction and nature of the texture. For instance, as mentioned by Lu at all (Lu et al., 1991), the square modulus of the FT can give information about the coarseness of the texture while the angular distribution can provide information about the orientation of the texture. Moreover some statistical measures can be derived from it such as (Augusteijn et al. 1995): Maximum Magnitude, Average Magnitude, Energy of Magnitude and Variance of Magnitude. Augustein at all (Augusteijn et al. 1995) also noticed that for some samples there are, so called, dominant frequencies in the spectrum that appear with higher amplitude than others so they can be used to characterize texture and that way the computation time can be lowered.

Nowadays, algorithms that use Gabor filters and Wavelet transforms are becoming more and more attractive to the computer science community. Many studies of human vision concluded that in the HVS there are certain cells that respond only to particular spatial frequencies and orientations (Feaugers, 1978; Julesz, 1975; Pollen et al., 1983). This was the origin of the idea of constructing Gabor filters that are basically a bank of filters where each filter is tuned to a specific frequency and orientation. These filters can be imagined as a Gaussian shaped window multiplied by a complex exponential term (Augusteijn et al. 1995; Lu et al., 1991; Buf et al., 1990). Once the Gabor pyramid is constructed the energy of each filter can be computed and numerical information about the examined texture obtained.

Other psycho-visual studies found that the HVS processes information in a multiscale way that involves spatial frequency analysis (Daugman, 1990). Therefore an algorithm that can construct both spatial and frequency representation of the image is needed. It can be achieved with Gabor function but this function looses the temporal information of the incoming signal while the Wavelet transform takes it into account.

Conclusively there are a lot of different approaches to the problem of texture analysis such as the Gray Level Co-concurrence Matrix (GLCM), Fourier analysis, Gabor pyramid analysis, Wavelet analysis and so on. All of them have some advantages and disadvantages that should be considered for a given application. As suggested by Unser (Unser, 1995) the problem of both the FT and the Gabor filter technique is the fact that they are computationally intensive, the results they provide are not orthogonal and it is not possible to invert them and perform for example texture synthesis. He also (Unser, 1995) proposes the usage of a multiresolution decomposition algorithm, Discreet Wavelet Frame, as he finds it to perform better than the conventional single resolution techniques showing better results in texture segmentation application. Keeping in mind that for this research segmentation is not of a curtail importance but characterization is, it was considered better to start the analysis with an approach that is easy to comprehend and implement. In this sense the GLCM approach provides a simple, statistical solution for the given problem of texture analysis. In addition this approach suggested by Haralick was implemented in a big number of studies that try to use and expand his work. With citations over 8000 times his article and recommended texture features in our opinion provide a good foundation and starting point of the process of texture characterization.

Once texture characterization is possible it would be of a great interest for both science and industry to define the effect of texture on the perceived color of a given object. For example in textile industry, an accurate visual match between the printed reproduction and the soft proof of a given material is of curtail importance for the quality of the product (Milic et al., 2011). In these cases for defining the color difference between samples with a standard color difference formula cannot be used with a satisfactory and reliable precision (Zhang et al., 1997; Johnson et al., 2003; Huertas et al., 2004) because the texture of the materials introduces a change in appearance that affects the perception of color. So far, in the topic of color differences only some general recommendations have been provided for some textures, as textile, but the change in color perception is texture dependent. Having in mind that the texture information is contained in the overall or spatial relationships present in the samples Zang and Wandell (Zhang et al., 1996) proposed a spatial extension to the CIELAB color metric that incorporates the influence of the surface structure on the perceived color difference. It takes into account the change in color sensitivity as a function of spatial pattern and simulates the spatial blurring produced by the human visual system. Therefore it is referred to as Spatial-CIELAB (S-CIELAB). The functionality and usability of this metric were tested on images with different spatial alterations (halftone, dithering etc.) and it is confirmed that S-CIELAB metric gives results that correspond with the human perceptual response better than the results obtained by the standard CIELAB metric (Zhang et al., 1997; Zhang et, al, 2007). It was also shown that SCIELAB fails to predict differences between images mapped with different tones (Bando et al., 2011) or to predict changes in images such as spatial resolution, noise, contrast or sharpening (Johnson et al., 2000). Even though this metric is not created to be a model of human vision (Johnson et al., 2000) it still provides much better results than simply using a pixel-by-pixel difference (Johnson et al., 2003). In a previous study an attempt was made to evaluate the usability of S-

CIELAB metrics for predicting the perceived differences of digitally generated textile samples (Tomic et al., 2011). The results suggested that the differences calculated in an S-CIELAB manner are closer to actual perceived differences than these obtained with standard CIELAB difference formula. Better match with perceptual data is gained for samples having higher texture strength encouraging the continuation of research in this field. As defining a metrics that incorporate changes of color with the change of surface structure and describe image differences in a manner that correlate with human perception is quite an ambitious task it needs more detailed research. We believe that by incorporating a detailed texture characterization and more detailed modeling of human texture perception into the existing color difference formulas and color appearance models can improve the color difference computation. Hence the research presented in this report was carried out to address this problem more in depth focusing first on characterizing texture.

3. Theoretical bascground

3. Theoretical background

3.1. What is texture?

One could begin the discussion about the definition of texture for example by observing the cave art of the Altamira in north of Spain (Figure 1). This approximately 300 meters long cave, famous for its Upper Paleolithic cave paintings, has drawings of wild mammals and human hands made more than 20 000 years ago (Gray, 2008). The Paleolithic art of Altamira consisting of predominantly bison figures (25 large drawings 125 and 170 cm in length), showing that the Old Stone Age man was using the natural shapes within the ceiling of the cave to get the desired effect on the drawings (Lasheras, 2004). Consciously or not the artist was using the distinct texture of the rocks for achieving different appearance of the bison. Starting from this time or maybe even earlier texture is present and important in everyday life. However, its definition is not as simple as the acceptance of its existence. One could go back all the way into the history and look for ways to define texture and lots of definitions would have been found. As the industry evolves different technologies and types of materials arise that every time adds something new to the definition of texture.

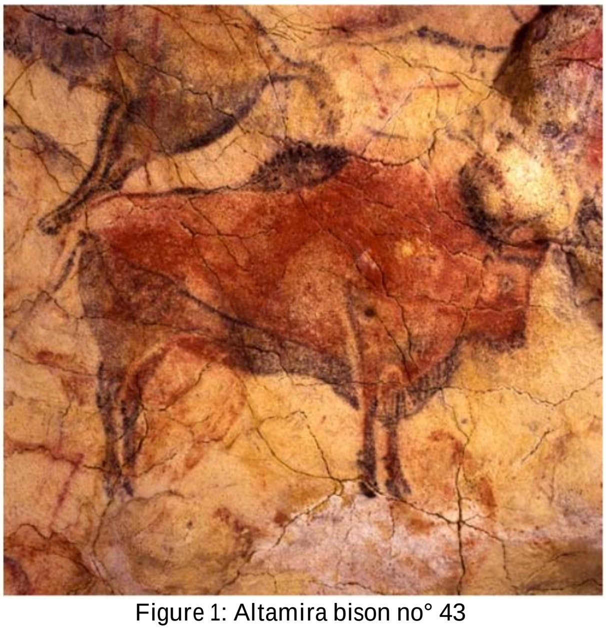


Figure 1: Altamira bison no° 43

Just the definition of texture is an important first-step in the approach to the problem. In order to define texture, in this work a little jump in time will be made from the Old Stone Age cave man to the mid XX century. If one is looking for a definition of texture, for example, in Urdang's dictionary a definition can be found stating that the word texture refers to surface characteristics and appearance of an object given by the size, shape, density, arrangement, proportion of its elementary parts (Urdang, 1968). However, this is not the only available definition. Many researchers have been trying to define textures from a certain perspective of their nature. Haralick considers a texture as an “organized area phenomenon” which can be decomposed into primitives having specific spatial distributions (Haralick et al., 1973). This definition, also known as structural approach, comes directly from human visual experience of textures. For instance, each texture in Alternatively, as Cross and Jain suggested, a texture is “a stochastic, possibly periodic, two-dimensional image field” (Mirmehdi, 2008). This definition describes a texture by a stochastic process that generates the texture, which is also known as stochastic approach. These different definitions usually lead to different computational approaches to texture analysis.

Despite all the available definitions, when working with textures one can face a problem with defining it, as texture can be treated as a property of an object, then it is a tangible property, or as a property of an appearance, than it is a simple sensation in the brain. This way texture can be separated in two big groups (Annon, 2013):

1. Tactile texture - texture as a property of a surface (also known as natural texture)

2. Visual texture – texture as a visual impression (also simulated, virtual textures belong to this group).

Tactile texture refers to the immediate tangible feel of a surface. It gives information about how an object feels like when it is touched and it can be considered as real, natural texture. What produces this tangible feeling is the difference between the high and low points on 3D surface of the material. Consequently if there is a large difference between high and low points of the surface texture can be described as rough or if there is little difference texture can be described as soft (Annon, 2013). Unfortunately the definition of texture is not that simple as natural textures often display contradicting properties, such as regularity versus randomness, uniformity versus distortion, which can hardly be described in a unified manner. These properties are the result of the non-homogeneity of the surface that results in a non-uniform surface reflectance. This basically introduces the concept of visual texture as it riches into the area of the perception of this tangible phenomena.

Visual texture refers to the visual impression that textures produces in the HVS. It is a sensation given by the eyes about how certain objects would feel like if they could be touched. Photography, paintings, drawings are good examples of producing visual textures by recreating the appearance of a texture in such a way that it produces the proper feeling. These textures are not tangible per se but the local spatial variations of simple stimuli like color, orientation and intensity in an image simulates the feeling of texture. Therefore when talking about visual texture one can refer to the perception of the natural texture or to a simulated texture that is basically an image texture (photograph, painting. drawing etc.). Image texture works in the same way as natural texture, except instead of elevation changes the highs and lows are brightness values (also called grey levels in image processing). What provides these brightness values is the mentioned non-homogeneity of the object surface. Almost all surfaces have some level of texture, or in other words elevations of different sizes that vary the reflectance of the surface locally. In many cases this difference arises from the surface roughness which tends to scatter the light randomly. In other cases the structure of the surface dominates it roughness which gives a different kind of periodic or non periodic variation. Also there are some textures that are a composite of small objects (Mirmehid et al., 2008). Depending on the mentioned type of the textures a feeling they produce will be different as well. For example if a set of textures produced due to roughness of the surface is observed the surface it creates can be rated as rough or smooth (see Figure 2).

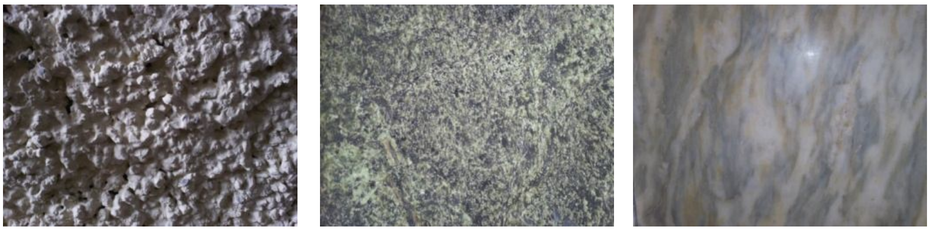


Figure 2: Examples of texture due to the roughness of the surface

If a set of textures produced due to a certain periodic or non-periodic structure is observed the surface can be rated as coarse, regular, periodic, organized, oriented, disorganized or random. These properties arise because of the grainy structure of the surface or a pattern that is repeated (see Figure 3).

Figure 3: Examples of texture due to periodic or non-periodic structure

However, the third group emphasizes the importance of the nature of the elementary objects that create texture. Sometimes what creates a perception of texture is a simple pile of elementary objects like cherry tomatoes for example. In this case the size of the element defines if the perception of a pile will be texture or a single tomato (see Figure 4).

Figure 4: Texture due to a pile of elementary objects

Therefore to some extent it can be stated that visual texture is a fiction for the HVS. This leads to the conclusion that forming any elementary, micro - object and repeating it in some meaner can produce a feeling of texture [6]. These elementary objects are called “textels” and their proper placement can produce certain appearance of texture moving its definition from a physical property of an object towards an image appearance phenomenon. Nowadays visual textures are mostly images of real, natural textures or simulated textures that are given by digitized images. Therefore textures became a matrix, a simple two dimensional array of variation. The real world reflectance variation is represented as a variation of the gray levels that an image has in the digital world. Instead of moving a finger over the surface, a "window" (usually square box) can be moved over the image to define this variation. Hence these textures can be referred to as virtual or digital textures. The variation can arise due to randomness, regularity, directionality and orientation (Mirmehid et al., 2008). This raises the level of complexity of the texture definition. The difficulty to create one uniform definition is demonstrated by the number of different texture definitions attempted by vision researchers. Coggins (Coggins, 1982) has compiled a catalogue of texture definitions in the computer vision literature and to present the level of the difficulty and variety of definitions some of them will be listed below:

> “We may regard texture as what constitutes a macroscopic region. Its structure is simply attributed to the repetitive patterns in which elements or primitives are arranged according to a placement rule.” (Tamura et al., 1978)

> “An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of its (tonal) primitives.” (Haralick. 1979)

> “Texture is defined for our purposes as an attribute of a field having no components that appear enumerable...Physically, nonenumerable (aperiodic) patterns are generated by stochastic as opposed to deterministic processes. Perceptually, however, the set of all patterns without obvious enumerable components will include many deterministic (and even periodic) textures.” (Richards et al., 1974)

These definitions all treat the same phenomenon in a totally different way. For some approaches digital texture is a structured repetition of a texture element, for others it is a variation of gray levels or a stochastic process. The selection of the definition depends on the particular application.

Mirmehdi, Xie and Suri state that it is interesting to define what texture is not. They say that if a variation in a certain texture sample is perfectly periodic it would be considered as a periodic pattern rather than texture. Likewise, any completely random pattern is treated as noise rather than texture. Therefore he emphasizes that in order to talk about texture in image processing it is curtail for the texture to have both randomness and regularity (Mirmehid et al., 2008). However, for the purpose of this work it is important to note that the line that separates noise from texture, or periodic pattern from texture is very subjective. Therefore any change of homogeneity of a given surface that can be noted by the human eye should be considered as texture because it exists and it changes the appearance of the surface.

A definition that everybody can surely agree on is that texture is a problem. It is problem because however useful it can be in some application it is not totally and precisely defined so it is a phenomenon that is not totally controllable. This is the reason because in color science texture has been normally postponed and only homogeneous samples have been usually studied. What is known is that texture is a variation of gray level values (Chen et al., 1998) in a digital image and these values can provide mathematical information that can be used to describe it. However, this description should be related with the actual perception of the gray levels that appears in the human eye. In that sense both the variation and the spatial arrangement of this variation should be taken into account. This leaves the definition open and allows combining different definitions in order to test the relation of image texture and its perception.

3.2. Texture and perception

The study of texture perception is useful both in understanding the impact of texture itself, and providing a better understanding of basic visual mechanisms that respond to texture and all visual stimuli.

To begin the explanation of the relation between texture and perception one can start analyzing an example provided by Landy and Graham presented in Figure 5 (Landy et al., 2002).

Figure 5: Example of human image analysis

On Figure 5 it can be noticed that the border between the sky and the trees/grass can be made based on a difference in luminance. In the HSV this type of variation can easily be signaled by a linear mechanism such as a simple cell in primary visual cortex. If the image would be in color this boundary and the boundary between the zebras and the background would also involve a change in chromaticity, which might be signaled by color-opponent mechanisms. But, the borders between pairs of zebras involve neither a difference in color nor in luminance. As Landy states these borders include stretches of boundary that are black on one side and white on the other and stretches where there is no local visual information to signal the boundary. Nevertheless, the HSV is able to perceive a smooth, continuous occlusion boundary at the edge of each animal. It is as if the HVS possesses the capability of segmenting regions of the image based on a local textural property by separating "vertical stuff" from "horizontal stuff" (Landy et al., 2002).

Therefore a uniformly textured region might be described as "predominantly vertically oriented", "like wood grain" or "like water." All these descriptions suggest that texture is a property that is statistically defined. Adelson and Bergen (Adelson et al., 1991) for example define texture as a property of "stuff" in the image, in contradistinction to visual features such as lines and edges.

Coming back to Figure 4 it can be noted that regions in the visual field can be characterized by differences in texture, brightness, color or other attributes. Relatively early processes in the visual system can use texture information to perform segmentation of the visual image into regions and divide the processing of the image information into subsequent computational stages. The analysis of a single textured image region can lead to the perception of categorical labels for that region. This categorization would lead to cognitive conclusions like "This looks like wood". Using this mechanism it is possible to discriminate the appearance of texture and determine whether two textured regions appear to be made of the same or different "stuff", leading to detection of a so called texture border. In the shown example this would help differentiating the zebras from the ground and recognizing 2D shapes.

Much of the work on the perception concerns the ability of observers to effortlessly discriminate certain textured areas. The traditional example for this phenomenon is shown on Figure 6.

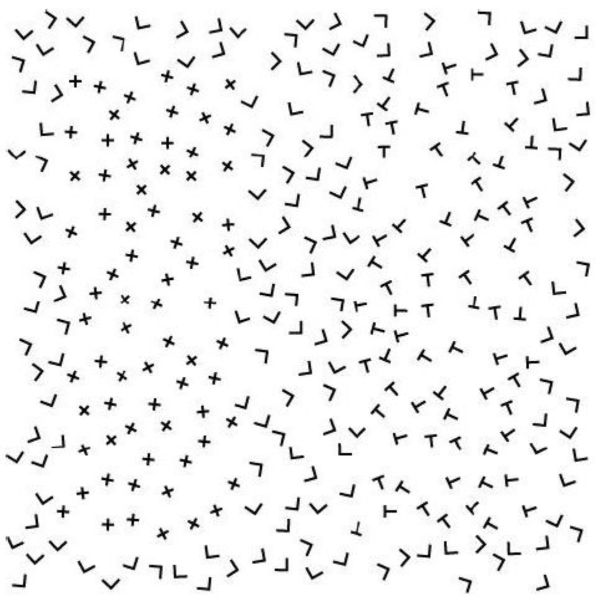


Figure 6: Example of texture segregation

Figure 5 shows rectangular regions of X's and of T's on a background of L's. Observers can easily perceive that there is a region of X's different from the background because this region has smooth, continuous borders. This is referred to as "the segregation of figure from ground" or segmentation of the image into homogenous regions. At the same time the region of T's is very hard to segregate because of not so clearly defined border. This phenomenon led, for example, Beck and Olson and their colleagues (Beck, 1972; Beck, 1973, Olson et al., 1970) to assume that textural segmentation occurs on the basis of the distribution of simple properties of "texture elements" where the simple properties were things like the brightness, color, size, and the slopes of contours and other elemental descriptors of a texture. Bergen and Julesz (Bergrn et al., 1982) suggested that this discrimination might be based on the density features as terminators, corners, and intersections within the patterns. Marr (Marr, 1976) added contour terminations as an important feature while Julesz's early efforts were centered on image statistics. He first suggested (Julesz et al., 1973) that differences joint image statistics of the gray levels are the most important for texture pairs to segregate. The work of Julesz and his colleagues led to a number of different theories related to which pairs of textures will segregate easily. Their early work led to conclusions that observers are sensitive only to differences in the first- and second-order statistics in a texture. However, because counterexamples to these conclusions have been pointed out by Yellott Julesz rephrased his conclusions in a sense that texture segregation result from differences in the characteristics of the elements (number, length, orientation, etc.) and number of terminators in the constituent textures. Later Victor (Victor, 1988) makes the case for the appropriateness of the use of population statistics for theorizing about texture segregation.

A number of investigators (Bergen et al., 1988; Caelli, 1993; Graham et al., 1992) have recently proposed computational models of texture segregation based on a set of linear spatial filters that are similar in form to cortical simple cells. Implementing a point-wise nonlinearity, and further linear spatial filtering it is possible to simulate responses similar to those of cortical complex cells. These models convert a difference in texture into a difference in response magnitude, allowing the texture edge to be enhanced and detected by conventional edge detection methods. The form of the models is inspired by neurophysiology. It has become a standard model in vision science that has unified the study of texture with other areas of spatial vision. They have been successful at modeling a variety of texture segregation phenomena such as the effects of texture element shape, size, and spacing. But it is not always true that texture element pairs lead to easy search if and only if they lead to good texture segregation (Wolfe, 1992). Even with a fixed pair of texture elements, there are often asymmetries in performance (Gurnsey et al., 1989), depending on which element is the target (or composes the foreground texture) and which the background is. In addition, the type of texture elements used is only one component of good performance on texture segregation tasks. The placement of the texture elements (at random, or in a set pattern) is also important, leading some researchers to concentrate on properties that lead to perceptual grouping of texture elements (Beck, 1982).

As it can be seen from the provided short overview there is a number of ways to explain the visual properties that are used to distinguish figure from ground and one object from neighboring objects. These properties include luminance, color, relative motion, and stereo disparity. Within a single surface there can be variation in surface reflectance, color, or surface roughness. These variations result in a textured image. These textural variations can be regular (textiles, brick walls etc.), random (sand), or in between (wood grain). The occurrence of texture in a scene is useful in a number of ways and its analysis in perception reached high importance. Texture can be used to

(1) identify the surface material (texture appearance)

(2) identify and localize edges

(3) deduce properties of the three-dimensional layout of objects and object shape

All of these capabilities have been studied both psychophysically and computationally, and there have been recent advances in understanding the neurophysiologic basis for texture perception. The selection of the type of texture perception interpretation depends highly on the application. What is common for all of them is that texture, from the neurophysiologic point of view happens in the early stages of vision. However, the perception of texture is much more complex and represents a rich and varied area of study. In the early coding of texture borders, there is some common ground between current psychophysical data and models and the physiology of primary visual cortex, such as the suggestion that texture border coding involves a succession of linear spatial filters and nonlinearities that include both static nonlinearities as well as contrast gain control mechanisms. Less well understood, however are such higher-level computations involving texture as the calculation of figure-ground, the coding of texture appearance, and the determination of depth and 3-D shape from texture cues. Therefore, accepting Julesz model of gray-level statistics, which connects image processing and vision, it seems to provide a comprehensive and applicable model for this particular research.

3.3. Texture analysis

The goal of texture analysis is to derive a general, efficient and compact quantitative description of any kind of textures. In addition it gives possibilities to perform mathematical operations for altering, transforming and comparing textures.

As mentioned in the introduction the main idea of this research is to characterize texture with numbers related with what its nature, behavior and appearance. These numbers could be the texture features defined in 1973 by Haralick (Haralick et al., 1973), but also some additional features that were proven to play an important role in texture analysis and synthesis. There are a lot to different approaches to the problem of texture analysis such as the Gray Level Co-concurrence Matrix (GLCM), Fourier analysis, Gabor pyramid analysis, Wavelet analysis and so on. This section is going to provide a short overview of the existing texture analysis methods.

3.3.1. Statistical approach

The statistical approach to texture analysis computes image signal statistics from the spatial domain of an image. Statistical methods analyze the spatial distribution of grey values and they can be classified as first order, second or even higher order. The first order statistics use only individual pixel information and calculate simple features like Mean, Standard deviation and Higher-order moments of the histogram. The second order statistics use the dependence of two pixels in order to consider pixel neighbor relationships. They define a pixel co-occurrence matrix called the Gray Level Co-occurrence Matrix. It is a so called single resolution technique that provides a relatively simple solution for calculating numerical values that can describe an image. These numerical values are statistical features that are in the texture analysis domain referred to as '*texture features*'. Texture can be thought of as a two dimensional array of variation or a frequency of change and arrangement of tones in an image[7]. As Haralick states to find features for describing texture it is necessary to follow the way the human visual system treats texture. The HVS is actually looking for spectral (average tone variation in various bands), textural (spatial distribution of tonal variations) and contextual (information from the surround) features. He states that tone and texture very often go together and that they are dependent on one another and sometimes one of them can be more dominant than the other. In this research it is assumed that the texture information in an image is contained in the overall or "average" spatial relationship which the gray tones in the image have to one another. This relationship can be represented by a gray tone spatial-dependence probability matrix also called as Gray-Level Co-occurrence Matrix (GLCM). Once the GLCM matrix is constructed texture features can be calculated from it. It is possible to compute 22 texture features as suggested in papers written by Haralick (Haralick et al., 1973, Soh et al., 1999, Clausi 2002).

3.3.2. Spectral approach

Many papers (Augustein et al., 1995; Unser, 1995; Lu et al., 1991; Buf et al., 1990; Livens et al., 1997; Feaugers, 1978; Julesz, 1975; Pollen et al., 1983; Daugman, 1990) suggest that texture analysis can be performed also in the frequency domain by using Fourier transform (FT), or Gabor functions (Augustein et al., 1995; Livens et al., 1997) or even by performing calculations based on multiresolution decomposition which implies the usage of the Wavelet transform (WT) (Unser, 1995; Livens et al., 1997).

In the Fourier approach all the computations are focused on the Fourier spectrum, especially on the real part of it. The information contained in the spectrum can be used to compute a set of features that can give information about the direction and nature of texture. The square modulus of FT the can be used to provide information about the coarseness of the texture while the angular distribution can provide information about the orientation of texture (Lu et al., 1991). Moreover some statistical measures can be derived (Augustein et al., 1995) such as: Maximum Magnitude, Average Magnitude, Energy of Magnitude and Variance of Magnitude. The

FT also gives a possibility to define dominant frequencies in the spectrum that appear with higher amplitude then others so they can be used to characterize texture and that way the computation time can be lowered(Augustein et al., 1995).

On the other hand many studies of human vision concluded that in the HVS there are certain cells that respond only to particular spatial frequencies and orientations (Livens et al., 1997; Feaugers, 1978; Julesz, 1975). This is how the Gabor filters, which are a bank of filters where each filter is tuned to a specific frequency and orientation, were constructed. These filters as basically a Gaussian shaped window multiplied by a complex exponential term defined in (Augustein et al., 1995; Lu et al., 1991; Buf et al., 1990). Once the Gabor pyramid is constructed the energy of each filter can be computed and numerical information about the examined texture can be obtained.

More psycho-visual studies found that the HVS processes information in a multiscale way that involves spatial frequency analysis (Daugman, 1990). Therefore an algorithm that can construct both spatial and frequency representation of the image is needed. It can be achieved with Gabor function but this function looses the temporal information of the incoming signal while the Wavelet transform takes it into account. Unser (Unser, 1995) stated that the problem of both the FT and the Gabor filter technique is the fact that they are computationally intensive, the results they provide are not orthogonal and it is not possible to invert them and perform for example texture synthesis. Therefore he (Unser, 1995) proposes the usage of a multiresolution decomposition algorithm for finite energy functions *f* of a continuous variable *x* – Wavelet performs better than the conventional single resolution techniques. Once the decomposition is performed the texture can be characterized by a set of *N* first-order probability density functions and alternatively channel variances can be calculated. This way, by using the Discreet Wavelet Frame that Unser proposed (Unser, 1995), the estimated texture features can be calculated with a lower variability and with better results in the final segmentation application.

The idea of the wavelet transform is to obtain detail information at different resolution levels so that some statistical calculations can be performed. When performing the WT on texture images the following pyramid can be expected:

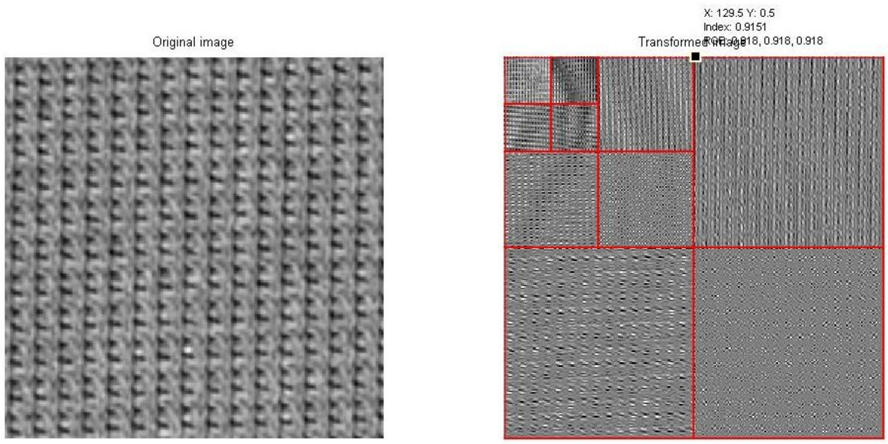


Figure 7: Original image (left) and its residual pyramid (right)

Three levels of the residual pyramid with decreasing resolution from the right bottom corner towards the top left corner can be seen on Figure 7. At every resolution level there is the vertical detail image on the top right, the horizontal detail on the bottom left and the diagonal detail on the bottom right. The image on the very top of the pyramid is the approximation image in the lowest resolution. Having this difference in resolution gives different details from the image. The low resolution provides very coarse details while high resolution gives fine detail information. Moreover the high resolution image always contains the information that is contained in the lower resolution images.

3.3.2. Generic approach

The main idea of the generic approach is application in synthesizing and better understanding of texture. It can be based on for example the structural information resent in a texture image in which hierarchy of spatial arrangements (placement rules) of texture primitive exists. Those primitives are called sub patterns (i.e. texton). In this method it is also possible to think about texture as a Complex pattern or a so called Fractal. Fractals are geometric shapes that can be split into parts, each of which is a reduced-size copy of the whole. Finally in this approach texture can also be generated by a particular stochastic process. As all these techniques are generic they are the most applicable for texture synthesis, but do not play an important role in texture characterization.

Despite the big variety of texture analysis methods not all of them can be applicable in all possible applications. Depending on the desired level of complexity and comprehension choice of a method has to be made. For the purpose of this Master Thesis the GLCM method was selected as it is proven to follow the human perception of texture and provides a computationally inexpensive way for analyzing a big set of texture samples. Therefore if it can be proven that this method relates to the effect that texture has on the perception of color it could find a computationally simple application in color difference calculations.

3.4. GLCM for texture analysis

As already mentioned this research texture will be thought of as a two dimensional array of variation or basically a frequency of change and arrangement of tones in an image (Haralick et al., 1973). As the HVS is actually looking for spectral (average tone variation in various bands), textural (spatial distribution of tonal variations) and contextual (information from the surround) features the definition of texture should follow this processing as well. It is also true that tone and texture very often go together and that they are dependent on one another and sometimes one of them can be more dominant than the other. Therefore in this research it is assumed that the texture information in an image is contained in the overall or "average" spatial relationship which the gray tones in the image have to one another. This relationship can be represented by a gray tone spatial-dependence probability matrix also called as gray-level co-occurrence matrix (GLCM). In the continuation the GLCM concept will be presented and its application in texture analysis.

3.4.1. What is GLCM?

GLCM contains information about how many times a combination of two neighboring pixels occurs in the image which can be also thought of as a probability of the occurrence of such pixel gray level combination. This can be seen schematically in the following figure.

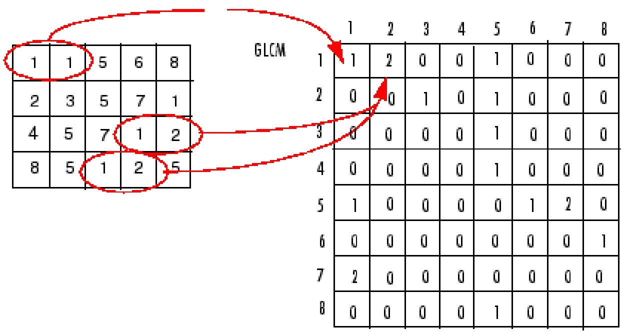


Figure 8: GLCM formation; Original image with the pixel values (right) and the horizontal GLCM matrix generated by counting how many times a combination of two neighbors appears

The reason why we decided to use the GLCM as the base for our calculations is mentioned in two of Julesz's papers (Julesz 1962, Julesz et al., 1973). In these perceptual studies based on psychology it was proven that GLCM matches the level of human perception of textures the best. In addition a huge number of studies were performed in the field of image segmentation based on texture that uses this method for feature extraction.

3.4.2. How is GLCM used in texture analysis?

The GLCM described in this research is used for a series of "second order" texture calculations. For comparison first order texture measures would be statistics calculated from the original image values, like variance, and do not consider pixel neighbor relationships while second order measures consider the relationship between groups of two (usually neighboring) pixels in the original image. There is a possibility of computing third or higher order texture measures (considering the relationships among three or more pixels) but they are not commonly implemented due to calculation time and interpretation difficulty (Annon, 2013).

GLCM considers the relation between two pixels at a time, called the reference and the neighbor pixel, then it uses second order statistics. Therefore in Figure 7 if a neighbor pixel is chosen to be the one to the right (east) of each reference pixel it can also be expressed as a (1,0) relation: 1 pixel in the *x* direction, 0 pixels in the *y* direction. Each pixel within the window becomes the reference pixel in turn, starting in the upper left corner and proceeding to the lower right. Pixels along the right edge have no right hand neighbor, so they are not used in the count. When building a GLCM some parameters like number of grey levels (N_g), distance of the GLCM (d) and orientation (θ) must be taken into account. Talking about gray-levels, it has to be considered that a real life texture is turned into a digital image that has a certain number of gray levels. This process is basically quantization of a real life texture. In the example on Figure 8 this number is 8. In this research this parameter will be set to 256 (8-bit representation).

After specifying the number of gray-levels to be used for generating the GLCM, the second parameter to be considered in this generation is a so called displacement, *D* (Soh et al., 1999). Distance, *D*, is basically the displacement between two pixels whose repetition is examined. It can be only one pixel distance or up to any that we want to use but within some reasonable range. For example if a huge displacement is applied for a fine texture it can happen that some texture information is skipped because for this kind of texture the important information is in a small region. Chen (Chen et al., 1989) used displacement values *D*=1, 2, 3, 4, 8, 16, 32 and found that single displacement value cannot be deducted for all existing textures because it depends on the type of the texture that is being investigated. Another study (Dikshit, 1996) showed that if a displacement is of the size of the texture element the image classification is better. Therefore in this study an attempt will be made to define a criterion for selecting the best distance for every texture sample based on the knowledge provide in the literature.

Finally the last important factor, the orientation in the GLCM generation, θ, was examined in different papers. For example both Haralick (Haralick et al., 1973) and Soh (Soh et al., 1999) are mentioning the importance of the orientation of the neighbor pixel. Four kinds of neighborhoods can be defined for each pixel (see Figure 9): horizontal (0°), vertical (90°) and two diagonal (-45° and 45°). The question is if this orientation affects the GLCM computations. Haralick (Haralick et al., 1973) obtained different values for each orientation while Soh states that, for example, in segmentation of ice pictures there is no systematic pattern based on orientation. Therefore the general recommendation is to use the average of the four directions, which would be followed in the work.

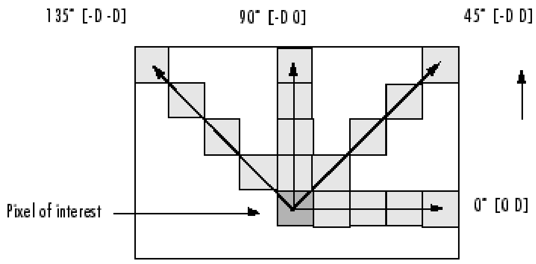
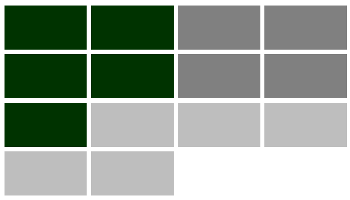


Figure 9: The spatial relationships of pixels that are defined by this array of offsets, where D represents the distance from the pixel of interest.

Once the important parameters are understood and defined the creation of the GLCM can begin. The first step in the GLCM construction is to create a so called Framework matrix. This matrix shows the possible gray level combinations for a given image. So if a simple example shown on Figure 10 is considered a framework matrix represented in Table 1 can be constructed.



0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

Figure 10: Image example and its corresponding gray level values

neighbor pixel value ref pixel value	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

Table 1: Framework matrix

The Framework matrix is showing that for this example 16 pixel grey level value combinations are possible and it will be filled in according to the observation angle. The top left cell will be filled with the number of times the combination (0,0) occurs in the image, i.e. how many times within the image area a pixel with grey level 0 (neighbor pixel) falls to the right of another pixel with grey level 0 (reference pixel). This would then create a so called *east Framework matrix* where *east* stands for the neighborhood angle (0° to the right). As there are 4 different angles there will be 4 different Framework matrixes. For each one of them the matrix will be filled according to the defined distance and angle. So if the angle is set to be the 0° (horizontal) and the distance is 1 pixel the spatial relationship framework matrix will look like this for the example on Figure 10:

2	2	1	0
0	2	0	0
0	0	3	1
0	0	0	1

Table 2: Horizontal framework matrix for distance 1

The meaning of this matrix is that in the example image on Figure 10 twice the reference pixel is 0 and its eastern neighbor is also 0. Twice the reference pixel is 0 and its eastern neighbor is 1. Three times the reference pixel is 2 and its neighbor is also 2.

The texture calculations from a GLCM require a symmetrical matrix. The next step is therefore to get the GLCM into this form. A symmetrical matrix means that the same values occur in cells on opposite sides of the diagonal. The east matrix calculated above is not symmetrical so to make it symmetric we perform the operations shown in Table 3. When counting is done in the described way, using one direction only, then the number of times the combination (2,3) occurs is not the same as the number of times the combination (3,2) occurs (for example 3 may be to the right of 2 three times, but to the left of 2 only once). However, symmetry will be achieved if each pixel pair is counted twice: once "forwards" and once "backwards". So the solution for this problem is to count the east matrix, transpose it and add together the original and the transposed matrix. This way a symmetric matrix will be obtained.

2	2	1	0		2	0	0	0		4	2	1	0
0	2	0	0	+	2	2	0	0	=	2	4	0	0
0	0	3	1		1	0	3	0		1	0	6	1
0	0	0	1		0	0	1	1		0	0	1	2

Table 3: Operations making the Framework matrix symmetric

After making the GLCM symmetrical, there is still one step to take before texture features can be calculated. The features require that each GLCM cell contains not a count, but the probability of the neighborhood appearance. This way it is possible as well to see if for example a horizontal combination of (2,2) in the original image is more likely than (2,3). The simplest definition of the probability of a given outcome is: "the number of times this outcome occurs divided by the total number of possible outcomes" (Annon, 2013). Therefore if the combination (2,2) occurs 6 times out of 24, for a probability of 1/4 or 0.250. This process is called normalizing the matrix and the normalization equation is shown below:

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N_g-1} V_{i,j}} \tag{3.1}$$

where *i* and *j* are the horizontal and vertical coordinates of the Framework matrix. The range of summation, (i,j=0) to (N_g-1) means simply that each cell in the GLCM should be considered. This way a probability matrix is obtained and this is the normalized GLCM.

Once the GLCM matrix is constructed texture features can be calculated from it. It is possible to compute 22 texture features which are explained in the following section. They can be calculated as suggested in papers written by Haralick (Haralick et al., 1973), Soh (Soh et al., 1999) and Clausi (Clausi, 2002).

3.4.3. GLCM texture feature description

In the following section important notations that were used to describe each feature mathematically can be found.

- *p(i; j) = (i; j)th* entry in a normalized GLCM probability value from the GLCM, i.e. how many times that reference value occurs in a specific combination with a neighbour pixel.
- N_g = the number of gray levels
- $p_x(i) = \sum_{j=1}^{N_g} p(i,j)$ *ith* entry in the marginal-probability matrix obtained by summing the rows of p(i,j)
- $p_y(i) = \sum_{i=1}^{N_g} p(i,j)$
- $p_{x+y}(k) = \sum_{i,j:i+j=k} p(i,j)$ for $k = 2, 3, \dots, 2N_g$
- $p_{x-y}(k) = \sum_{i,j:|i-j|=k} p(i,j)$ for $k = 0, 1, \dots, N_g - 1$
- μ = mean of $p(i,j)$
- μ_x, μ_y = means of p_x and p_y respectively
- $\mu_{x-y}(i) = \sum_{i=0}^{N_g-1} i p_{x-y}(i)$
- σ_x, σ_y = standard deviation of p_x and p_y respectively
- HX, HY = entropies of px and py respectively
- $HXY1 = -\sum_i \sum_j p(i,j) \log(p_x(i) p_y(j))$
- $HXY2 = -\sum_i \sum_j p_x(i) p_y(j) \log(p_x(i) p_y(j))$

It is important to keep in mind that from the texture sample first the GLCM was constructed and then the calculations of texture features from this matrix were performed. These calculations are actually second order statistical features. These features can help to look for ways to describe texture. In order to be able to do this description it is important to understand the meaning of all these features. Some of the below listed features have actual, physical meaning but some of them are simply a mathematical tool that can be used to numerically describe texture. The following section describes every feature and explains the physical meaning if any found in the actual texture analysis case. Please note that the order of the features in the explanation corresponds to their order in the code used for calculation. Also in the used code Correlation and Homogeneity were calculated two times – once as suggested in the cited papers and once with the embedded formula in MATLAB®. It turns out that the results for both ways of calculation are the same therefore only one of these can be used. In total the 22 features are the following ones (Haralick et al., 1973; Soh et al., 1999; Clausi, 2002)

1. Autocorrelation

$$Autocorrelation = \sum_{i,j} (ij) p(i,j) \qquad (3.2)$$

The autocorrelation function was created with the idea to detect non-randomness in certain data. Is a correlation coefficient that defines correlation between the image itself and the image translated with a displacement vector, d = (dx, dy). In the case of GLCM this displacement was defined when the matrix itself was constructed. Initially autocorrelation was used directly on the texture image itself to detect its repetitive nature and describe it as fine or coarse. The obtained function will drop off slowly if the texture is coarse and rapidly it is fine while regular textures will have repetitive peaks and valleys and random textures would have only one peak. (From the good presentation found) This is an interesting parameter to study because it might give us some basic information about the main nature of texture that we can use later to select features to be calculated. For example if we have a very fine texture it might be not of big help to calculate contrast because it will not provide any significant information and so on.

2. Contrast

$$Contrast = \sum_{i,j} |i-j|^2 p(i,j) \qquad (3.3)$$

Contrast is in general the measure of local gray-level variations in an image. In our case it would be the local grey level variation in the grey level co-occurrence matrix. It can be thought of as a linear dependency of grey levels of neighboring pixels meaning that the contrast is calculated between a pixel and its neighbor over the whole image. If the neighboring pixels are very similar in their grey level values then the contrast in this image is very low. In the case of texture we can use this feature to get information the amount of variation present in it.

This feature is typically high, when the scale of local texture is larger than the *distance selected for the formation of GLCM*. Therefore we could expect high contrast values for heavy textures and lower for smooth, soft textures.

The range of the contrast is [0 (size (GLCM, 1)-1) ^2] where Contrast is 0 for a constant image.

3. Correlation

In general correlation describes the strength and direction of the linear relationship between two variables. In our case it measures the linear dependency of grey levels of neighboring pixels in a texture image. It returns a measure of how correlated a pixel is to its neighbor over the whole image. Meaning how linearly dependent a pixel of grey level i in relation to a neighbor with grey level j is. The absolute value of this feature can tell us how strong the relationship between the examined neighbors is while the sign tell us if the correlation is positive of negative. Positive correlation means that neighbor's values are changing (increasing / decreasing) together (as the values of one increase / decrease, the values of the second also increase / decrease). Negative correlation defines opposite change of neighbor's values (as the values of one increase, the values of the second decrease and as the values of one decrease, the values of the second increase).

$$Correlation = \frac{\sum_i \sum_j (ij)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{3.4}$$

For the purpose of this research it is interesting for us to see how the correlation is behaving with different angles and distances for the GLCM. If we have higher values in one direction it gives information about the orientation of texture for example. We can expect high values of correlation for uniform patches and strong textures especially if the displacement value selected is smaller than the texture element. In the case of smooth texture with small texture elements the correlation can be expected to be smaller because at some size texture can turn into noise and noise is very much uncorrelated.

The range of this feature is [-1 1].

Correlation is 1 or -1 for a perfectly positively or negatively correlated image and is not defined (NaN in MATLAB®) for a constant image. It can be typically high when the scale of local texture is larger than the *distance*.

4. Cluster Prominence

$$Cluster\ Prominance = \sum_{i,j} \left(i + j - \mu_x - \mu_y\right)^4 p(i,j) \tag{3.5}$$

5. Cluster Shade

$$Cluster\ Shade = \sum_{i,j} \left(i + j - \mu_x - \mu_y\right)^3 p(i,j) \tag{3.6}$$

6. Dissimilarity

$$Dissimilarity = \sum_{i,j} |i - j| p(i,j) \tag{3.7}$$

Dissimilarity is another feature that measures the variation of gray level pairs in an image. It is the closest to Contrast with a difference in the weight – Contrast unlike Dissimilarity grows quadratically. Therefore we can expect that these two measures will behave in the same way for the same texture because they basically calculate the same thing just with different weights. Contrast will always give slightly higher values than Dissimilarity. Dissimilarity has the range [0 1] and it is maximum when the gray level of the reference and neighbor pixel is at the extremes of the possible gray levels in the texture sample.

7. Angular second moment (Energy)

$$\mathrm{ASM} = \sum_{\mathrm{i,j}} p(i,j)^2 \tag{3.8}$$

Angular second moment (ASM) can also be referred to as the Energy of the given data. If we take a look at the formula the ASM is the sum of the squared elements of the GLCM matrix. ASM is a measure of local homogeneity therefore it represents the opposite of the Entropy. Basically this feature will tell us how homogenous, how uniform the texture we are analyzing is. We could expect that form a very strong texture with big texture elements we are going to get lower homogeneity while small texture elements may give higher homogeneity values.

In classical image processing applications the ASM would have been calculated over the pixels enclosed by a certain sliding window. In that case high values of ASM occur when the pixels in the window are very similar. Our case is not much different concerning the out coming result because the GLCM preserves the information about the relationship of the neighboring pixels and the ASM can be calculated directly on it.

Conclusively: the higher the value of ASM, the bigger the homogeneity of the texture. The range of ASM is [0 1] where ASM is 1 for a constant image or in our case a sample without any texture.

8. Entropy

$$Entropy = -\sum_{i,j} p(i,j) \log\left(p(i,j)\right) \tag{3.9}$$

Entropy comes from thermodynamics describing a quantity of energy that is permanently lost every time a reaction or a physical transformation occurs. This entropy cannot be useful or recovered therefore it represents a disorder or more precisely chaos. In the case of our texture analysis entropy is a measure of spatial disorder in an image. If the disorder is high the entropy is high as well. This will occur is the GLCM has many elements with small values meaning that there is no repetition of same kind of neighbor combination in the texture. A completely random distribution would have very high entropy because it in its sense represents chaos. This feature can be useful to tell us if entropy is bigger for heavy textures or for the smooth textures giving us information about which type of texture can be considered statistically more chaotic.

9. Homogeneity

$$Homogeneity = \sum_{i,j} \frac{1}{1-(i-j)^2} p(i,j) \tag{3.10}$$

Homogeneity gives information about how little change there is in an image. The equation above shows that the homogeneity basically weights values by the inverse of contrast weight. From the statistical point of view, to be homogeneous means to be statistically stationary which in the, case of texture, means that certain signal statistics of each texture region are having the same values. Therefore strong homogeneous textures contain ideal repetitive structures while weak homogeneity refers to variation in texture elements in their spatial arrangements. An inhomogeneous texture mostly refers to an image where repetition and spatial self-similarity are absent.

If we are performing homogeneity calculations on the GLCM we are actually measuring the closeness of the distribution of elements in the GLCM to the GLCM diagonal. The diagonal elements all represent pixel pairs with no grey level difference (0-0, 1-1, 2-2, 3-3 etc.). The farther we go from the diagonal, the greater the difference between pixel grey levels is. Therefore the GLCM homogeneity of any texture is high if GLCM concentrates along the diagonal meaning that there are a lot of pixels with the same or very similar gray level value. The larger the changes in gray values, the lower the GLCM homogeneity making higher the GLCM contrast. This implies that if the contrast of a texture is low for example for a very smooth texture we can expect to get high homogeneity. This feature can help in defining the initial nature of the texture examined and check and compare it results with the values of the contrast.

The range of homogeneity is [0 1] where homogeneity is 1 for a diagonal GLCM and low values are associated with low homogeneity and high values with high homogeneity. If the image has little variation it has high homogeneity and if there is no variation, meaning that neighboring pixels have same gray level values, homogeneity is 1.

10. Maximum probability

$$\text{Maximum probability} = \underset{i,j}{\text{MAX}}\ p(i,j) \tag{3.11}$$

Maximum probability is simply the largest entry in the given matrix or image, and corresponds to the strongest response. In the case of the GLCM maximum probability will occur with high value if one combination of pixels dominates the in the texture sample. This can give additional information about the orderliness of the texture and we can also test the behavior of this feature with heavy and smooth textures to see if it gives significant information about the nature of texture.

11. Sum of Squares (Variance)

$$Variance = \sum_{i,j} (i-\mu)^2 p(i,j) \tag{3.12}$$

In probability theory and statistics, the variance is a measure of how far a set of numbers is spread out. It is one of several descriptors of a probability distribution, describing how far the numbers lie from the mean. This mean can be usually thought of as an expected value. In the case of GLCM variance relies on the mean and the dispersion around the mean of cells in the GLCM matrix. More precisely a cell in the GLCM matrix is a combination of a reference pixel and its neighbor pixel. Therefore we are checking the variance of this relationship. As in regular use of variance also here the more the pixels vary from the mean the bigger the variance. At this point the question about the range of variance arises because it can be any positive number. It is important to note and keep being alerted on what can make the variance be very high. One possibility is a large spread in the data; the other is the data may contain an outlier(s) that is causing it to be too high or a combination of both. Keeping this in mind can help us notice some possible mistakes in the texture or big changes in certain direction of the GLCM.

Once we have the value of variance it is easy to calculate the standard deviation that can give additional information about the range of data which some references find not too useful. What is more important is to get information about what the dispersion of the difference between the reference and the neighbor pixels in this window is.

12. Sum average

$$Sum\ Average = \sum_{1=2}^{2N_g} ip_{x+y}(i) \tag{3.13}$$

13. Sum variance

$$Sum\ Variance = \sum_{1=2}^{2N_g} (i - Sum\ Entropy)^2 p_{x+y}(i) \tag{3.14}$$

14. Sum entropy

$$Sum\ Entropy = -\sum_{1=2}^{2N_g} p_{x+y}(i) \log\{p_{x+y}(i)\} \tag{3.15}$$

15. Difference variance

$$Difference\ Variance = variance\ of\ p_{x-y} \tag{3.16}$$

16. Difference entropy

$$Difference\ Entropy = -\sum_{1=0}^{2N_{g-1}} p_{x-y}(i) \log\{p_{x-y}(i)\} \tag{3.17}$$

17. Information measure of correlation 1

$$Information\ Measure\ of\ Correlation1 = \frac{HXY - HXY1}{\max\{HX, HY\}} \tag{3.18}$$

18. Information measure of correlation 2

$$Information\ Measure\ of\ Correlation2 = (1 - \exp[-2(HXY2 - HXY)])^{1/2} \tag{3.19}$$

19. Inverse difference normalized (INN)

$$Inverse\ difference = \sum_{i,j} \frac{p_{ij}}{1 + |i - j| / N_g} \tag{3.20}$$

20. Inverse difference moment normalized (IDN)

$$Inverse\ difference\ moment\ norm. = \sum_{i,j} \frac{p_{ij}}{1 + (i - j)^2 / N_g} \tag{3.21}$$

4. Method and results

4. Method and results

4.1. Plan and algorithm of the experimental part

In order to reach the goal of this research, that is to find appropriate texture features, related with its perception that can be used for describing texture in an objective and numerical sense and use these findings to describe its effect on the perceived color differences the methods described in the theoretical background were implemented. As it is a complex task the method in this research was divided into three big phases:

1. Computation of texture features
2. Realization of the visual experiment
3. Computation of color difference

Figure 11 show the algorithm and the three most important phases.

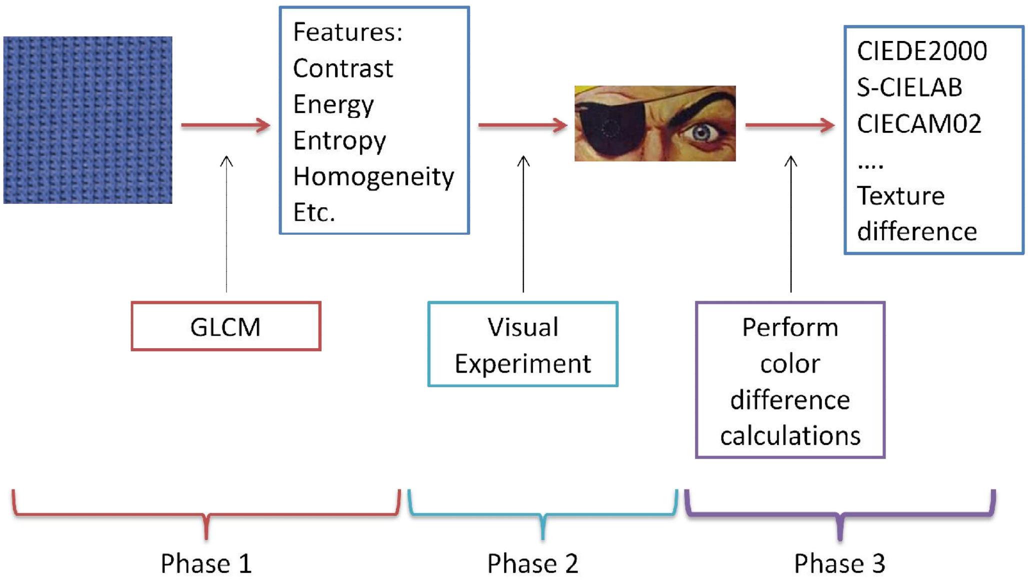


Figure 11: The algorithm of this research and the three most important phases

As Figure 11 suggests the first phase of this experimental research basically represents the computational experiments and it can be divided into the following subsections:

1.1. Texture database selection
1.2. Selection of computational tools
1.3. GLCM distance experiment
1.4. Sample resolution experiment
1.5. Scale experiment
1.6. Principal Component Analysis (PCA)

1.7. Summary of the results, conclusions and discussion

Therefore in this phase the careful selection of samples was performed with an idea to have a set of different texture images. Once it has been selected the preparation of the computational tools was made by writing codes in MATLAB®. To test how different parameters affect the results different computational experiments were performed. These experiments allowed seeing the effect of resolution, GLCM distance and scale on texture feature computations. PCA dimensionality reduction technique was applied with an idea to select the most important texture features and reduce the redundancy between them and select samples for the visual experiment. Finally all the results were examined and a list of conclusions from this phase is provided suggesting a new criterion for the GLCM distance selection for each texture sample, providing only 5 most important texture features and sets of texture images for the visual experiment.

The second phase is performing visual experiments and relating the results they provide with the results from the computational experiments. It can be divided into the following subsections:

2.1. Preparation of the samples
2.2. Preparation of the laboratory
2.3. Observer selection and tasks
2.4. Testing observer's reliability
2.5. The Sorter Experiment
2.6. The Grouper Experiment
2.7. Summary of the results, conclusion and discussion

In order to perform the visual experiment from the big set of samples 6 sets were selected according to the PCA performed in the first phase. The laboratory was prepared with the aim to remove any stray light or items that can disturb the observer's attention. They were asked to perform two different experiments each one of them two times on two different occasions. Finally the results were examined and compared with the computational experiments.

The third phase is the commutation of color differences between a pure, homogenous color sample and a sample having the same color but an additional texture. Of necessity the third phase will be left as future work. In order to perform these computations the following phases are planned to be followed:

3.1. Preparation of the samples
3.2. Computation of color differences
3.3. Summary of the results, conclusion and discussion

After performing the preparation of the samples different color difference formulas like CIE76, CIE94, CIEDE200, DIN99de, CIECAM02, S-CIELAB can be applied to them. The initial results, obtained in previous research (Tomic et al., 2011), shown that the different performance of the color difference formulas and the need for further visual experiments that will indicate which one of them models the perception of texture in the best way.

According to the analysis performed in this research it can be seen that texture characterization can be done by relying on the results of the visual experiment. It also suggests application of different dimensionality reduction technique in order to select more independent features. Conclusively it represents the first step towards having a feature scale that will be related with the human perception of texture.

4.2. Computation of texture features

4.2.1. Texture database selection

In order to conduct a reliable research it is important to have a reliable database of samples. Therefore the very first step of this thesis was to select the texture database. One of the most well known and most used texture databases in computer vision and signal processing is the Brodatz texture database. Despite the popularity Brodatz textures are copyrighted therefore other textures databases have been taken into consideration. More precisely two: KTH-TIPS and KTH-TIPS2. These two databases are a continuation of a so called CUReT texture database.

The CUReT database is a collection of 61 real-world surfaces. Its name stands for “Columbia-Utrecht Reflectance and Texture Database” (Annon, 2013). The samples in this database were chosen in such way that they span a wide range of geometric and photometric material properties. The categories include specular surfaces (aluminum foil, artificial grass), diffuse surfaces (plaster, concrete), isotropic surfaces (cork, leather, styrofoam), anisotropic surfaces (straw, corduroy, corn husk), surfaces with large height variations (crumpled paper, terrycloth, pebbles), surfaces with small height variations (sandpaper, quarry tile, brick), pastel surfaces (paper, cotton), colored surfaces (velvet, rug), natural surfaces (moss, lettuce, fur) and man-made surfaces (sponge, terrycloth, velvet) (Annon, 2013). This database is used for texture segmentation and classification mostly. However, a relatively small number of studies considered variation within each texture class. Usually experiments use the exact same sample, or different patches from the same image as training and test sets (Caputo et al., 2005). Therefore, in order to be able to use a texture database to recognize categories of textures the CUReT database was extended in two directions. By providing variations in scale, pose and illumination, and by imaging other samples as a subset of its material category in different settings categories of textures can be made.

This is how KTH-TIPS and KTH-TIPS2 were born. The names of the database stand for “**K**ungliga **T**ekniska **H**ögskolan - **T**extures under varying **I**llumination, **P**ose, and **S**cale”. The idea of this database is to keep the variety of real-world surfaces as initiated in the CUReT database and add more textures and variations of each texture in illumination, pose and scale. KTH-TIPS and KTH-TIPS2 incluse three illumination conditions: from the front, from the side at roughly 45° and from the top at roughly 45°. They also include three poses of the camera frontal, rotated 22.5° left and rotated 22.5° right [5]. For each texture type images were taken at 9 different scales, where the scale is a distance between the camera and the sample. In order to construct the databases their authors used an Olympus C-3030ZOOM digital camera at a resolution of 1280 × 960 pixels to acquire texture images. As many of the full-size images contain not only the sample, but also some background all of them were cropped to have a final 200x200 pixels resolution.

1. KTH-TIPS database: Contains 10 texture types from those available in the CUReT database. Table 4 shows those texture types and their corresponding reference numbers (Fritz et al, 2004) and Figure 12 the textures themselves.

Material	Corresponding CUReT sample number
Sandpaper	6
Crumpled aluminum foil	15
Styrofoam	20
Sponge	21
Corduroy	42
Linen	44
Cotton	46
Brown bread	48
Orange peel	55
Cracker B	30

Table 4: The materials present in the KTH-TIPS database

Figure 12: Images of the materials present in the KTH-TIPS database in the resolution 200x200px

For each texture type images were taken at 9 different scales, where the central scale corresponds to the distance between the camera and the sample of 28cm, and it corresponds roughly to the default scale in the CUReT database. From this central scale the images were equally spaced logarithmically over two octaves. The distances corresponding to the scales are shown in Table 5.

Scale number	Relative scale	Distance to camera (cm)
1	$2^{-1.00}$=0.500	14.00
2	$2^{-0.75}$=0.595	16.65
3	2^{-50}=0.707	19.80
4	$2^{-0.25}$=0.841	23.55
5	$2^{-0.00}$=1.000	28.00
6	$2^{+0.25}$=1.189	33.30
7	$2^{+0.50}$=1.414	39.60
8	$2^{+0.75}$=1.682	47.09
9	$2^{+1.00}$=2.000	56.00

Table 5: The scales present in the KTH-TIPS database

For each scale one example of the corresponding images can be seen in the following figure.

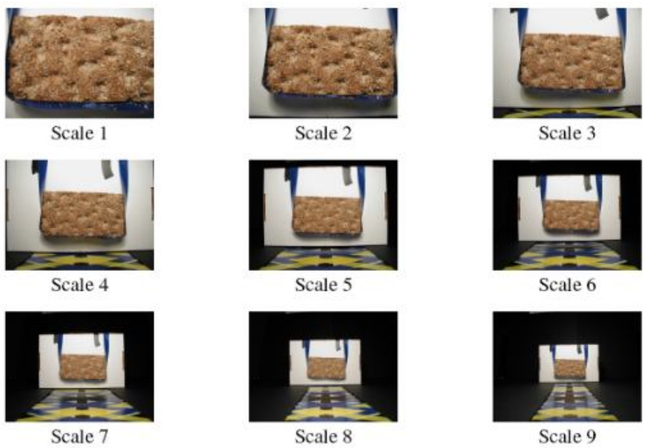


Figure 13: Full-size images depicting the variation of scale present in the KTH-TIPS database

Figure 13 shows that the scale in this database is the distance between the sample and the camera taking the image of it. The bigger the distance the scale of the texture is smaller therefore for Scale#1 the texture is bigger than for Scale#9 where the sample becomes almost homogenous.

In addition, for each one of the 9 sales, 9 images were taken by changing the pose of the sample and the position of the illumination. The three poses were frontal, rotated 22.5° left and rotated 22.5° right (changing row wise in Figure 13); and the three illumination conditions were: from the front, from the side at roughly 45° and from the top at roughly 45° (changing column wise in Figure 14) (Fritz et al, 2004).

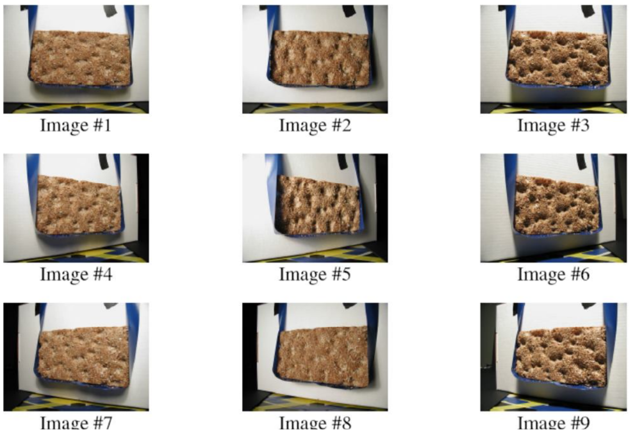


Figure 14: The variation of pose and illumination present in the KTH-TIPS database. In each row the pose is constant, whereas in each column the illumination is the same

From Figure 14 it can be noted that the change of pose and illumination produces different brightness changes in an image and produces in fact different texture effect. This way the initial material is kept but the variation of the observation conditions changes its appearance producing a set of images on which categorization can be performed. In addition on both Figure 11 and 12 it can be seen that the images include the background and that they had to be cut to the size 200x200px in order to include the texture only.

2. KTH-TIPS2 database: Contains 11 materials from those available in the CUReT database and 6 present in the KTH – TIPS database. Table 6, shows those texture types and their corresponding reference numbers (Mallikarjuna et al., 2006) and Figure 15 the textures themselves.

Material	Corresponding CUReT sample number	Present in KTH-TIPS
Crumpled aluminium foil	15	x
Cork	16	
Wool	22	
Lettuce leaf	23	
Coruduroy	42	x
Linen	44	x
Cotton	46	x
Brown bread	48	x
White bread	52	
Wood	54	
Cracker	59 and 60	x

Table 6: The materials present in the KTH-TIPS2 database

Figure 15: The variations within each category of the new TIPS2 database.

Figure 15 shows that within every material group or texture category there are four different texture samples expanding the usefulness for categorization of this dataset. Besides the difference that KTH-TIPS2 has 4 samples for each texture category (opposed to only one in KTH-TIPS), it adds one more illumination (fluorescent ambient lab light) and it removes the Scale#1 as it was proven to give blurry images for some textures in KTH-TIPS and adds one more scale, named 10, to have in total 9. Table 7 summarizes the scales used in KTH-TIPS2.

Scale number	Relative scale	Distance to camera (cm)
2	$2^{-0.75}$=0.595	16.65
3	2^{-50}=0.707	19.80
4	$2^{-0.25}$=0.841	23.55
5	$2^{-0.00}$=1.000	28.00
6	$2^{+0.25}$=1.189	33.30
7	$2^{+0.50}$=1.414	39.60
8	$2^{+0.75}$=1.682	47.09
9	$2^{+1.00}$=2.000	56.00
10	$2^{+1.25}$=2.378	64.41

Table 7: The scales present in the KTH-TIPS2 database

Figure 16 shows one example of images obtained under 9 different scales. In this case the first scale is Scale#2 and the last one is Scale#10.

Figure 16: Full-size images depicting the variation of scale present in the KTH-TIPS2 database.

Starting the scales from Scale#2 insures that all the images will be in focus. Adding one more scale gives a possibility to have in total 9 scales as it was the case in KTH-TIPS but from these 9 scales only 8 (Scale 2 to Scale 9) are common in the two databases.

Figure 17 shows the illumination and pose variations used in this dataset. The three poses were again frontal, rotated 22.5° left and rotated 22.5° right (changing row wise in Figure 17); and the three illumination conditions were: from the front, from the side at roughly 45° and from the top at roughly 45° (changing column wise in Figure 17). In addition there is one more illumination (fluorescent ambient lab light) in the last row (Mallikarjuna et al., 2006).

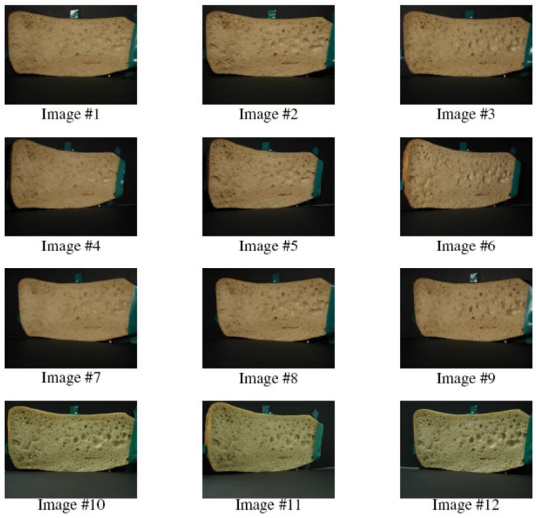


Figure 17: The variation of pose and illumination present in the KTH-TIPS2 database.

Introducing additional fluorescent lamp changes not only the brightness levels in images but also the color of the sample introducing additional variability.

As the goal of the research is not to test the effect of the pose of the sample on texture but to test the usability of certain texture features for texture characterization, using the whole database is not necessary. In addition it will introduce to many degrees of freedom and parameters to control. However, it is interesting to see if the parameters characterizing textures are independent of the distance, viewing angle, etc. Therefore for the purpose of this thesis, which is to characterize texture, there is no need to test its change with the pose, which results in visually quite different textures, however the position of the illumination and the scale can be interesting factors. Therefore all the images obtained by varying the pose of the sample were neglected and only the images obtained as a combination of the frontal position of the camera and all illumination positions were considered.

In addition not all the scales were considered. From the KTH-TIPS Scale#1 (see Table 12) was neglected because it was proven by the authors that the majority of the images for this scale are blurry (Fritz et al., 2004; Mallikarjuna et al., 2006). From KTH-TIPS2 the Scale#10 (see Table 14) was neglected as it produces mostly very homogeneous samples and additionally it does not have its corresponding scale in KTH-TIPS. This way for all the samples from both databases the same number of scales can be used. These criteria apply for all the texture types – 10 in KTH-TIPS and 11 in KTH-TIPS2.

Conclusively the final dataset employed in this work looks as follows:

- KTH-TIPS: images 1,2,3 (Figure 14) and scales from 2 to 9 (Figure 13). This gives a total of: 3 illuminations x 8 scales x 10 groups = 240 samples
- KTH-TIPS2: images 1,2,3,10 (Figure 17) and scales from 2 to 9 (Figure 16). This gives a total of: 4illuminations x 4 samples for each group x 8scales x 11 groups = 1408 samples

TOTAL: 1648 different images

The final set of samples gives a big database that can be useful to test texture features and even give a possibility of generalizing the results.

4.2.2. Selection of computational tools

In order to perform the computations in this phase the GLCM method was selected. This method implies that the texture information in an image is contained in the overall or "average" spatial relationship which the gray tones in the image have to one another. The gray tone spatial-dependence probability matrix also called as gray-level co-occurrence matrix (GLCM) represents this tonal relationship. Containing the probability of the occurrence of a pixel gray level combination the GLCM contains information about how many times a combination of two neighboring pixels occurs in an image. This can be seen schematically in the following figure.

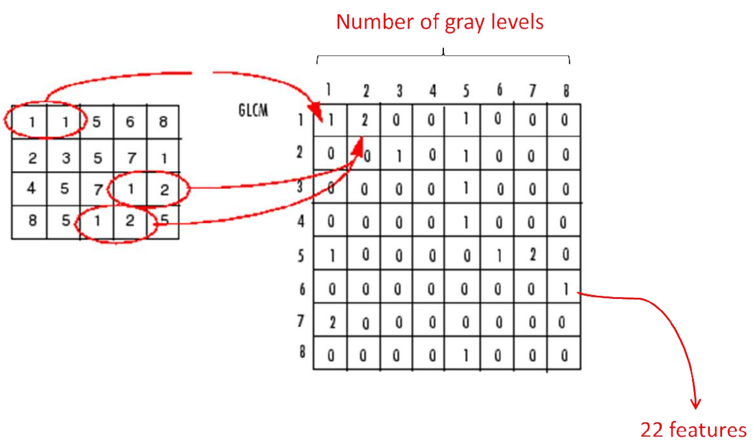


Figure 18: GLCM formation; Original image with the pixel values (right) and the horizontal GLCM matrix generated by counting how many times a combination of two neighbors appears

Once the number of combination repetitions is calculated the values are normalized so that the final entries in the GLCM are the probability values of the occurrence of a certain pixel gray level combination. Using these probabilities 22 texture features can be computed. However, before performing the computations some parameters should be taken into consideration. These parameters are the resolution of the images, scale used in the texture database and the parameters defined for the GLCM computations like the angle and the distance, as mentioned before. The meaning of parameters is graphically represented on the following figure:

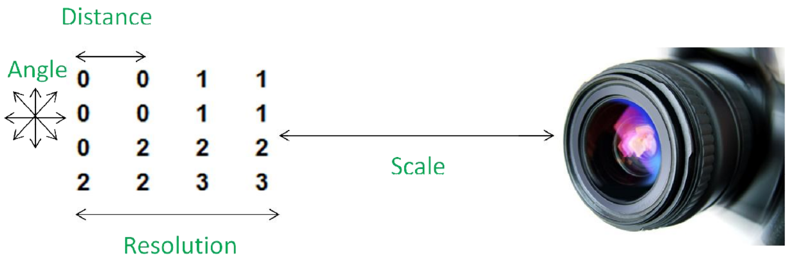
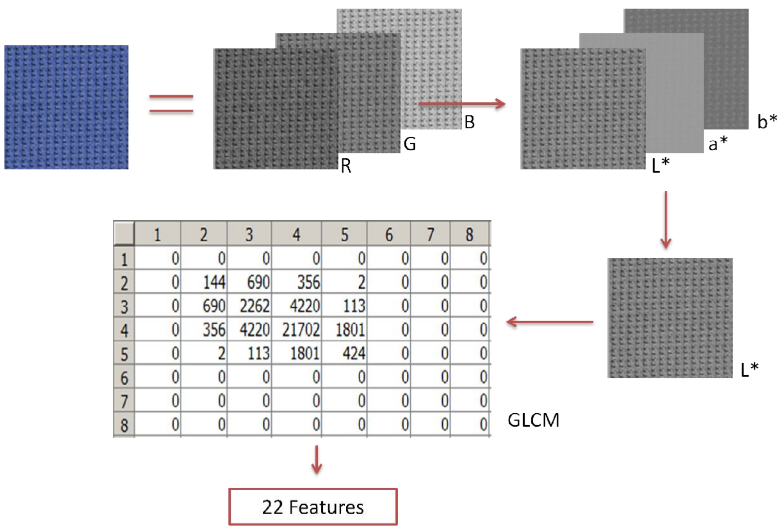


Figure 19: Parameters to be considered in the feature computations

In the continuation different computational experiments were performed in order to select the proper values of each one of the listed parameters. However prior to the computational experiments it is interesting to comment on the relation between the texture information and the channels of a texture image. A texture image is an RGB image and it has three color channels R, G and B. These three channels are dependent between themselves and their mixture produces the final image. As Figure 19 suggests the texture information in an RGB image is mixed between the three channels but the nature of this mixture is not known and for different images it is different. Therefore, it is desirable to move from the RGB space to another space where texture can be represented more clearly and independently.



	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	144	690	356	2	0	0	0
3	0	690	2262	4220	113	0	0	0
4	0	356	4220	21702	1801	0	0	0
5	0	2	113	1801	424	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0

Figure 20: Preview of the steps followed in the texture feature computations

Figure 20 shows that by transforming the image to L*a*b* space it can be noticed that the texture information is mostly concentrated on the lightness channel. Some information is concentrated on the chroma and hue channels but it is the minority of the information. In addition statistical data showed that the texture of an image has the greatest influence on the L* channel, a less intense but still significant influence on the C* channel while the H channel is approximately constant and almost not influenced by it (Milic et al., 2010). These findings encouraged a lot of researchers, like Shen and Xin to use the *L*a*b** or *LCH* color spaces for mapping color onto texture samples (Xin et al., 2003; Xin et al., 2005). Therefore all the calculations in this work will be performed on the lightness channel of the *L*a*b** image. In order to transform the RGB image to the *L*a*b** image, sRGB was assumed and the traditional transformation matrix was applied to every pixel in the RGB image. This matrix is shown below:

$$\begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \tag{4.1}$$

The lightness channel is isolated and its values were normalized by dividing with 100 in order to change the range to [0 1] and those values were used for the GLCM computations. The GLCM can be computed for 4 different angles and for any desirable distance. In this research the mean angle was used as suggested in the literature. The code used generates a normalized GLCM by computing the sum of all the values in each GLCM in the array and dividing each element by this sum. This way the probability of the occurrence of a certain pixel gray level combination is obtained. The 22 features are then computed from these probability values as described in the section 3.5.3.

With these steps all the computational tool are ready to be used. In the continuation these tools will be used to select the most proper distance for the GLCM computation and to test the effect of the sample resolution and scale on the computed feature values.

4.2.3. GLCM distance experiment

In this experiment a set of computations were performed in order to define the proper distance for the GLCM creation. Distance of the GLCM, D, is basically the displacement between the two pixels whose repetition is examined. It can be for example only one pixel distance or up to any within some reasonable range. For example if a huge displacement is applied for a fine texture it can happen that the texture information gets missed because for this kind of texture the information is in a small region. Chen (Chen et al., 1989) used displacement values d=1, 2, 3, 4, 8, 16, 32 and found that single displacement value cannot be deducted because it depends on the type of the texture that is being investigated. Another study (Dikshit, 1996) showed that if a displacement is of a size of a texture element the image classification is better. Therefore a question arises about which distance to use during the experiments. Figure 20 illustrates the defined problem. Different textures should have different distances as they have different natures. Focusing on the black and white images in the lower row of Figure 21 it can be noted that if a distance of 4 pixels is used for the first image it will be a good choice as it includes the texture element. However using the same distance for the third image will skip the texture element and basically average it out from the computation. More than one texture element would lead to a kind of a averaging and softening of the actual texture because all those pixels are going to be skipped in the GLCM generation which is not desirable. Therefore, if a texture is for example very homogenous opposed to a very irregular these two cannot have the same distance for the GLCM computations in order to avoid missing out the important gray level combination information contained in the image.

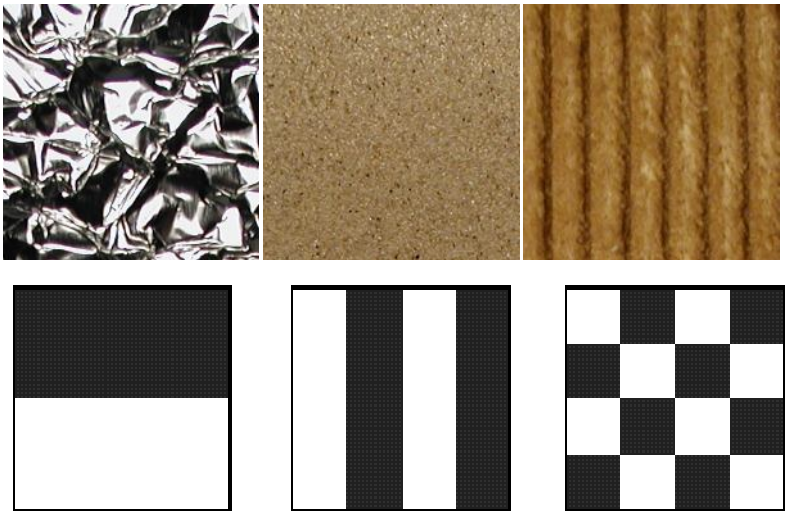


Figure 21: Graphical representation of the GLCM distance problem

Relaying on the findings of our references an idea to find the size of the distance that will correspond to the smallest number of pixels contain the texture element was born. Following the example in the lower row on Figure 10 it can be notices that to enclose the texture element it is good to look for such neighborhood were the difference between the two pixels is the highest. Big difference in gray values implies high contrast. Therefore we are suggesting the Maximum Contrast Distance (MCD) as the distance for the GLCM that gives maximum contrast could define and include the texture element the best. To test this idea, two experiments were performed – computational and empirical.

To perform the computational experiment it is assumed that for each texture different GLCM distance value must be selected as it depends on the type of the texture and that this distance should be the one that gives the highest contrast. It is also assumed that higher contrast means that there is a big difference between the two pixels selected to be neighbors, which suggest a texture element according to the initial definition of texture. For that purpose from the samples 15d, 16c, 22b and 22d from database KTH-TIPS2 for all scales of images 1 were used. These samples were selected because they appear to have a nice transition between different scales without any moving of the sample leaving the possibility of testing the effect of the distance on the GLCM features as well. Images taken by the frontal camera pose and all illumination position were used for the computations. For all the samples 5 features from the 22 (Contrast, Dissimilarity, Energy, Entropy and Homogeneity) were considered as they are the most used features in the literature. To follow the idea of selecting the distance that gives the maximum contrast texture features were computed for different distances. They were computed using MATLAB® for 9 different distances

(2,4,6,8,10,12,14,16,18) and for all angles (0°, 45°, 90°, -45°). The results of the 0° angle for one texture image can be seen in Table 8.

Feature values of the 0° GLCM; Sample:16c_sl2_im1									
feature\distance	2	4	6	8	10	12	14	16	18
Contrast	0.560	0.829	0.974	1.063	1.117	1.153	1.169	1.177	1.174
Dissimilarity	0.404	0.539	0.610	0.658	0.689	0.708	0.719	0.724	0.723
Energy	0.264	0.231	0.216	0.208	0.203	0.201	0.200	0.198	0.199
Entropy	1.913	2.023	2.059	2.076	2.084	2.087	2.089	2.090	2.089
Homogeneity	0.813	0.759	0.731	0.711	0.698	0.690	0.685	0.683	0.683

Table 8: Features values for different GLCM distance for 0° angle of the GLCM for 16c_scale2_im1 texture sample

In order to comment on the results in Table 8 the focus should be placed on the computation of contrast and it should be related to the results of the empirical experiment. The empirical experiment included a simple manual selection of 1x1 up to 18x18 pixel area in Photoshop and visual evaluation and comparison of the selected area. If it is possible to see a single texture element in the selected area this means that the distance for that particular area will be the appropriate distance for the GLCM computations for the given sample. This way enclosing the texture element will be guaranteed. The results of the empirical method can be seen on the following figure.

Figure 22: Zoomed area of the image enclosed by a certain distance from 2 to 18 pixels with step of 2 for sample1 (16c_scale2_im1)

It can be seen that for this sample the image corresponding to D=16px (marked in red) looks like one texture element and it indeed has the maximum contrast (marked in red in Table 8). Looking at the original texture (Figure 23) from which this slices are coming from it can be concluded that visually this 16x16px slice looks like it can be the texture element for this sample.

Figure 23: Sample 16c_scale2_im1

The same method has been applied to a different texture. As Figure 23 shows a quite random texture a more organizes and repetitive structure is shown in Figure 24.

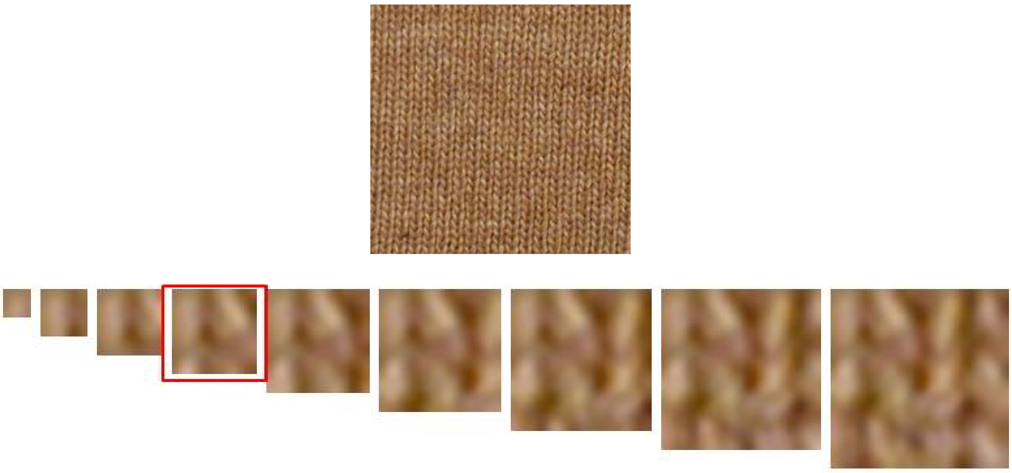


Figure 24: Samples 22b-scale_5_im_1 and the corresponding slices

Looking now at the contrast information for the texture sample shown on Figure 24 it can be see that now the maximum contrast happens for a totally different distance (See table 9). However, looking at the empirical results, this contrast again corresponds to a slice that looks like a texture element for the given texture sample.

Feature values of the 0 degree GLCM angles									
feature\distance	2	4	6	8	10	12	14	16	18
Contrast	1.415	1.187	0.920	1.516	0.696	0.986	1.446	0.854	1.383

Table 9: Contrast feature for different GLCM distance for 0° angle of the GLCM for 22b-scale_5_im_1 texture sample

The same conclusions can be made from all tested cases. Therefore we can conclude that the maximum contrast distance (MCD) can be used to define the appropriate distance value for each texture. This will give a different distance value for each texture in our dataset which is expected as those are all different textures by nature. However, this criterion will guarantee to enclose one texture element at a time for each sample. With this satisfying the conclusions suggested by our references.

Conclusively, based on the two experiments shown it can be suggested that the distance which gives the maximum contrast should be the best for the GLCM computations as it restricts the feature calculations to surely enclose only one texture element and it lowers the possible averaging.

4.2.4. Sample resolution experiment

The aim of this experiment is to see the behavior of texture features when the resolution of the samples is changed. Sample resolution represents the number of pixels that is used to represent the texture image. This number can be, in our case, 200x200px (as the texture images were cut to this size) or lower. If there is no significant change in the features with scale it means that the resolution of the sample is not relevant and can be reduced, reducing the computation time.

For the purpose of this experiment from all sample groups from KTH-TIPS three images corresponding to Scale#2 (1 - frontal, 2 - frontal camera 45 top illumination, 3 - frontal camera 45 size illumination) were considered. This way a set of 30 samples (10groups x 1scale x 3illuminations) was obtained. The main idea is to test the behavior of the features only with the change of the resolution this is why the scale was fixed. In order to perform the analysis all samples were resized to the following resolutions: 200x200px, 150x150px, 100x100px and 50x50px, and texture features were computed for every resolution. In MATLAB® there are different ways to change the resolution of an image. For example: sub-sampling and simple cropping of the image. Cropping was found to be preferable over sub-sampling because it does not alter the main nature of the texture but only reduces its size. On all of the images the Maximum Contrast Distance (MCD) and the contrast feature were computed. If the distance and the contrast are the same for different sample resolutions it applies that sample resolution is not a relevant factor in calculating the texture features. Appendix 1 summarizes the results of the experiment.

In general the results suggest variation in the values of the two parameters examined (MCD and contrast). This variation can be explained by the fact that by changing the resolution of the sample the size of the input for the GLCM is also changed. Different number of pixels gives different number of possible neighbor combinations which leads to different probability values and ultimately to different output for the texture features.

Considering only the MCD it can be noticed that if the 50x50px size is neglected the intra-sample variance of MCD on average is small. This makes the 50x50px size not reliable - in other words very small in order to get detect the nature of the texture. In addition it shows that all other sizes can be used for obtaining the MCD of any of the textures examined. On the other hand the inter-sample variance is changing depending on the type of the samples (it can also be called as an intra-type variance). This inter-sample variance refers to the variance between the samples under different illumination for the same type. Exactly half of the samples do not exhibit inter-sample variance while the other half exhibits a big inter-sample variance. Those two groups can be seen on the following figure:

Figure 25: Samples with big inter-sample variance

Figure 26: Samples with no inter-sample variance

This applies that a small visual experiment can be conducted to see if these textures can be grouped as hard and soft, or organized and not organized so that a precise interpretation of the results can be made.

The inter-type variance is different because it was proven that every texture type has a different MCD which is expected and proven in section 4.2.3. From the results it cannot be defined exactly which size is the best neither which one is the worst as the change in the resolution changes the number of repetitions of the same neighborhood in the image. Therefore a decision was made to use the biggest sample size 200x200px. The decision is based on the fact that reducing the size did not improve significantly the computational time and in addition from the 30 samples tested the maximum contrast was distributed as follows:

200x200px - 11images

150x150px - 8images

100x100px - 11images

36% of the samples have maximum contrast at a size 200x200px in addition this size is the original size of the image taken by the authors in the database. Therefore is not altered and can be suitable for the visual experiments in the future. However the reduction of the size does not improve significantly the computation time of texture features but requires an additional step of reducing the size of the sample in the experiment. Having this in mind in the continuation of this research a 200x200px resolution will be used.

4.2.5. Scale experiment

In this part of the research the main idea was to see how the change of texture scale affects the feature calculations. Once the texture database, the MCD criterion and the sample size were established the next step is to calculate texture features on them. As mentioned before texture features are derived from the Grey Level Co-occurrence Matrix (GLCM) that can be constructed from the grey values for each pixel in the image. By calculating texture features for the samples available in the selected dataset it is possible to see how they behave at different scales. The hypothesis that leads this experiment is that features that describe the same texture have to be the same or very similar when the scale is changed. The final goal of the experiment is to define what the effect of the scale on the features is and select which scale can be used as a default scale for the following experiments.

For the purpose of this experiment the feature calculations were performed for both databases. The scales in the databases are fixed as described in the following tables:

Scale number	Relative scale	Distance to camera (cm)
1	$2^{-1.00}$=0.500	14.00
2	$2^{-0.75}$=0.595	16.65
3	2^{-50}=0.707	19.80
4	$2^{-0.25}$=0.841	23.55
5	$2^{-0.00}$=1.000	28.00
6	$2^{+0.25}$=1.189	33.30
7	$2^{+0.50}$=1.414	39.60
8	$2^{+0.75}$=1.682	47.09
9	$2^{+1.00}$=2.000	56.00

Scale number	Relative scale	Distance to camera (cm)
2	$2^{-0.75}$=0.595	16.65
3	2^{-50}=0.707	19.80
4	$2^{-0.25}$=0.841	23.55
5	$2^{-0.00}$=1.000	28.00
6	$2^{+0.25}$=1.189	33.30
7	$2^{+0.50}$=1.414	39.60
8	$2^{+0.75}$=1.682	47.09
9	$2^{+1.00}$=2.000	56.00
10	$2^{+1.25}$=2.378	64.41

Table 10: Top - the scales present in the KTH-TIPS database; Bottomt - the scales present in the KTH-TIPS2 database

Table 10 top shows that for this databases Scale#5 (marked with red) was fixed as the central scale which corresponds to the distance between the camera and the target of 28cm and it was selected by the authors in order for it to correspond to the default scale in the CUReT database that is the base of KTH-TIPS databases [5, 6]. From this central scale the distances were equally spaced logarithmically over two octaves. However, in KTH-TIPS the scale goes from 1 to 9 and in KTH-TIPS2 from 2 to 10. The change of the closest distance happened because of problems of focus in the KTH-TIPS with Scale#1. Consequently it was removed from KTH-TIPS2 and an additional Scale#10 was added. As explained in 4.2.2. to avoid having different scales for the two databases a decision was made to neglect Scale#1 from KTH-TIPS and Scale#10 from KTH-TIPS2 from the further analysis. This way a equal set of 8 scales from 2 to 9 for both databases was made. In addition, it was noticed that some of the samples don't have the required resolution all scales therefore those samples were neglected. In KTH-TIPS Brown bread, Orange peel and Cracker were neglected and the experiment was performed on all the other samples. In total it makes 24 [8 scales times x 3orientations] samples x 7 types = 168 samples. In KTH-TIPS2 the same problem appeared only for the Cracker a,b and d therefore these samples were neglected and the computation was performed on all the other samples. In total it makes 32 images [8 scales times 4 orientations] x 4 subtypes for each type x 10 sample types + 32 images for the Cracker c = 1312 samples. The final number of samples for this experiment is 1480. The images below (Figure 27) show two examples of how the scale affects the images.

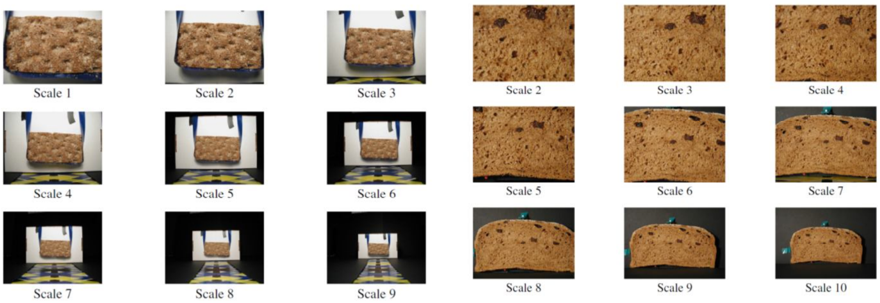


Figure 27: Left – example of the effect of the scale in KTH-TIPS; Right – example of the effect of the scale in KTH-TIPS2

The computations were performed on all the mentioned samples in MATLAB®. The resolution of the samples is 200x200px, as explained in 4.2.4., and the distance for the GLCM was computed to be the one that gives the maximum contrast (MCD) for every given texture individually.

As the leading hypothesis of this experiment is that the features that describe the same texture have to be the same or very similar when the scale is changed as they are describing the same physical texture, five texture features were computed for all the mentioned scales and their behavior was examined. The five selected features were the ones that have been used the most often in the available literature: Contrast, Dissimilarity, Homogeneity, Energy and Entropy. It is noticed that the behavior of these features depends mostly on the type of the texture.

By considering different scales in this experiment it is possible to check the change of the features with scale. Note that the scale is the distance between the sample and the camera. Contrast, Dissimilarity, Energy, Entropy and Homogeneity were calculated for 9 different scales (2,4,6,8,10,12,14,16,18). Figure 29 graphically shows graphically the results of two of them.

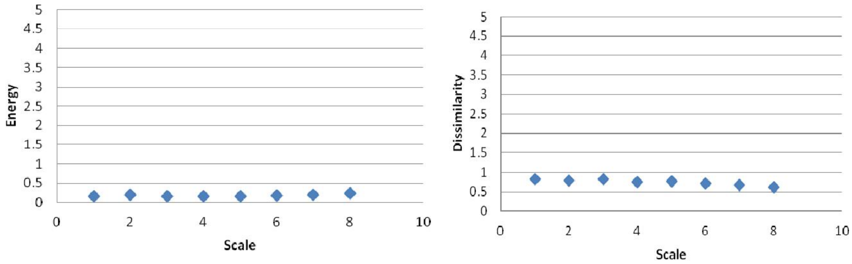
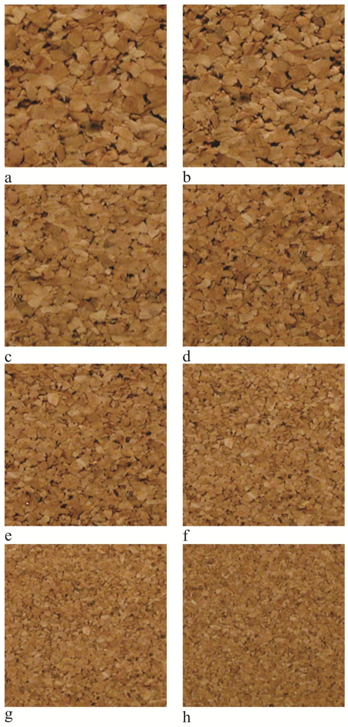


Figure 28: Energy and Dissimilarity results for different scales for sample 16c

Looking at the left graph it can be noted that the Energy feature is constant with the scale. Similar behavior can be note for the majority of the calculated features. Therefore, it can be concluded that by defining the MCD the majority of texture features are constant with scale suggesting that the MCD criterion is able to discount the effect of the scale as for every new image a new distance is computed. The farther the camera is the more homogenous the sample is and a smaller GLCM distance will be used. Therefore the usability of the MCD criterion becomes evident. Figure 29 depicts this point visually proving that the texture element becomes smaller with increasing scale (scales from #2 to #9 respectivelly).



a) 16c-scale_2_im_1_col; b) 16c-scale_3_im_1_col;
c) 16c-scale_4_im_1_col; d) 16c-scale_5_im_1_col;
e) 16c-scale_6_im_1_col; f) 16c-scale_7_im_1_col;
g) 16c-scale_8_im_1_col; h) 16c-scale_9_im_1_col;

Figure 29: Example of one texture in different scales

From a mathematical point of view changing the scale means changing the amount of the gray levels that will be present in the final image. As the sample moves away from the camera the texture becomes less and less visible which results in some grey level change in the final image that the camera produces. This change can be thought of as a sort of averaging of the gray levels and smoothing of the texture pattern. Change in the gray level changes the neighbor information needed for the GLCM. Following the mathematical point of view it can be stated that texture basically changes with distance and, even though it is the same material from a mathematical point of view with every scale it becomes a different set of numbers. Without the MCD criterion every scale would have different feature values for the same material which would mean different texture, which does not correspond to our perception. This way some uncontrolled computations, unwanted averaging or skipping of important information can happen. However, from the perceptual point of view this is the same material. Therefore it is desirable to find a criterion that will adapt to the scale change as the material examined is the same just observed from different distance. This change can be minimized by using the MCD criterion as it will find at any scale the optimal, maximum difference between the neighboring pixels and this way no additional averaging of the gray levels is going to be introduced.

From Figure 28 it can also be seen that for example Dissimilarity is somewhat changing with distance. This happens because Contrast and Dissimilarity are features computed in a same manner (if we refer to the formula) just with a different waiting factor. However, Scale#5 shows the average value of this feature at different scale for all samples. This concludes that for the constant features the selection of any scale will not influence the performance of features suggesting that these features could be good texture descriptors. These features are candidates for becoming true texture features that can be able to describe it independently on its size and illumination orientation. However there are some features that are not distance invariant. For the features changing with scale the middle position, which is Scale#5, represent the average of all the scales. Therefore in further continuation it is possible to neglect all other scales and work only with Scale 5. We suggest as well that the MCD should be computed prior to any calculations in order to define the suitable distance for each one of the texture samples.

4.2.6. Principal Component Analysis (PCA)

The aim of this phase of the research is to apply PCA in order to reduce the redundancy of texture feature and possibly reduce their number. As noted in section 3 there are 22 texture features that can be computed form the GLCM. However, these 22 are correlated and therefore they should provide redundant information. If they are redundant there is no need to compute all of them as they provide very similar information about the texture sample. In addition for the purpose of texture characterization it would be of great interest to have features that are different so that they can describe the texture image more completely and from different aspects. Therefore the selection of the best set of features becomes a dimensionality and redundancy reduction task. This task can be solved by applying dimensionality reduction techniques like Principal Component Analysis (PCA) or Independent Component Analysis (ICA). In this experiment the PCA will be performed.

For the purpose of the experiment some of the texture images from KTH-TIPS and KTH-TIPS2 were selected. From both databases Scale#5 was found to be the best for the purpose of all calculations as concluded in section 4.2.5. and therefore from all the samples only this scale was used for the performance of the PCA analysis. This gives a total of 206 samples from which 30 are from KTH-TIPS (10 groups x 1 type x 1 scale x 3 illuminations) and 176 were from KTH-TIPS2 (11 groups x 4 types x 1 scale x 4 illuminations). All the samples for this scale had the resolution of 200x200 pixels. Once selected the samples, 22 texture features were computed and the PCA was performed on these 22 features. As from the GLCM values four different angles are available the average of the four directions was made. Prior to the PCA calculation all the features were normalized in order to have the data in the range from 0 to 1 using the following formula:

(value - minimum)/(maximum - minimum)

- by keeping the sign of the values so that the most negative value becomes 0 and the biggest becomes 1. The feature calculation was performed in MATLAB® while the PCA analysis in MSExcel® plug-in called XLSTATS.

As the goal is to reduce the number of the features used for texture characterization the idea is to use PCA to see which features give redundant information and from those which do select one that will be representative for the whole group. Therefore in this case 206 images represent the observed data and the 22 features are the variables to be reduced.

From the PCA results first it can be noticed that five PCs can describe the 97.572% of the data variability (Table 11). Figure 30 graphically shows the same results.

	PC1	PC2	PC3	PC4	PC5
Eigenvalue	12.407	3.270	2.431	1.912	1.445
Variability %	56.395	14.865	11.052	8.690	6.570
Cumulative %	56.395	71.260	82.312	91.002	97.572

Table 11: Eigenvectors and their variability

Table 11 suggests that five PCs are enough for describing almost 98% of the given dataset. This means that 5 Principal Components (PC) can be used instead of 22 variables and they would explain a high variation of the data. This motivates the analysis towards finding only five features that can be used as a representative for each one of the PC and reduce the dimensionality form 22 to only 5 features. Surprisingly five features is a number that the majority of researchers in the field use for different tasks but without an actual objective reasoning for the selection. In this experiment we are suggesting objective reasoning for feature selection based on feature redundancy. Figure 29 shows the cumulative variability and suggests high importance of PC1 while after PC5 the importance of the components becomes less and less significant.

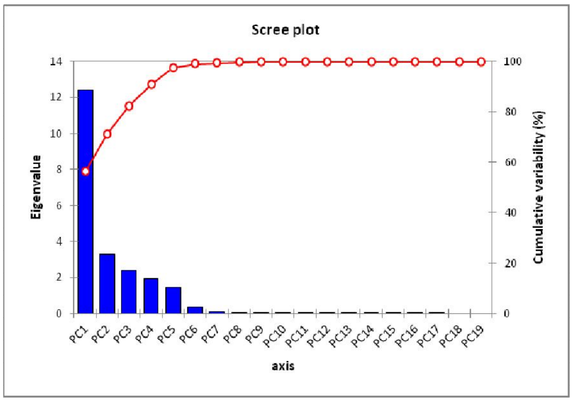


Figure 30: Screen plot of the Eigenvectors, Eigenvalues and the Cumulative variability

The PCA provides information about how many PC can be used to reduce dimensionality but for this work it is more important to understand the meaning of these components. To start understanding the reduction of the dimensionality a visual assessment of the correlation circle can be made for each principal plane. As an example Figure 31 shows one plane formed by PC1 and PC2 the rest of the correction circles can be found in Appendix 2.

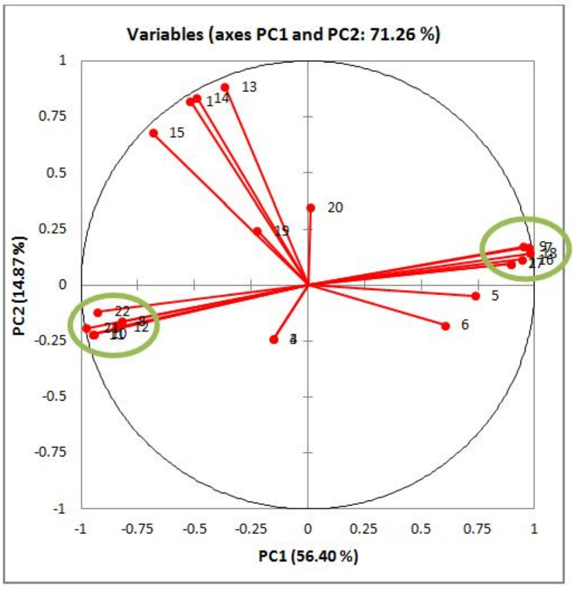


Figure 31: Correlation circle for PC1 and PC2

Figure 31 will be used to explain the conclusions for the first principal plain but the same analogy can be followed for the rest of the planes. This plot clearly shows two groups of variables that are highly correlated to PC1 and therefore should give redundant information about this component. In total there are 12 variables trying to explain the same component therefore there is no need to use all of them as removing variables will not significantly change the information that the factor is giving. In order to decide which feature can be the representative of the group the flow charrt showed on the following figure was used:

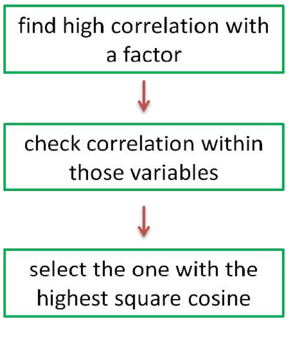


Figure 32: Algorithm to select the feature describing the PC the best

The algorithm follows the following steps:

Step 1: Find all the features that have high correlation with a given factor. High means around 0.8 and bigger. Refer to Appendix 3 Table 1.

Step 2: Check how correlated are these variables between themselves. If correlated (high around 0.8 and bigger) go to step 3 if not consider both variables as they are not redundant (note: this will never happen because only the variables close to each other are compared). Refer to Appendix 3 Table 2.

Step 3: To select the best variable pick the one that has the highest square cosine for a given factor. Refer to Appendix 3 Table 3.

The list of 10 features having high Squared Cosine with PC1 is listed in the following table. The feature marked with yellow is the one having the maximum value from the listed ones.

List of selected features for each PCs	
Feature name	Squared cosine
Contrast	0.805
Dissimilarity	0.951
Entropy	0.899
Homogeneity	0.890
Homogeneity	0.901
Sum entropy	0.888
Difference variance	0.805
Difference entropy	0.959
Inverse difference normalized	0.954
Inverse difference moment normalized	0.858
Highest Squared cosine	

Table 12: List of selected features with highest squared cosine value with PC1

This way from 10 features for factor 1 only Difference Entropy (number 18 on the plot) can be selected as the most important and all the rest can be neglected as redundant. Following the same algorithm for the other four factors the following features can be selected for each PC:

PC 1 - difference entropy (0.979)
PC 2 - sum of squares: variance (0.886)
PC 3 - correlation (0.789)
PC 4 - information measure correlation2 (0.835)
PC 5 - information measure correlation1 (0.519)

The next plot that gives important information is the biplot. The biplot contains all the samples and all the variables together. It uses points to represent the scores of the observations on the PCs, and it uses vectors to represent the coefficients of the variables on the PCs. It is basically a projection of the data point onto a principal plain. Figure 33 shows one example of a biplot obtained for all the variables and all the samples projected on the first principal plane.

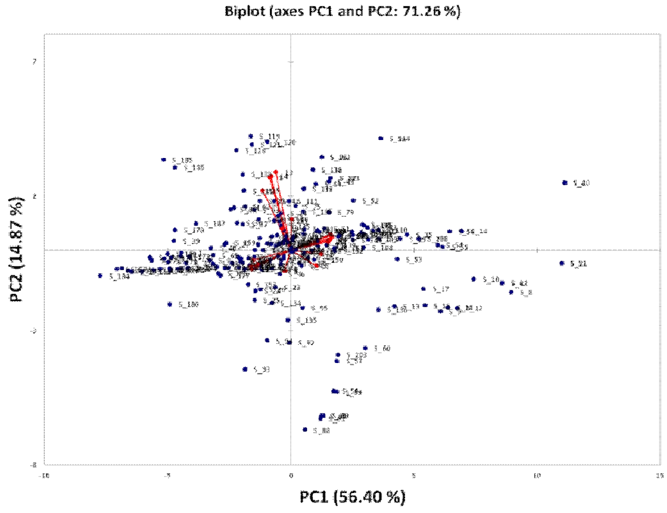


Figure 33: Biplot for the first principal plane

Biplot shows that the majority of the data are quite centered. As values close to zero on a biplot suggest that those samples are not consistent with the main variation of the data we can conclude that these samples show average behavior. In this case it can suggest that the samples can be similarly described with the more principal components encouraging the idea of reducing the number of features. This plot can be very useful for this research in selecting the samples for the future visual experiment by using it to select samples that are the best described by each factor. This selection can be done by looking for samples on both left and right side of each axis. Figure 34 shows the flow chart for selecting the samples and one example of the selected set of images (for PC1).

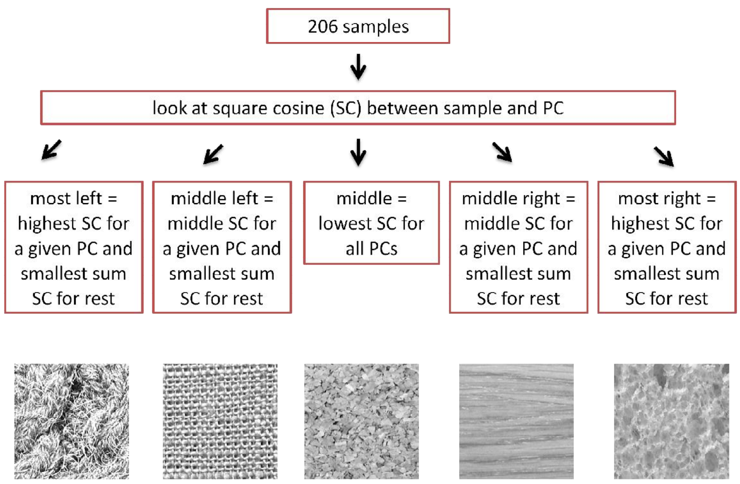


Figure 34: The algorithm for selecting the samples and one example of the selected set of images (for PC1)

The sample in the middle is the sample that has 0 Squared Cosine and it represents the average sample of the dataset. Moving to the left and right from the center and following the squared cosine values, the samples become more described by the given factor. This way it is possible to make a scale of images described by a given PC. As every PC has a feature that represents its meaning this image scale should contain images varying in only one feature while the others should be as constant as possible. Performing the algorithm shown on Figure 34 for all the five PC five different sets of images can be made. The selected sets of images are shown in section 4.3.

The usability of the PCA for reducing the number of features used for texture characterization was proven to give one possible objective selection of texture feature. The algorithm that was followed showed that if some variables have similarly high values of correlation with a PC and they are between themselves highly correlated, the one with the highest squared cosines could be selected as the representative variable for the given PC. Repeating the same algorithm for each PC the set of 22 texture features was narrowed down to only 5. In addition the biplot was found to be useful for selecting samples for the visual experiment with the goal to have variability of the sample types for a given factor.

4.2.7. Summary of the results, conclusions and discussion

In Section4 of this research different computational experiments were performed. These experiments included defining the distance for the GLCM computations, testing the effect of the resolution and scale on the texture features and perform PCA in order to reduce the redundancy and select the samples for the visual experiment.

Conclusively, it can be suggested that the distance which gives the maximum contrast should be the best for the GLCM computations as it restricts the feature calculations to surely enclose only one texture element and it lowers the possible averaging.

The size of 200x200px was selected to be used as this size is the original size of the image taken by the authors in the database therefore is not altered and can be suitable for the visual experiments in the future. In addition the reduction of the size does not improve significantly the computation time of texture features but requires an additional step of reducing the size of the sample in the experiment.

It was proven that the MCD criterion compensates for the effect of the scale by providing a different distance for GLCM computation with scale. As a result the majority of the features become constant with scale. This concludes that for the constant features the selection of any scale will not influence the performance of features suggesting that these features could be good texture descriptors. These features are candidates for becoming true texture features that can be able to describe it independently of its size and illumination orientation. However there are some features that are not scale invariant. For the features changing with scale the middle position, which is Scale#5, represent the average of all the scales. Therefore in further continuation it is possible to neglect all other scales and work only with Scale 5.

The usability of the PCA for reducing the number of features used for texture characterization was proven to give one possible objective selection of texture features. The algorithm that was followed showed that if some variables have similarly high values of correlation with a PC and they are between themselves highly correlated, the one with the highest squared cosines could be selected as the representative variable for the given PC. Repeating the same algorithm for each PC the set of 22 texture features was narrowed down to only 5. In addition the biplot was found to be useful for selecting samples for the visual experiment with the goal to have variability of the sample types for a given factor.

4.3. Realization of the visual experiment

In this study two visual experiments were performed. The first experiment is called “The Sorter” and the second “The Grouper”. In The Sorter experiment the observers were asked to order the presented images from least to most textured according to any criteria they select. While doing that they were asked to focus on the texture itself rather than the color or nature of the image and to try to make their response as spontaneous as possible. In The Grouper experiment the observers were asked to group the images according to any criteria they select focusing on the texture that appears on them. They were allowed to make as many groups and as many samples within them as they consider. Again they were asked to focus on texture rather than color or nature of the image. For this study 6 sets of texture images were considered selected by using PCA described previously. The first 5 were used for 5 sub experiments in the sorter experiment in order to sort the 5 different sets of images corresponding to each PC separately. The 6th set of samples was used for the grouper experiment in order to group the images that exhibit similar appearance. The main idea of the experimental part is to compare the perceptual results with the computations and derive conclusion about texture perception for the given set of samples.

4.3.1. Preparation of the samples

In this section the preparation of the samples for the visual experiment will be explained. Those samples were selected using the result of the PCA explained in section 4.2.6. As color influences the perception of texture and vice versa to allow the observers to focus on texture as much as possible all selected color samples (43 images) are mapped to gray using the LCH mapping method (Milic et al., 2011). This method enables altering L^*, C^*_{ab} and h_{ab} value of each pixel in an image in order to change its appearance. Mapping was performed by taking into account the pixel deviation to the mean chroma and luminance values (Milic et al., 2010). C^*_{ab} and h_{ab} values were set to 0, while L^* value was altered to obtain 70. Additive mapping was used for each sample, and mean luminance value was set to L*=70 so that it is different from the neutral gray (L*=53) used as the background color. Since images were to be displayed on the computer screen, after mapping, mean luminance value in Adobe RGB colour space was normalized by adjusting the image histogram. Luminance was calculated in a manner that follows perception of a brightness, ie.

0.299xR + 0.587xG + 0.114xB. Mean luminance value in each image was set to 171 with the maximum deviation of 0. Figure 35 shows an example of one texture image before and after the color and histogram adjustments.

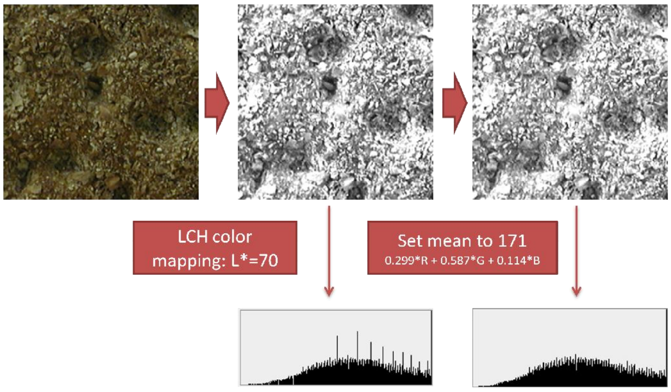
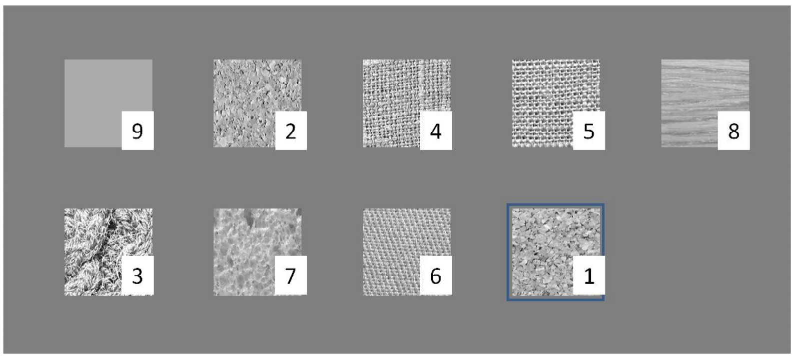


Figure 35: Example of one texture image before and after the color and histogram adjustments.

In Figure 35 it can be noted that the histogram of the first gray image indicates high peaks for some gray values suggesting possible contrast changes in some image areass. To avoid the effect of the contrast on texture perception the histogram was adjusted in such way that the luminance follows the perception of a brightness, ie. 0.299xR + 0.587xG + 0.114xB and its mean is 171. This step was of a big importance as a survey that was performed before the experiment suggested that color, contrast and lightness affects the observers so much that they forget about texture and analyze images as lighter and darker instead of more and less textured.

Figure 36 shows the five sets of samples used in The Sorter experiment, with their notation that has been used. To give the observers a benchmark a solid gray sample was added to the each one of the 5 sets. In addition the sample marked in blue is the average sample and it is present in all the five sets. The samples were selected according to the Squared Cosine criteria observed from the PCA biplot explained in section 4.2.6.



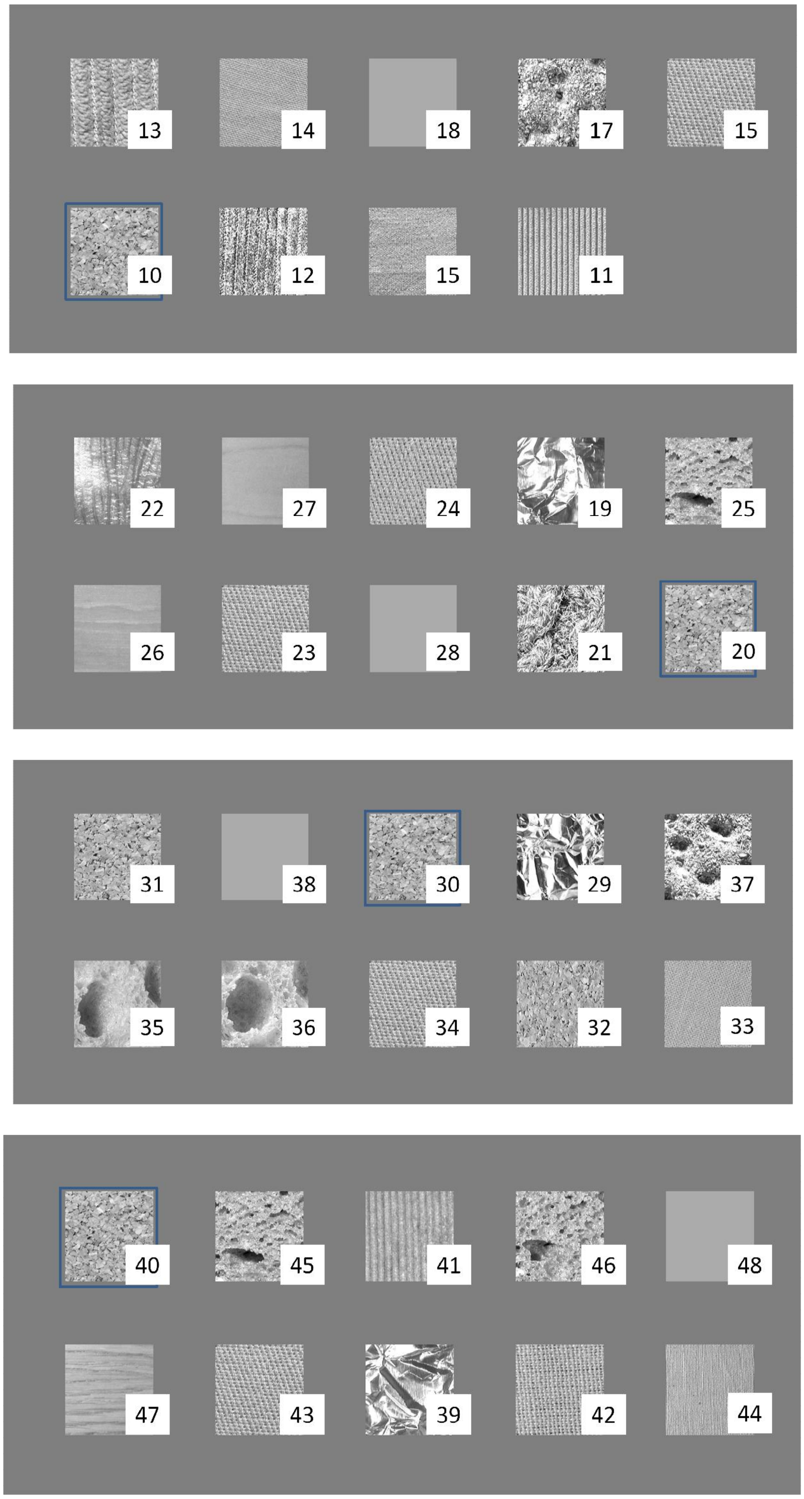


Figure 36: Images used in The Sorter experiment

4.3.2. Preparation of the laboratory

For the purpose of the visual experiments the selected images were presented to the observers in a dark room on calibrated LCD HP 2510i monitor, where white point was set to chromacity coordinates – 0.3244 0.3418, with a luminance of 248.5 cd/m^2. Black point luminance was 0.247cd/m^2. All the values were measured with a spectrophotometer (Photo Research 704) and the monitor was calibrated using Gretag Machbet Eye-One Match 3 colour management system. Monitor resolution was set to its native, 1920x1080px. In order to remove any external influence the screen was isolated with gray panels (see Figure 37) making the observer focus only on the information presented on the screen.

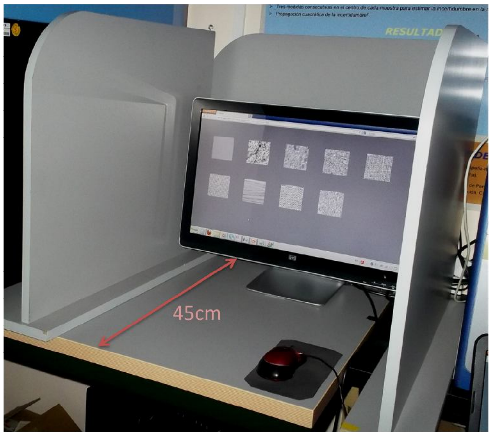


Figure 37: Laboratory setup

JavaScript code was written in order to display and manage the experiments. In The Sorter experiment the images were presented in two rows on a grey background (L*=53) covering the whole screen (Figure 38). Each image sample subtended 7.5° of visual angle from the position of the observer, which was approximately 45 cm from the monitor. Experiment was carried out in a complete dark room eliminating the influence of any ambient illumination.

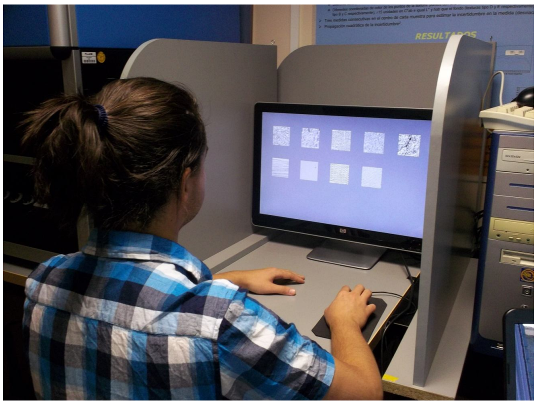


Figure 38: The Sorter experiment setup

In The Grouper experiment the images were presented in three rows subtending the same 7.5° of visual angle from the position of the observer (Figure 39).

Figure 39: The Grouper experiment setup

4.3.3. Observer selection and tasks

A panel of 28 observers (16 experts and 12 non-experts) with normal or corrected vision and normal colour vision (tested with Ishihara test) participated in The Sorter experiment in the age range between 21 and 51 years. From the 16 experienced observers 11 are female and 5 male while from the non-experts 8 are female and 4 are male. This makes a total of 19 female and 9 male observers. Table 13 shows the observer number and gender information for this experiment.

	expert	non-expert	total
total	16	12	28
female	11	8	19
male	5	4	9

Table 13: Observer information for the sorter experiment

In The Grouper experiment a panel of 15 observers (10 experts and 5 non-experts) with normal or corrected vision and normal colour vision (tested with Ishihara test) participated in the experiment in the age range between 21 and 51 years. From the 10 experienced observers 7 are female and 3 male while from the non-experts 1 is female and 4 are male. This makes a total of 8 female and 7 male observers. Table 14 shows the observer number and gender information for this experiment.

	expert	non-expert	total
total	10	5	15
female	7	1	8
male	3	4	7

Table 14: Observer information for the grouper experiment

The observers were adapted to the grey background for 2 min before each session. In The Sorter experiment observers were instructed to arrange presented images according to their texture visibility, where the first in order should be image with no texture (solid colour) starting in the upper left corner of the scale (Figure 36). Accordingly, the last one should be an image where texture is most noticeable in the bottom right corner of the scale. Observers were allowed to drag and drop images, changing their position in the rows. They were not time-limited, each observer took as much time as needed in order to create the desired order. Next sequence was presented when assessor hovered over a previously hidden "Next" button in the bottom of the screen. The current order was stored in a database using AJAX call to Ruby on Rails application. Database system used was PostgreSQL. Each observer performed the test two times.

In The Grouper experiment observers were instructed to group the presented images according to their similar appearance (Figure 37). There were not time-limited and they were allowed to create as many groups and with as many samples as they consider. Next sequence was presented when assessor pressed the "Next" button in the low left corner of the screen.

For both of the experiments the observers were asked to perform two repetitions on two different days.

4.3.4. Testing observer's reliability

To check the reliability of the observers we calculate the standardized indexes in color science, STRESS and PF3, on the results of The Sorter experiment (Melgosa et al., 2011). In this case for the intra observer variability the measures were calculated between the two repetitions the observers performed for each of the five sets of images and their mean was calculated. The inter observer variability was obtained by calculating the measures for the global mean scale from all the observers for a given set and each observers mean scale. Then the mean of the five was obtained. Table 15 shows the values of the measures.

intra observer variability - all observers		
observer\measure	PF/3	100*STRESS
mean of 5 exp.	29.47	23.59
deviation	15.71	10.83

inter observer variability - all observers		
experiment\measure	PF/3	100*STRESS
mean of 5 exp.	31.83	27.01
deviation	6.59	4.07

Table 15: STRESS and PF3 values for the intra (left table) and inter (right table) observer variability for The Sorter experiment

From Table 15 it can be seen that the STRESS and PF\3 are around 30% which is in the desired range according to the standard (Melgosa et al., 2011). Thus the observer's results are reliable. Big deviation of the intra observer variability would suggest that some of the observers changed their criteria during the two repetitions.

If the observer's answers are to be separate into expert and non-experts interesting observations can be made. They are summarized in Table 16.

intra observer variability - expert		
observer\measure	PF/3	100*STRESS
mean of 5 exp.	27.08	21.57
deviation	18.18	12.04

inter observer variability - expert		
experiment\measure	PF/3	100*STRESS
mean of 5 exp.	35.00	29.58
deviation	8.36	5.39

intra observer variability – non-expert		
experiment\measure	PF/3	100*STRESS
mean of 5 exp.	26.88	22.94
deviation	5.32	2.95

inter observer variability – non-expert		
observer\measure	PF/3	100*STRESS
mean of 5 exp.	33.06	26.64
deviation	10.99	8.39

Table 16: STRESS and PF3 values for the intra (left table) and inter (right table) observer variability for The Sorter experiment for experts (first row) and non-experts (second row)

It can be seen from Table 16 that the intra observer variability is lower for expert observers, suggesting that the experts perform better within the repetition. This means that non-experts would need more repetitions as they are not consistent in their answer. It is interesting to see that the deviation of intra observer variability for expert observers is higher suggesting that some observers have big deviation in their answers or not the same criteria within the two repetitions. However, different observers respond differently to the presented samples in the case of experts showing bigger inter observer variability.

4.3.5. The Sorter Experiment

In this experiment 28 observers were asked to order 5 sets of samples, from minimum to maximum textured, according to any criteria they select focusing on the texture itself rater than on the nature or color of the samples. From the 28 observers 16 were expert and 12 non-expert. In general each observer performed two repetitions at different days.

After examining the performance of the observers the examination of the constructed scales was performed for each one of the 5 sets of samples. This analysis includes the analysis of the correlation between the values of the 22 features computed for the sample sets and the mean order that the perceptual experiment provides. Computing the mean perceptual scale for each set of samples gives information about a position in a scale that the observers assigned to a texture sample. The results are summarized in Table 17. In this table the mean position (average of all observers answers) of each sample within a set is presented and its standard deviation. As well the sum of these deviations and the mean position values.

Mean visual scales experiment 1.1												
experiment\image	1	2	3	4	5	6	7	8	9		sum deviation	mean
Experiment 1.1	5.38	5.13	7.91	6.58	6.98	5.66	4.13	2.23	1.00			5.00
deviation	1.27	1.30	2.24	1.31	1.37	1.87	2.10	0.80	0.00		12.26	

Mean visual scales experiment 1.2												
experiment\image	10	11	12	13	14	15	16	17	18		sum deviation	mean
Experiment 1.2	5.45	5.34	6.42	6.04	3.98	5.11	4.17	7.49	1.00			5.00
deviation	2.20	1.56	1.70	1.78	2.59	1.53	2.20	2.47	0.00		16.02	

Mean visual scales experiment 1.3												
experiment\image	19	20	21	22	23	24	25	26	27	28	sum deviation	mean
Experiment 1.3	7.17	6.70	8.64	6.02	6.34	6.40	7.62	3.02	2.09	1.00		5.50
deviation	2.57	1.54	1.71	2.02	1.78	1.95	1.20	0.31	0.30	0.00	13.37	

Mean visual scales experiment 1.4												
experiment\image	29	30	31	32	33	34	35	36	37	38	sum deviation	mean
Experiment 1.4	7.79	5.25	5.55	4.62	4.06	4.77	6.77	7.23	7.96	1.00		5.50
deviation	2.95	1.63	1.39	1.58	3.06	2.42	2.02	2.08	2.07	0.00	19.20	

Mean visual scales experiment 1.5												
experiment\image	39	40	41	42	43	44	45	46	47	48	sum deviation	mean
Experiment 1.5	7.62	6.60	4.32	6.55	6.34	4.74	7.58	7.81	2.43	1.00		5.50
deviation	3.19	1.55	1.41	1.75	1.82	2.30	1.95	1.80	1.05	0.00	16.80	

low position
high position
mean sample

Table 17: Mean visual scales and the standard deviation for each sample mean position

In general it can be observed from the sum deviation that the smallest deviation between the observers appears in the first set of samples (red circle). This suggests that for the samples corresponding to PC1 the observers have the most constant discrimination. This can be expected because these samples represent the ones with the biggest variation. Therefore this experiment and this set can be considered as the easiest for the observers.

It can also be seen that low sample positions (red) have in general small deviation while high sample positions have the big deviation (orange). This can suggest that the observers are more constant in deciding about small texture differences or weaker textures, the ones very close to the neutral sample whereas the big differences are perceived differently. This finds analogy with color discrimination as it is known that small color differences are discriminated and quantified more easily than big color differences. It is interesting to see that also for texture the discrimination between the neutral and the sample with the weakest texture is very easy for the observers to quantify while big texture difference is simply confusing.

It is interesting to see that average sample (blue) is more or less around the middle of the scale for every experiment supporting the PCA findings about the average sample of the dataset used.

Before examining the results of the correlation it is interesting to see what the expectations of this experiment are. Table 18, as a reminder, summarizes the results obtained by PCA. As there is 22 available texture features it was previously stated that redundancy between them can be expected. Performing PCA helped to define which features are redundant and possibly helped selecting a smaller number of features that are more independent and can be representative for a group of redundant features. According to the squared cosine criteria defined previously the features shown in Table 18 can be one possible set of features standing out from the set of redundant features describing each principal component.

List of selected features for each PCs		
	Feature name	Squared cosine
PC1	difference entropy (denth)	0.959
PC2	sum of squares: variance (sosvh)	0.785
PC3	correlation (corrp)	0.623
PC4	information measure correlation2 (inf2h)	0.697
PC5	information measure correlation1 (inf1h)	0.270

Table 18: Selected features from all that PCA indicates to be redundant in describing one PC

The criterion used in the PCA suggests that the listed features can be one possible selection of features that describe the given PC the best. Therefore dimensionality reduction can be performed. Additionally it can be expected that the biplot in the PCA provides the information about the position of the sample in the plane formed by two PCs and this position has to be related to the value of the selected feature. The relation should be in a manner that the central sample must have central values for the selected feature and as we move from the sample the value of the feature should be changing. This way it provides information about the change of the selected feature for a certain set of samples. Consequently, the idea of the visual experiment is to construct 5 different sets of samples that will have only one feature changing and the rest constant. Again the squared cosine criteria provided the 5 different sets of samples as explained in 4.2.6. Therefore, when calculating all the features for the selected set of samples it is expected to have the biggest change and therefore the biggest standard deviation for the feature that is selected to be the representative for the group of samples. Table 19 summarizes the five feature values for each one of the samples for the first sample set. The value represented is the mean of the four angels used in the GLCM computations. The results will be explained for the first sample set but the analogy applies for the other four as well and the corresponding tables can be found in Appendix 4.

Angular mean for each sample for features selected by PCA											
feature\image	1	2	3	4	5	6	7	8	9	mean	deviation
MCD	16	16	18	4	4	18	18	10	2		
denth	1.228	1.248	1.789	1.571	1.321	1.293	0.974	0.660	0.000	1.120	0.529
sosvh	35.109	35.221	37.017	36.140	35.440	35.663	35.226	34.853	35.813	35.609	0.657
corrp	-0.003	-0.007	0.027	-0.082	-0.130	-0.048	0.009	0.121	0.000	-0.013	0.071
inf2h	0.037	0.034	0.048	0.153	0.211	0.171	0.054	0.248	0.000	0.106	0.090
inf1h	-0.001	0.000	-0.001	-0.008	-0.016	-0.014	-0.002	-0.075	0.000	-0.013	0.024
								selected feature for this PC			

Table 19: Mean of the four directions for the five selected features for the first set of samples in the sorter experiment (Experiment 1.1)

According to the expectations stated above it can be expected that the feature that was selected by the PCA for each sample set has the biggest change therefore the biggest standard deviation (marked in yellow). However, this is not the case as it can be noted that all the features are suffering a change. Suggesting that the dataset has not the required samples and, in addition, exploring the biplot is not as straightforward as expected because it shows only the projection of the sample onto one principal plain. For PC1 and PC2 the selected features shows higher standard deviation than the ones selected for the rest of the PCs because these two PCs represent the highest variation of the data set used. For the rest of the PC is hard to spot the representative samples mathematically as the projection to these planes span a very small space that has low variation for each feature in it. This suggests that finding independent features mathematically is not so easy in the given set which is also confirmed with the fact that first PC spans only around 56% of the variation suggesting redundancy between the features. Another dimensionality reduction technique like Independent Component Analysis (ICA) could be used to get more independent components.

The next step is to see how important are the features perceptually and which ones are the most important for each set of samples. It can be done, for example, by calculating R^2, coefficient of determination between the two scales. Two scales means the scale obtained by computing the features on the samples and this scale will be referred to as *the feature scale* and the mean scale made by the observers which will be called *the perceptual scale*. What can be expected is to have the highest correlation between the positions defined by the values that the PCA selected feature provide for each sample in a given set of the samples and the position that the observers defined. Table 20 summarizes the correlation values for each feature experiment wise.

Correlation betwee the feature and perceptua scale					
features\experimnt	Exp 1.1	Exp 1.2	Exp 1.3	Exp 1.4	Exp 1.5
autoc	0.8142	0.7165	0.5694	0.3187	0.6825
contr	0.7160	0.5446	0.676	0.4882	0.6674
corrm	0.2934	0.0612	0.0114	0.2328	0.0002
corrp	0.2934	0.0612	0.0114	0.2328	0.0002
cprom	0.3875	0.3839	0.4158	0.5541	0.4616
cshad	0.3452	0.3247	0.3154	0.6963	0.2978
dissi	0.9157	0.6885	0.8822	0.6389	0.7843
energ	0.7932	0.6938	0.9088	0.6691	0.7957
entro	0.9479	0.7694	0.9541	0.8376	0.8868
homom	0.9659	0.7206	0.9454	0.7047	0.8255
homop	0.9706	0.7152	0.9414	0.7002	0.8174
maxpr	0.9170	0.6831	0.9112	0.7374	0.8242
sosvh	0.2616	0.1129	0.1125	0.2776	0.0858
savgh	0.7551	0.8191	0.8307	0.7332	0.7624
svarh	0.8581	0.7827	0.9437	0.8076	0.8572
senth	0.9056	0.801	0.9338	0.9055	0.8722
dvarh	0.7160	0.5446	0.676	0.4882	0.6674
denth	0.9298	0.7769	0.9579	0.7603	0.8749
inf1h	0.1258	0.0056	0.0007	0.0781	0.0001
inf2h	0.0151	0.0203	0.1657	0.1551	0.0249
indnc	0.9491	0.7093	0.9156	0.6751	0.8019
idmnc	0.7666	0.5699	0.7229	0.5135	0.6814
				maximum correlation	
				features selected in the PCA	

Table 20: Correlation between the scale made by the calculated features (features scale) and the mean scale made by the observers (perceptual scale)

Blue color shows all the features with high correlation for each experiment while yellow shows the features selected to be representative for the given set by the PCA.

The results show that the feature with the highest correlation is not the feature selected by the PCA for each one of the PCs. This suggests that the results the PCA provides are not perceptual, meaning that visually other features are more important for the observers. Thus, PCA gives different features for a mathematical description of the texture, but does not provide features more related with the perception of the texture. Looking at Table 21 which shows all the correlation between the features and the PCs it can be seen that PCA gives good indications which features are redundant, especially for PC1. However, it cannot select precisely the one that has the biggest perceptual importance. Looking back not at the tables in Appendix 4 it can be seen that the features having the highest correlation do not have necessarily the highest deviation in the given set of samples. This means that the perceptual and feature scale are not the same in a sense that small numerical change in a feature (which is considered in PCA analysis) might mean a big perceptual change and vice versa. This can be proven by looking at the feature "*homop*". It has smaller standard deviation but it is a feature most correlated with the experiment 1.1 (see Table 1 Appendix 4). On the other hand feature "*cprom*" has very high deviation but very low correlation. This means that a small change in "*homop*" is visually more significant for the discrimination of the samples than a big change in "*cprom*".

Correlations between features and PC:					
features\PC	PC1	PC2	PC3	PC4	PC5
autoc	-0.521	0.823	0.147	-0.113	-0.122
contr	0.897	0.096	0.284	-0.202	0.199
corrm	-0.151	-0.240	0.789	0.299	-0.451
corrp	-0.151	-0.240	0.789	0.299	-0.451
cprom	0.737	-0.047	0.546	-0.239	0.264
cshad	0.605	-0.178	0.530	-0.179	0.324
dissi	0.975	0.170	0.047	-0.064	0.070
energ	-0.819	-0.163	0.267	-0.278	0.316
entro	0.948	0.172	-0.056	0.110	-0.217
homom	-0.943	-0.218	0.215	-0.089	0.083
homop	-0.949	-0.221	0.189	-0.075	0.063
maxpr	-0.842	-0.186	0.290	-0.259	0.266
sosvh	-0.367	0.886	0.212	-0.160	-0.088
savgh	-0.488	0.836	0.139	-0.117	-0.129
svarh	-0.684	0.681	0.166	-0.190	0.033
senth	0.943	0.114	0.082	0.129	-0.265
dvarh	0.897	0.096	0.284	-0.202	0.199
denth	0.979	0.142	-0.020	-0.008	-0.079
inf1h	-0.225	0.244	0.145	0.747	0.519
inf2h	0.012	0.348	0.092	0.835	0.367
indnc	-0.977	-0.191	0.042	0.012	-0.021
idmnc	-0.926	-0.119	-0.226	0.167	-0.169
				high correlation	

Table 21: Correlation between the features and the PC

Conclusively, it can be seen that the PCA is a good idea for dimensionality reduction but it does not follow completely the perception of texture, as shown form the obtained experimental results. For high variance PC it is a good indicator where to look for the desired feature but it cannot select the perceptually best features. Even though it did not answer the question which features are perceptually the best it gave an initial criteria for selecting the samples for the experiment. The interpretation of the principal plains was not clear from the PCA results as the texture dataset is very centered and does not have a sufficient variation. This emphasized the redundancy of the 22 features and suggests a different way of sample selection. This way can involve for example selecting the samples according to the most changing features directly. The projection of the samples does not separate the given set of samples completely and moreover visually.

However, having these results gives a possibility to find the features that are perceptually significant and those features are the ones having the highest correlation with each one of the experiment. The list of these features with the corresponding correlation value is the following:

PC1 – Homogeneity (0.9706)
PC2 – Sum average (0.8191)
PC3 – Difference entropy (0.9579)
PC4 – Sum entropy (0.9055)
PC5 – Entropy (0.8868)

What can be seen is that from the perceptual point of view in general the Entropy is quite an important feature and it also exhibits big deviation compared to the mean in tables in Appendix 4. This reminds us of our initial experiment we published last year in which we came to the same conclusions (Gebejes et al., 2012). On the other hand it shows the redundancy of the features one more time.

Looking at the three formulas for different entropy calculations the redundancy can be seen (Equations 3.9; 3.15; 3.17). Therefore they are redundant and there is no need to use all of them. This suggests that two of the five features selected according to The Sorter experiment can be kept and the other three should be chosen according to other criteria with an idea of removing the redundancy. As Sum Entropy has the highest correlation from the three with all the other sample sets it can be kept as it is a good feature to explain all the images and it is different forom Homogeneity and Sum average (see Table 20). For experiment 1.3 Sum variance can be a better feature than Difference Entropy as it has higher correlations with all perceptual scales and it is different from Homogeneity, Sum entropy and Sum average. And finally for the fifth feature Maximum probability can be selected as it has higher correlation with the majority of the perceptual scales and it is different from Homogeneity, Sum entropy, Sum variance and Sum average. Therefore the new and final list of features can be defined as follows (correlation value in the brackets):

PC1 – Homogeneity (0.9706)
PC2 – Sum average (0.8191)
PC3 – Sum variance (0.9437)
PC4 – Sum entropy (0.9055)
PC5 – Maximum probability (0.8242)

Even though PCA was shown to be not related to perception it gave initial steps towards finding the features with high perceptual correlation. Firstly it allowed selecting the samples for the visual experiment and computing the features with the highest perceptual correlation. The final set of perceptually most important features was then proposed based on having independent features with the highest perceptual correlation.

4.3.5. The Grouper Experiment

In this experiment 15 observers were asked to group a sets of 14 samples according to any criteria they select focusing on the texture itself rater than on the nature or color of the samples. From the 15 observers 10 were expert and 5 non-expert. In general each observer performed two repetitions at different days.

To average the results of the two repetitions intersection criterion was used which considers as final group only the samples that appear together in the two repetitions. Once the intersection is performed the final groups were formed by calculating the weight of appearance for each one of the samples in a group. In this step a group was considered to be a set of minimum two images. The weight was calculated as the radio between the number of times a sample appears in a group from the 15 observations and the total number of possible appearances (which is 15).

$$weight = \frac{number\ of\ times\ it\ appears}{total\ number} \tag{4.2}$$

Table 22 summarizes the results of the weights and defines the final groups the observers made.

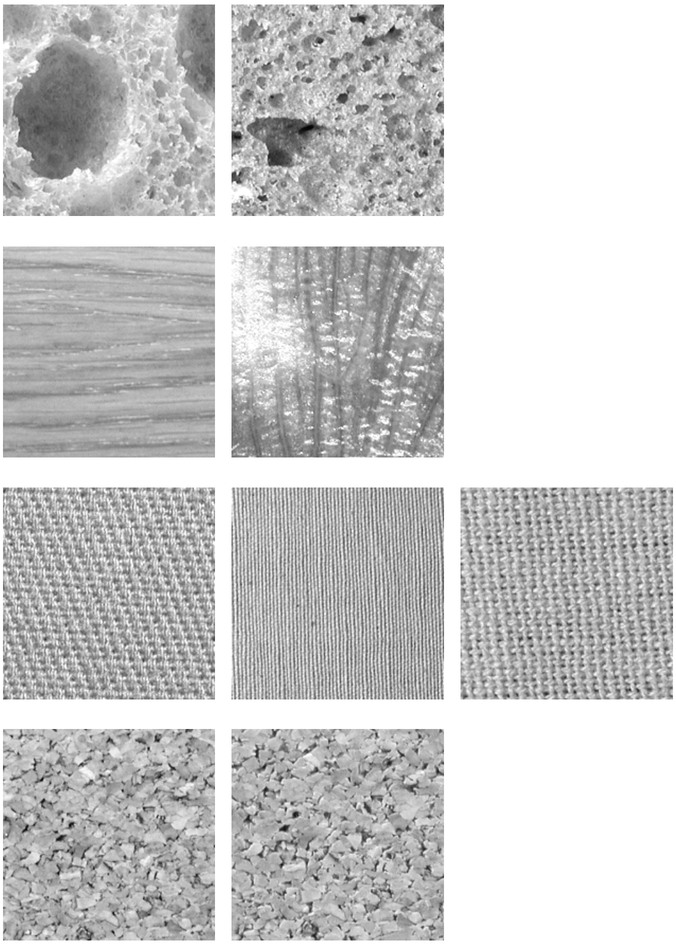
	Weight of each sample in each group											
images\groups	1	2	3	4	5	6	7	8	9	10	11	12
1	0.1	0	0	0	0.2	0	0	0	0.7	0	0	0
2	0	0	0	1	0	0	0	0	0	0	0	0
3	0	0	0	1	0	0	0	0	0	0	0	0
4	0.1	0	0.1	0	0.2	0.3	0.1	0	0	0.3	0	0
5	0	0.7	0.1	0	0	0.1	0.1	0	0	0	0.3	0
6	0	0.4	0.1	0	0	0.3	0.1	0	0	0	0	0.4
7	0	0.1	1	0	0	0	0.7	0	0	0	0	0
8	0	0.1	1	0	0	0	0.7	0	0	0	0	0
9	0	0.1	0.7	0	0	0	0.9	0	0	0	0	0
10	0	0.1	0.7	0	0	0	0.9	0	0	0	0	0
11	0	0.1	0.7	0	0	0.1	0.5	0	0	0	0	0
12	0.8	0	0	0.1	0	0	0	0	0	0	0	0
13	0.8	0	0	0.1	0	0	0	0	0	0	0	0
14	0	0.7	0.1	0	0	0	0.1	0.3	0	0	0	0
grouped images	12,13	5,14	9,10,11	2,3			7,8,9,10					
ungrouped images								14	1	4	5	6

Table 22: Weights of samples in each group and selection of the samples forming one group

Further on to select the final samples that are forming one group only the ones that have a weight bigger or equal to 0.7 were considered. Weight 0.7 suggests that 70% of the observers considered these samples to be in a same group. This way 5 groups can be formed as shown in Table 22. As the PCA also gave 5 groups of samples is it interesting to see that the idea of having 5 main features and 5 groups of variation has also perceptual meaning. Four samples appear alone for some observations but from all of them only one, sample number 1, can be considered as absolutely solitary sample. This sample stands out from the rest visually. Samples 4 and 6 didn't find high weight in any of the groups suggesting that these samples might be perceptually average samples that can go into any group and they are very hard to classify. Figure 40 shows the mentioned samples.

Figure 40: Samples 1, 4 and 6 respectively

When commenting on The Grouper experiment results it is good to see the groups visually. Figure 41 shows the final perceptual groups obtained from the observers answers.



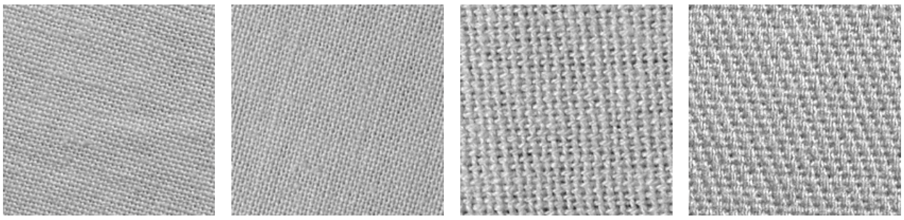


Figure 41: The grouped samples – first row 12, 13; second row 5, 14; third row 9, 10, 11; forth row 2,3 and fifth row 7, 8, 9, 10

By looking at the actual groups it can be seen that the observers in the majority of the cases (group 1, 3, 4 and 5) focused their attention very much on the material and nature of the sample. In the case of the bread for example it is obvious that the big hole in one of the samples and the small holes in the other do not form the same texture from the numerical point of view but perceptually the HSV is able to neglect the big hole and treat them as the same texture. In this case we can expect our feature calculation to fail as it will not give the same values for these two samples for all features whereas the observers threat them as very similar. Similar behavior can be seen in the 3rd group and the 5th as well. Interestingly the majority of the observers did not use the same material criteria for the second group, as they put together two totally different samples with even different orientation of the texture. This is an exception to the behavior that should be examined in more detail.

The next step in the analysis is to compute all the 22 features and see how they behave within a perceptual group. Appendix 5 contains tables that show the feature calculated for each of the sample within a group, their mean and standard deviation. The following table shows as an example the values for the first group.

Group 1 features				
features\images	12	13	mean	deviation
autoc	0.269	0.472	0.370	0.143
contr	0.309	0.174	0.242	0.095
corrm	0.526	1.000	0.763	0.335
corrp	0.526	1.000	0.763	0.335
cprom	0.190	0.246	0.218	0.040
cshad	0.464	0.399	0.432	0.046
dissi	0.476	0.314	0.395	0.115
energ	0.107	0.110	0.108	0.002
entro	0.701	0.638	0.669	0.045
homom	0.334	0.515	0.425	0.128
homop	0.359	0.542	0.451	0.130
maxpr	0.163	0.113	0.138	0.035
sosvh	0.168	0.165	0.166	0.002
savgh	0.410	0.365	0.388	0.032
svarh	0.243	0.205	0.224	0.027
senth	0.674	0.741	0.707	0.047
dvarh	0.309	0.174	0.242	0.095
denth	0.598	0.443	0.521	0.110
inf1h	0.976	0.562	0.769	0.293
inf2h	0.145	0.705	0.425	0.396
indnc	0.466	0.637	0.552	0.120
idmnc	0.652	0.797	0.725	0.103
		least changing		
	features selected in the PCA			

Table 23: 22 features for the samples in group 1 and their mean and standard deviation

By finding the feature for each perceptual group that has the lowest deviation we find the commune feature for the given set therefore the criterion for grouping. For the majority we find that the same group has more than one feature with minimum deviation supporting the idea of some of them being redundant.

So there is not one clear feature that is the same in a group but more than one. The following list shows the features with low deviation for each one of the groups.

1: Energy, Variance

2: Information measure of correlation1

3: Contrast, Correlation, Difference variance, Sum entropy

4: Sum entropy, Information measure of correlation1

5: Variance

Conclusively this experiment shows that when grouping the HVS is focusing a lot on the material and nature of texture. It has an ability to discard the subtle or even big changes in texture of the same material type and treat it as same. Therefore for some features the computations might give different groupings. This is why it is important to look for features that are changing the least for the given set of samples because they can mathematically describe the grouping criteria. For each group we find more than one feature as a possible candidate for a grouping criterion. This is why for the future work it would be better to select samples according to similarities in features rather than relying on the PCA results.

4.3.6. Summary of the results, conclusion and discussion

In this section two perceptual experiments were performed. One of them was testing the relation between the feature scale and the visual scale. The other one was used to see what the observer's criteria for grouping images is.

The results of The Sorter experiment suggested that the observers are more constant in deciding about small texture differences, the ones very close to the neutral sample whereas the big differences are perceived differently. The results also suggest that finding independent features mathematically is not so easy which is also confirmed with the fact that first PC spans only around 56% of the variation suggesting redundancy between the features. Conclusively PCA was shown to be insufficient for defining independent features with perceptual importance. Another dimensionality reduction technique like Independent Component Analysis (ICA) could be used to get more independent components.

This experiment also provided a possibility to suggest a final list of features that are highly correlated with perception (correlation value in the brackets):

PC1 – Homogeneity (0.9706)

PC2 – Sum average (0.8191)

PC3 – Sum variance (0.9437)

PC4 – Sum entropy (0.9055)

PC5 – Maximum probability (0.8242)

Even though PCA was shown to be not related to perception it gave initial steps towards finding the features with high perceptual correlation and a possibility for defining a feature scale.

The Grouper experiment showed that when grouping the HVS is focusing a lot on the material and nature of texture. It has an ability to discard the subtle or even big changes in texture of the same material type and treat it as same. Therefore for some features the computations might give different groupings. This is why it is important to look for features that are changing the least for the given set of samples because they can mathematically describe the grouping criteria. For each group more than one feature was found to be a possible candidate for grouping. This is why for the future work it would be better to select samples according to similarities in features rather than relying on the PCA results.

5. Conclusions

5. Conclusions

In this research the problem of texture characterization and its effect of color perception were studied. The emphasis was put on defining a way to numerically characterize texture images by implementing the GLCM and computing certain texture features from it. An extensive overview of the problem was provided and it was taken to a different level by suggesting applying an image processing texture analysis technique in order to describe the effect of texture in color science. By implementing this simple statistics based texture analysis method it becomes possible to characterize texture with texture features that are related to perception. PCA was implemented in order to reduce the number of possible texture features from 22 to only 5 based on redundancy. In addition PCA provided a way to select samples for the perceptual experiments. To relate the computations with perception of texture, perceptual experiments were performed. These experiments provided a possibility to define perceptually important texture features and suggest how HVS looks at texture. We suggested an application of one, statistical method for texture characterization.

The obtained results suggest that that the distance which gives the maximum contrast should be the best for the GLCM computations as it restricts the feature calculations to surely enclose only one texture element and it lowers the possible averaging. This conclusion gives us a possibility to define a new criterion for the GLCM computations that we call the Maximum Contrast Distance (MCD) criterion. By implementing this criterion the majority of texture features exhibit constant behavior with the change of scale as it recomputed the distance for the feature calculations with every distance and it adjusts the change that the change of scale is introducing.

The usability of the PCA for reducing the number of features used for texture characterization was proven to give one possible objective selection of texture feature. However, the perceptual experiment proved that these features are not related with perception. The reason is that the feature scale and the perceptual scale do not mach in a sense that a small numerical change in one feature has perceptually bigger importance that a big change in another feature and vice versa. Therefore instead of the initial set of five features defined in the PCA another set of five can be derived from The Sorter experiment. This set contains the following features:

PC1 – Homogeneity (0.9706)
PC2 – Sum average (0.8191)
PC3 – Sum variance (0.9437)
PC4 – Sum entropy (0.9055)
PC5 – Maximum probability (0.8242)

These five are proven to have the biggest perceptual importance and provide a first attempt to have a perpetual scale. The Grouper experiment showed that when grouping the HVS is focusing a lot on the material and nature of texture. It has an ability to discard the subtle or even big changes in texture of the same material type and treat it as same. Therefore for some features the computations might give different groupings. This is why it is important to look for features that are changing the least for the given set of samples because they can mathematically describe the grouping criteria. For each group more than one feature was found to be a possible candidate for grouping. This is why for the future work it would be better to select samples according to similarities in features rather than relying on the PCA results. As PCA cannot provide perceptually meaningful feature selection in the future another dimensionally reduction technique like Independent Component Analysis (ICA) could be tested on the given dataset and its results can be related to perception.

Finally the implementation of the results in the color difference calculation can be performed and texture difference can be defined mathematically and perceptually.

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7. Appendix

Appendix 1

NOTE:
The samples are the first three images for scale 2 for each one of the texture types. The numbers reffere to a certain texture in the following maner:
06 - Sandpaper
15 - Aluminium foil
20 - Styrfoam
21 - Sponge
42 - Corduroy
44 - Linen
46 - Cotton
48 - Brown bread
55 - Orange peel
60 - Cracker B

im_1 is an image with frontal camera position and frontal illumination
im_2 is an image with frontal camera position and 45° from top illumination
im_2 is an image with frontal camera position and 45° from side illumination

MCD is the Maximum Contrast Distance.
Max Contrast is the maximum value of the contrast for the ideal distance from all the angles in the GLCM.

	MCD	Max Contrast
06-scale_2_im_1_col		
200x200	14	0.332607527
150x150	6	0.302228009
100x100	14	0.275813953
50x50	18	0.397460938
06-scale_2_im_2_col		
200x200	14	0.483350676
150x150	14	0.451935554
100x100	12	0.407840909
50x50	18	0.370117188
06-scale_2_im_3_col		
200x200	6	1.156804124
150x150	6	1.129583333
100x100	8	1.125869565
50x50	16	1.149653979
15-scale_2_im_1_col		
200x200	18	12.8100471
150x150	18	13.084309
100x100	18	14.50104105
50x50	14	13.34953704
15-scale_2_im_2_col		
200x200	18	10.35397295
150x150	18	10.45087236
100x100	18	13.60425342

50x50	14	18.6257716
15-scale_2_im_3_col		
200x200	18	10.4614177
150x150	18	10.40972222
100x100	18	13.34042237
50x50	12	13.26246537
20-scale_2_im_1_col		
200x200	10	0.549529086
150x150	14	0.580588235
100x100	2	0.629216993
50x50	18	0.64
20-scale_2_im_2_col		
200x200	2	0.635674931
150x150	2	0.57354821
100x100	2	0.593571429
50x50	2	0.542916667
20-scale_2_im_3_col		
200x200	2	1.68375676
150x150	2	1.688915267
100x100	2	1.623802582
50x50	16	1.679411765
21-scale_2_im_1_col		
200x200	18	0.534972527
150x150	12	0.49957992
100x100	12	0.498063017
50x50	16	0.527647059
21-scale_2_im_2_col		
200x200	18	0.71905567
150x150	18	0.749885216
100x100	18	0.769036288
50x50	16	0.625882353
21-scale_2_im_3_col		
200x200	18	2.096373626
150x150	18	2.134584481
100x100	18	2.250743605
50x50	10	1.940625
42-scale_2_im_1_col		
200x200	16	0.955428875
150x150	16	1.01253063
100x100	16	0.975952381
50x50	14	1.067901235
42-scale_2_im_2_col		
200x200	16	1.668537335
150x150	16	1.641741294
100x100	16	1.744614512

50x50	14	1.800154321
42-scale_2_im_3_col		
200x200	16	1.849509688
150x150	16	1.830585877
100x100	16	1.977891156
50x50	16	2.23183391
44-scale_2_im_1_col		
200x200	4	1.841446272
150x150	4	1.733111278
100x100	4	1.571614583
50x50	4	1.643194707
44-scale_2_im_2_col		
200x200	4	1.874453353
150x150	4	1.890223306
100x100	4	1.809570313
50x50	4	1.769848771
44-scale_2_im_3_col		
200x200	4	3.792143898
150x150	4	3.713923813
100x100	4	3.883789063
50x50	4	3.844517958
46-scale_2_im_1_col		
200x200	10	0.878531856
150x150	10	0.873265306
100x100	10	0.841358025
50x50	10	0.824375
46-scale_2_im_2_col		
200x200	4	2.019392961
150x150	4	2.033308313
100x100	4	1.975368924
50x50	16	1.894117647
46-scale_2_im_3_col		
200x200	10	2.079806094
150x150	16	2.038761417
100x100	10	1.955679012
50x50	16	2.049307958
48-scale_2_im_1_col		
200x200	16	1.274293478
150x150	14	1.316519608
100x100	14	1.192325581
50x50	16	0.873702422
48-scale_2_im_2_col		
200x200	12	0.973149615
150x150	16	1.001442786
100x100	18	0.968902439

50x50	12	0.997922438
48-scale_2_im_3_col		
200x200	18	3.363763736
150x150	18	3.549747475
100x100	14	3.524067063
50x50	14	3.025555556
55-scale_2_im_1_col		
200x200	10	0.503157895
150x150	10	0.549190476
100x100	12	0.640340909
50x50	10	0.615625
55-scale_2_im_2_col		
200x200	14	0.502580645
150x150	12	0.445942029
100x100	14	0.317790698
50x50	16	0.16349481
55-scale_2_im_3_col		
200x200	10	0.530526316
150x150	10	0.533190476
100x100	10	0.620111111
50x50	10	1.073125
60-scale_2_im_1_col		
200x200	18	1.801141167
150x150	18	1.93503214
100x100	18	1.734384295
50x50	12	1.445290859
60-scale_2_im_2_col		
200x200	18	2.17552228
150x150	16	1.92199005
100x100	18	2.019928614
50x50	18	2.233398438
60-scale_2_im_3_col		
200x200	18	3.932224369
150x150	18	3.929292929
100x100	18	3.544913742
50x50	18	4.226875

Table app1.1: Results of the resolution test experiment

Appendix 2

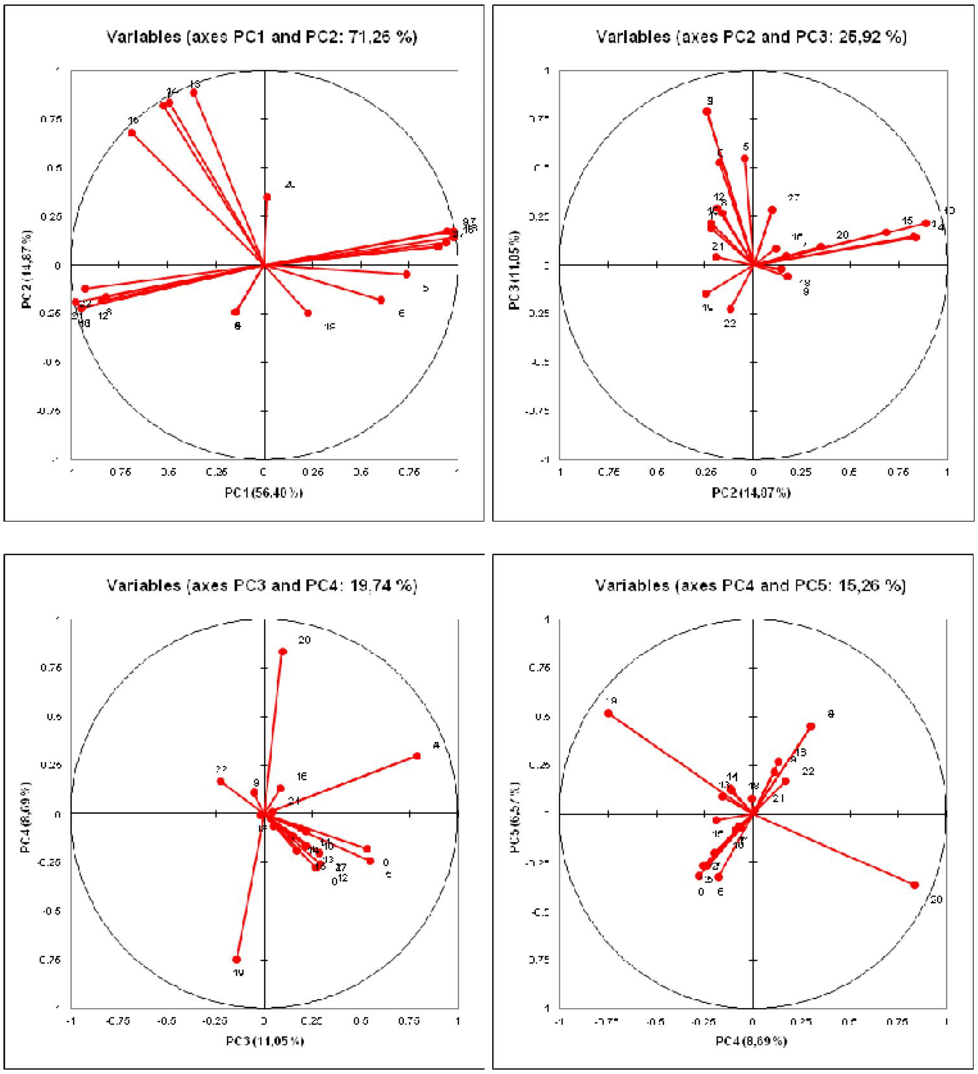

Figure app 2.1: The four correlation circles for two consecutive PCs

Appendix 3

Correlations between variables and factors:					
	F1	F2	F3	F4	F5
1	-0.521	0.823	0.147	-0.113	-0.122
2	0.897	0.096	0.284	-0.202	0.199
3	-0.151	-0.240	0.789	0.299	-0.451
4	-0.151	-0.240	0.789	0.299	-0.451
5	0.737	-0.047	0.546	-0.239	0.264
6	0.605	-0.178	0.530	-0.179	0.324
7	0.975	0.170	0.047	-0.064	0.070
8	-0.819	-0.163	0.267	-0.278	0.316
9	0.948	0.172	-0.056	0.110	-0.217
10	-0.943	-0.218	0.215	-0.089	0.083
11	-0.949	-0.221	0.189	-0.075	0.063
12	-0.842	-0.186	0.290	-0.259	0.266
13	-0.367	0.886	0.212	-0.160	-0.088
14	-0.488	0.836	0.139	-0.117	-0.129
15	-0.684	0.681	0.166	-0.190	0.033
16	0.943	0.114	0.082	0.129	-0.265
17	0.897	0.096	0.284	-0.202	0.199
18	0.979	0.142	-0.020	-0.008	-0.079
19	-0.225	0.244	0.145	0.747	0.519
20	0.012	0.348	0.092	0.835	0.367
21	-0.977	-0.191	0.042	0.012	-0.021
22	-0.926	-0.119	-0.226	0.167	-0.169

Table app3.1: Correlations between variables and factors

Correlation matrix (Pearson (n)):

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	1	-0.355	0.016	0.016	-0.344	-0.385	-0.367	0.317	-0.346	0.343	0.342	0.322	0.982	0.989	0.960	-0.366	-0.355	-0.384	0.187	0.157	0.362	0.359
2	-0.355	1	-0.077	-0.077	0.904	0.714	0.944	-0.538	0.783	-0.769	-0.790	-0.578	-0.171	-0.324	-0.460	0.796	1.000	0.865	-0.171	-0.035	-0.897	-0.995
3	0.016	-0.077	1	1.000	0.134	0.147	-0.196	0.158	-0.097	0.300	0.294	0.207	0.002	0.006	-0.002	0.051	-0.077	-0.166	0.085	0.067	0.235	0.108
4	0.016	-0.077	1.000	1	0.134	0.147	-0.196	0.158	-0.097	0.300	0.294	0.207	0.002	0.006	-0.002	0.051	-0.077	-0.166	0.085	0.067	0.235	0.108
5	-0.344	0.904	0.134	0.134	1	0.889	0.760	-0.326	0.568	-0.524	-0.545	-0.338	-0.179	-0.328	-0.391	0.632	0.904	0.678	-0.145	-0.057	-0.687	-0.872
6	-0.385	0.714	0.147	0.147	0.889	1	0.583	-0.233	0.423	-0.380	-0.397	-0.225	-0.261	-0.381	-0.393	0.495	0.714	0.545	-0.109	-0.010	-0.519	-0.685
7	-0.367	0.944	-0.196	-0.196	0.760	0.583	1	-0.754	0.931	-0.935	-0.948	-0.794	-0.195	-0.331	-0.531	0.913	0.944	0.971	-0.174	0.043	-0.993	-0.970
8	0.317	-0.538	0.158	0.158	-0.326	-0.233	-0.754	1	-0.904	0.912	0.892	0.976	0.225	0.291	0.554	-0.889	-0.538	-0.851	0.146	-0.158	0.814	0.594
9	-0.346	0.783	-0.097	-0.097	0.568	0.423	0.931	-0.904	1	-0.973	-0.975	-0.921	-0.206	-0.313	-0.569	0.984	0.783	0.977	-0.211	0.080	-0.960	-0.832
10	0.343	-0.769	0.300	0.300	-0.524	-0.380	-0.935	0.912	-0.973	1	0.999	0.942	0.206	0.308	0.552	-0.929	-0.769	-0.964	0.167	-0.111	0.971	0.821
11	0.342	-0.790	0.294	0.294	-0.545	-0.397	-0.948	0.892	-0.975	0.999	1	0.926	0.201	0.306	0.547	-0.930	-0.790	-0.970	0.162	-0.110	0.980	0.841
12	0.322	-0.578	0.207	0.207	-0.338	-0.225	-0.794	0.976	-0.921	0.942	0.926	1	0.222	0.289	0.553	-0.889	-0.578	-0.861	0.135	-0.165	0.853	0.637
13	0.982	-0.171	0.002	0.002	-0.179	-0.261	-0.195	0.225	-0.206	0.206	0.201	0.222	1	0.976	0.919	-0.225	-0.171	-0.230	0.162	0.159	0.199	0.177
14	0.989	-0.324	0.006	0.006	-0.328	-0.381	-0.331	0.291	-0.313	0.308	0.306	0.289	0.976	1	0.939	-0.336	-0.324	-0.351	0.183	0.149	0.325	0.326
15	0.960	-0.460	-0.002	-0.002	-0.391	-0.393	-0.531	0.554	-0.569	0.552	0.547	0.553	0.919	0.939	1	-0.587	-0.460	-0.578	0.216	0.099	0.543	0.481
16	-0.366	0.796	0.051	0.051	0.632	0.495	0.913	-0.889	0.984	-0.929	-0.930	-0.889	-0.225	-0.336	-0.587	1	0.796	0.964	-0.217	0.072	-0.931	-0.835
17	-0.355	1.000	-0.077	-0.077	0.904	0.714	0.944	-0.538	0.783	-0.769	-0.790	-0.578	-0.171	-0.324	-0.460	0.796	1	0.865	-0.171	-0.035	-0.897	-0.995
18	-0.384	0.865	-0.166	-0.166	0.678	0.545	0.971	-0.851	0.977	-0.964	-0.970	-0.861	-0.230	-0.351	-0.578	0.964	0.865	1	-0.238	0.027	-0.983	-0.904
19	0.187	-0.171	0.085	0.085	-0.145	-0.109	-0.174	0.146	-0.211	0.167	0.162	0.135	0.162	0.183	0.216	-0.217	-0.171	-0.238	1	0.870	0.172	0.171
20	0.157	-0.035	0.067	0.067	-0.057	-0.010	0.043	-0.158	0.080	-0.111	-0.110	-0.165	0.159	0.149	0.099	0.072	-0.035	0.027	0.870	1	-0.069	0.012
21	0.362	-0.897	0.235	0.235	-0.687	-0.519	-0.993	0.814	-0.960	0.971	0.980	0.853	0.199	0.325	0.543	-0.931	-0.897	-0.983	0.172	-0.069	1	0.933
22	0.359	-0.995	0.108	0.108	-0.872	-0.685	-0.970	0.594	-0.832	0.821	0.841	0.637	0.177	0.326	0.481	-0.835	-0.995	-0.904	0.171	0.012	0.933	1

Values in bold are different from 0 with a significance level alpha=0.05

Table app3.2: Pearson Correlations matrix between features

Squared cosines of the variables:					
	F1	F2	F3	F4	F5
1	0.271	**0.677**	0.022	0.013	0.015
2	**0.805**	0.009	0.081	0.041	0.040
3	0.023	0.057	**0.623**	0.090	0.204
4	0.023	0.057	**0.623**	0.090	0.204
5	**0.543**	0.002	0.298	0.057	0.070
6	**0.365**	0.032	0.281	0.032	0.105
7	**0.951**	0.029	0.002	0.004	0.005
8	**0.670**	0.026	0.071	0.078	0.100
9	**0.899**	0.030	0.003	0.012	0.047
10	**0.890**	0.047	0.046	0.008	0.007
11	**0.901**	0.049	0.036	0.006	0.004
12	**0.709**	0.035	0.084	0.067	0.071
13	0.135	**0.785**	0.045	0.026	0.008
14	0.239	**0.698**	0.019	0.014	0.017
15	**0.468**	0.463	0.027	0.036	0.001
16	**0.888**	0.013	0.007	0.017	0.070
17	**0.805**	0.009	0.081	0.041	0.040
18	**0.959**	0.020	0.000	0.000	0.006
19	0.051	0.060	0.021	**0.557**	0.270
20	0.000	0.121	0.008	**0.697**	0.135
21	**0.954**	0.037	0.002	0.000	0.000
22	**0.858**	0.014	0.051	0.028	0.028

Table app3.3: Squared cosines of the variables

Appendix 4

Mean features for the samples in experiment 1.1											
features\image	1	2	3	4	5	6	7	8	9	Mean	Deviation
autoc	34.43	34.50	33.84	34.26	34.43	34.74	34.96	34.86	36.00	34.67	0.60
contr	1.72	1.82	6.71	4.13	2.39	2.21	0.89	0.35	0.00	2.25	2.07
corrm	0.00	-0.01	0.03	-0.08	-0.13	-0.05	0.01	0.12	0.00	-0.01	0.07
corrp	0.00	-0.01	0.03	-0.08	-0.13	-0.05	0.01	0.12	0.00	-0.01	0.07
cprom	12.23	13.89	135.86	35.45	9.41	11.46	2.65	0.93	0.00	24.65	43.03
cshad	-1.79	-1.96	-7.42	-2.05	-0.15	0.43	-0.10	-0.02	0.00	-1.45	2.44
dissi	0.92	0.93	2.05	1.57	1.21	1.16	0.66	0.33	0.00	0.98	0.62
energ	0.14	0.14	0.03	0.05	0.07	0.07	0.19	0.44	1.00	0.24	0.31
entro	2.49	2.52	3.75	3.36	2.85	2.84	2.04	1.23	0.00	2.34	1.14
homom	0.65	0.65	0.45	0.50	0.56	0.57	0.70	0.84	1.00	0.66	0.17
homop	0.62	0.62	0.37	0.44	0.51	0.53	0.69	0.84	1.00	0.62	0.20
maxpr	0.29	0.30	0.07	0.10	0.13	0.13	0.37	0.63	1.00	0.33	0.31
sosvh	35.11	35.22	37.02	36.14	35.44	35.66	35.23	34.85	35.81	35.61	0.66
savgh	11.74	11.75	11.62	11.73	11.76	11.80	11.83	11.80	12.00	11.78	0.10
svarh	103.73	103.64	93.01	97.68	102.77	102.88	110.25	118.18	144.00	108.46	15.10
senth	1.64	1.66	2.35	2.03	1.71	1.75	1.37	0.95	0.00	1.50	0.68
dvarh	1.72	1.82	6.71	4.13	2.39	2.21	0.89	0.35	0.00	2.25	2.07
denth	1.23	1.25	1.79	1.57	1.32	1.29	0.97	0.66	0.00	1.12	0.53
inf1h	0.00	0.00	0.00	-0.01	-0.02	-0.01	0.00	-0.07	0.00	-0.01	0.02
inf2h	0.04	0.03	0.05	0.15	0.21	0.17	0.05	0.25	0.00	0.11	0.09
indnc	0.91	0.91	0.82	0.85	0.88	0.88	0.93	0.96	1.00	0.90	0.06
idmnc	0.98	0.97	0.92	0.95	0.97	0.97	0.99	0.99	1.00	0.97	0.03
										most changing	
										highest correlation	
										our selection	
										features selected in the PCA	

Table app4.1: Mean of the four directions for all features for the first set of samples in the sorter experiment (Experiment 1.1)

Mean features for the samples in experiment 1.2											
features\image	10	11	12	13	14	15	16	17	18	Mean	Deviation
autoc	34.43	34.33	34.32	34.63	34.43	34.73	34.74	34.39	36.00	34.67	0.53
contr	1.72	3.01	5.89	1.54	2.39	1.47	2.21	4.89	0.00	2.57	1.82
corrm	0.00	-0.10	0.04	0.03	-0.13	-0.20	-0.05	0.04	0.00	-0.04	0.09
corrp	0.00	-0.10	0.04	0.03	-0.13	-0.20	-0.05	0.04	0.00	-0.04	0.09
cprom	12.23	17.75	100.12	8.67	9.41	2.76	11.46	71.13	0.00	25.95	34.98
cshad	-1.79	-0.43	-3.30	-0.04	-0.15	-0.06	0.43	-1.80	0.00	-0.79	1.23
dissi	0.92	1.36	1.93	0.93	1.21	0.93	1.16	1.75	0.00	1.13	0.56
energ	0.14	0.06	0.03	0.10	0.07	0.13	0.07	0.03	1.00	0.18	0.31
entro	2.49	2.92	3.60	2.59	2.85	2.29	2.84	3.56	0.00	2.57	1.06
homom	0.65	0.54	0.46	0.63	0.56	0.62	0.57	0.48	1.00	0.61	0.16
homop	0.62	0.48	0.39	0.60	0.51	0.59	0.53	0.41	1.00	0.57	0.18
maxpr	0.29	0.10	0.08	0.21	0.13	0.23	0.13	0.05	1.00	0.25	0.29
sosvh	35.11	35.65	37.08	35.22	35.44	35.29	35.66	36.65	35.81	35.77	0.67
savgh	11.74	11.74	11.70	11.76	11.76	11.81	11.80	11.71	12.00	11.78	0.09
svarh	103.73	101.57	94.75	103.71	102.77	109.48	102.88	95.25	144.00	106.46	14.78
senth	1.64	1.79	2.30	1.66	1.71	1.39	1.75	2.23	0.00	1.61	0.67
dvarh	1.72	3.01	5.89	1.54	2.39	1.47	2.21	4.89	0.00	2.57	1.82
denth	1.23	1.34	1.72	1.16	1.32	1.12	1.29	1.64	0.00	1.20	0.50
inf1h	0.00	-0.10	0.00	-0.01	-0.02	-0.04	-0.01	0.00	0.00	-0.02	0.03
inf2h	0.04	0.48	0.10	0.15	0.21	0.30	0.17	0.07	0.00	0.17	0.15
indnc	0.91	0.87	0.82	0.90	0.88	0.90	0.88	0.84	1.00	0.89	0.05
idmnc	0.98	0.96	0.92	0.98	0.97	0.98	0.97	0.94	1.00	0.96	0.02
										most changing	
										highest correlation	
										our selection	
										features selected in the PCA	

Table app4.2: Mean of the four directions for all features for the second set of samples in the sorter experiment (Experiment 1.2)

Mean features for the samples in experiment 1.3												
features\image	19	20	21	22	23	24	25	26	27	28	Mean	Deviation
autoc	35.90	34.43	33.84	35.06	34.55	34.74	34.34	35.93	35.49	36.00	35.03	0.77
contr	4.47	1.72	6.71	1.30	1.87	2.21	2.66	0.03	0.09	0.00	2.11	2.13
corrm	0.27	0.00	0.03	0.38	-0.05	-0.05	0.05	0.05	0.08	0.00	0.08	0.14
corrp	0.27	0.00	0.03	0.38	-0.05	-0.05	0.05	0.05	0.08	0.00	0.08	0.14
cprom	120.60	12.23	135.86	22.91	9.28	11.46	35.66	0.05	0.15	0.00	34.82	50.60
cshad	-2.98	-1.79	-7.42	2.98	-0.51	0.43	-3.98	-0.01	-0.10	0.00	-1.34	2.88
dissi	1.58	0.92	2.05	0.82	1.05	1.16	1.20	0.03	0.09	0.00	0.89	0.68
energ	0.05	0.14	0.03	0.10	0.09	0.07	0.08	0.93	0.83	1.00	0.33	0.41
entro	3.29	2.49	3.75	2.65	2.67	2.84	3.00	0.20	0.41	0.00	2.13	1.38
homom	0.54	0.65	0.45	0.66	0.59	0.57	0.58	0.98	0.96	1.00	0.70	0.20
homop	0.48	0.62	0.37	0.64	0.56	0.53	0.54	0.98	0.96	1.00	0.67	0.23
maxpr	0.14	0.29	0.07	0.19	0.17	0.13	0.17	0.96	0.91	1.00	0.40	0.39
sosvh	37.95	35.11	37.02	35.53	35.30	35.66	35.49	35.76	35.34	35.81	35.90	0.89
savgh	11.85	11.74	11.62	11.77	11.76	11.80	11.71	11.99	11.91	12.00	11.81	0.12
svarh	98.90	103.73	93.01	100.87	103.71	102.88	99.15	139.47	133.91	144.00	111.96	19.15
senth	2.30	1.64	2.35	1.88	1.66	1.75	1.90	0.18	0.35	0.00	1.40	0.88
dvarh	4.47	1.72	6.71	1.30	1.87	2.21	2.66	0.03	0.09	0.00	2.11	2.13
denth	1.61	1.23	1.79	1.12	1.21	1.29	1.40	0.15	0.29	0.00	1.01	0.63
inf1h	-0.03	0.00	0.00	-0.06	-0.03	-0.01	-0.01	-0.01	-0.03	0.00	-0.02	0.02
inf2h	0.30	0.04	0.05	0.39	0.28	0.17	0.14	0.05	0.07	0.00	0.15	0.13
indnc	0.85	0.91	0.82	0.91	0.89	0.88	0.88	1.00	0.99	1.00	0.91	0.06
idmnc	0.94	0.98	0.92	0.98	0.97	0.97	0.96	1.00	1.00	1.00	0.97	0.03
											most changing	
											highest correlation	
											our selection	
											features selected in the PCA	

Table app4.3: Mean of the four directions for all features for the third set of samples in the sorter experiment (Experiment 1.3)

Mean features for the samples in experiment 1.4												
features\image	29	30	31	32	33	34	35	36	37	38	Mean	Deviation
autoc	34.48	34.36	34.43	34.50	34.77	34.74	34.82	35.34	34.51	36.00	34.79	0.51
contr	7.44	1.77	1.72	1.82	1.27	2.21	1.46	1.33	6.38	0.00	2.54	2.39
corrm	0.03	-0.02	0.00	-0.01	-0.05	-0.05	0.44	0.49	0.09	0.00	0.09	0.20
corrp	0.03	-0.02	0.00	-0.01	-0.05	-0.05	0.44	0.49	0.09	0.00	0.09	0.20
cprom	149.74	11.64	12.23	13.89	3.98	11.46	34.16	47.65	141.87	0.00	42.66	56.19
cshad	-6.38	-1.74	-1.79	-1.96	-0.20	0.43	-3.27	-7.26	-6.76	0.00	-2.89	2.92
dissi	2.13	0.93	0.92	0.93	0.84	1.16	0.87	0.80	1.97	0.00	1.05	0.61
energ	0.04	0.14	0.14	0.14	0.14	0.07	0.07	0.11	0.03	1.00	0.19	0.29
entro	3.58	2.49	2.49	2.52	2.23	2.84	2.84	2.63	3.65	0.00	2.53	1.00
homom	0.46	0.64	0.65	0.65	0.65	0.57	0.65	0.67	0.47	1.00	0.64	0.15
homop	0.38	0.61	0.62	0.62	0.62	0.53	0.62	0.65	0.39	1.00	0.61	0.17
maxpr	0.11	0.31	0.29	0.30	0.25	0.13	0.13	0.18	0.09	1.00	0.28	0.27
sosvh	38.02	35.06	35.11	35.22	35.22	35.66	35.36	35.82	37.51	35.81	35.88	1.04
savgh	11.72	11.73	11.74	11.75	11.80	11.80	11.70	11.78	11.69	12.00	11.77	0.09
svarh	95.84	103.52	103.73	103.64	108.62	102.88	98.17	101.09	94.71	144.00	105.62	14.11
senth	2.35	1.64	1.64	1.66	1.43	1.75	1.99	1.92	2.36	0.00	1.67	0.66
dvarh	7.44	1.77	1.72	1.82	1.27	2.21	1.46	1.33	6.38	0.00	2.54	2.39
denth	1.81	1.25	1.23	1.25	1.05	1.29	1.16	1.12	1.76	0.00	1.19	0.49
inf1h	-0.01	0.00	0.00	0.00	-0.07	-0.01	-0.11	-0.11	-0.01	0.00	-0.03	0.05
inf2h	0.17	0.04	0.04	0.03	0.39	0.17	0.52	0.49	0.12	0.00	0.20	0.20
indnc	0.81	0.90	0.91	0.91	0.91	0.88	0.91	0.92	0.82	1.00	0.90	0.05
idmnc	0.91	0.97	0.98	0.97	0.98	0.97	0.98	0.98	0.92	1.00	0.97	0.03
											most changing	
											highest correlation	
											our selection	
											features selected in the PCA	

Table app4.4: Mean of the four directions for all features for the fourth set of samples in the sorter experiment (Experiment 1.4)

Mean features for the samples in experiment 1.5											
features\image	39	40	41	42	43	44	45	46	47	48	Mean	Deviation
autoc	34.61	34.43	34.69	34.20	34.41	34.74	34.34	34.40	34.77	36.00	34.66	0.51
contr	4.46	1.72	0.87	3.79	1.99	2.21	2.66	2.32	0.28	0.00	2.03	1.42
corrm	0.11	0.00	-0.14	-0.32	-0.15	-0.05	0.05	0.08	0.09	0.00	-0.03	0.13
corrp	0.11	0.00	-0.14	-0.32	-0.15	-0.05	0.05	0.08	0.09	0.00	-0.03	0.13
cprom	69.13	12.23	1.48	14.57	6.72	11.46	35.66	26.57	0.60	0.00	17.84	21.38
cshad	0.23	-1.79	0.00	-0.42	-0.39	0.43	-3.98	-2.60	-0.09	0.00	-0.86	1.45
dissi	1.64	0.92	0.64	1.56	1.08	1.16	1.20	1.15	0.27	0.00	0.96	0.52
energ	0.04	0.14	0.23	0.08	0.10	0.07	0.08	0.07	0.52	1.00	0.23	0.30
entro	3.32	2.49	1.80	2.72	2.63	2.84	3.00	3.00	1.02	0.00	2.28	1.04
homom	0.51	0.65	0.71	0.51	0.59	0.57	0.58	0.58	0.87	1.00	0.66	0.16
homop	0.44	0.62	0.70	0.44	0.55	0.53	0.54	0.54	0.86	1.00	0.62	0.18
maxpr	0.08	0.29	0.41	0.14	0.19	0.13	0.17	0.16	0.70	1.00	0.33	0.30
sosvh	36.66	35.11	34.94	35.92	35.22	35.66	35.49	35.37	34.72	35.81	35.49	0.56
savgh	11.72	11.74	11.79	11.77	11.75	11.80	11.71	11.71	11.79	12.00	11.78	0.08
svarh	95.97	103.73	113.42	106.50	104.67	102.88	99.15	99.13	120.89	144.00	109.03	14.30
senth	2.21	1.64	1.17	1.56	1.60	1.75	1.90	1.89	0.81	0.00	1.45	0.64
dvarh	4.46	1.72	0.87	3.79	1.99	2.21	2.66	2.32	0.28	0.00	2.03	1.42
denth	1.60	1.23	0.94	1.33	1.25	1.29	1.40	1.34	0.59	0.00	1.10	0.47
inf1h	-0.01	0.00	-0.08	-0.24	-0.03	-0.01	-0.01	-0.01	-0.08	0.00	-0.05	0.08
inf2h	0.17	0.04	0.36	0.72	0.27	0.17	0.14	0.14	0.24	0.00	0.22	0.20
indnc	0.85	0.91	0.93	0.85	0.89	0.88	0.88	0.88	0.97	1.00	0.90	0.05
idmnc	0.94	0.98	0.99	0.95	0.97	0.97	0.96	0.97	1.00	1.00	0.97	0.02

most changing
highest correlation
our selection
features selected in the PCA

Table app4.5: Mean of the four directions for all features for the fifth set of samples in the sorter experiment (Experiment 1.5)

Appendix 5

Group 1 features				
features\images	12	13	mean	deviation
autoc	0.269	0.472	0.370	0.143
contr	0.309	0.174	0.242	0.095
corrm	0.526	1.000	0.763	0.335
corrp	0.526	1.000	0.763	0.335
cprom	0.190	0.246	0.218	0.040
cshad	0.464	0.399	0.432	0.046
dissi	0.476	0.314	0.395	0.115
energ	0.107	0.110	0.108	0.002
entro	0.701	0.638	0.669	0.045
homom	0.334	0.515	0.425	0.128
homop	0.359	0.542	0.451	0.130
maxpr	0.163	0.113	0.138	0.035
sosvh	0.168	0.165	0.166	0.002
savgh	0.410	0.365	0.388	0.032
svarh	0.243	0.205	0.224	0.027
senth	0.674	0.741	0.707	0.047
dvarh	0.309	0.174	0.242	0.095
denth	0.598	0.443	0.521	0.110
inf1h	0.976	0.562	0.769	0.293
inf2h	0.145	0.705	0.425	0.396
indnc	0.466	0.637	0.552	0.120
idmnc	0.652	0.797	0.725	0.103
		most changing		
		least changing		
		our selection		
	features selected in the PCA			

Table app5.1: 22 features for the samples in group 1 and their mean and standard deviation

Group 2 features				
features\images	5	14	mean	deviation
autoc	0.591	0.493	0.542	0.069
contr	0.149	0.000	0.075	0.106
corrm	0.919	0.574	0.746	0.244
corrp	0.919	0.574	0.746	0.244
cprom	0.163	0.000	0.081	0.115
cshad	1.000	0.712	0.856	0.204
dissi	0.282	0.000	0.141	0.200
energ	0.169	1.000	0.584	0.588
entro	0.562	0.000	0.281	0.397
homom	0.551	1.000	0.775	0.318
homop	0.579	1.000	0.790	0.297
maxpr	0.225	1.000	0.613	0.548
sosvh	0.218	0.000	0.109	0.154
savgh	0.683	0.817	0.750	0.095
svarh	0.312	1.000	0.656	0.486
senth	0.662	0.000	0.331	0.468
dvarh	0.149	0.000	0.075	0.106
denth	0.407	0.000	0.203	0.287
inf1h	0.753	0.694	0.724	0.042
inf2h	0.512	0.310	0.411	0.143
indnc	0.670	1.000	0.835	0.233
idmnc	0.825	1.000	0.912	0.124
		most changing		
		least changing		
		our selection		
	features selected in the PCA			

Table app5.2: 22 features for the samples in group 2 and their mean and standard deviation

Group 3 features					
features\images	9	10	11	mean	deviation
autoc	0.450	0.274	0.435	0.354	0.114
contr	0.145	0.257	0.293	0.275	0.025
corrm	0.345	0.219	0.352	0.285	0.094
corrp	0.345	0.219	0.352	0.285	0.094
cprom	0.023	0.043	0.078	0.060	0.025
cshad	0.694	0.676	0.755	0.716	0.056
dissi	0.295	0.438	0.481	0.459	0.031
energ	0.260	0.170	0.110	0.140	0.043
entro	0.396	0.554	0.640	0.597	0.061
homom	0.512	0.353	0.309	0.331	0.031
homop	0.544	0.380	0.333	0.356	0.033
maxpr	0.319	0.225	0.106	0.165	0.084
sosvh	0.120	0.118	0.261	0.190	0.101
savgh	0.794	0.594	0.784	0.689	0.134
svarh	0.620	0.463	0.392	0.428	0.050
senth	0.344	0.460	0.573	0.516	0.080
dvarh	0.145	0.257	0.293	0.275	0.025
denth	0.349	0.524	0.561	0.542	0.026
inf1h	0.696	0.875	0.945	0.910	0.050
inf2h	0.518	0.343	0.197	0.270	0.103
indnc	0.650	0.499	0.454	0.477	0.032
idmnc	0.828	0.703	0.663	0.683	0.028
				most changing	
				least changing	
				our selection	
				features selected in the PCA	

Table app5.3: 22 features for the samples in group 3 and their mean and standard deviation

Group 4 features				
features\images	2	3	mean	deviation
autoc	0.249	0.286	0.267	0.027
contr	0.223	0.215	0.219	0.006
corrm	0.392	0.411	0.402	0.013
corrp	0.392	0.411	0.402	0.013
cprom	0.079	0.084	0.082	0.003
cshad	0.547	0.542	0.544	0.004
dissi	0.351	0.342	0.346	0.006
energ	0.275	0.260	0.268	0.011
entro	0.498	0.500	0.499	0.002
homom	0.501	0.503	0.502	0.002
homop	0.523	0.529	0.526	0.004
maxpr	0.428	0.400	0.414	0.020
sosvh	0.067	0.083	0.075	0.011
savgh	0.470	0.519	0.494	0.035
svarh	0.418	0.426	0.422	0.006
senth	0.488	0.489	0.488	0.000
dvarh	0.223	0.215	0.219	0.006
denth	0.520	0.504	0.512	0.012
inf1h	1.000	1.000	1.000	0.000
inf2h	0.000	0.001	0.001	0.001
indnc	0.605	0.613	0.609	0.006
idmnc	0.747	0.758	0.753	0.008
			most changing	
			least changing	
			our selection	
			features selected in the PCA	

Table app5.4: 22 features for the samples in group 4 and their mean and standard deviation

Group 5 features						
features\images	7	8	9	10	mean	deviation
autoc	0.174	0.432	0.450	0.274	0.362	0.125
contr	0.541	0.176	0.145	0.257	0.201	0.080
corrm	0.000	0.154	0.345	0.219	0.282	0.090
corrp	0.000	0.154	0.345	0.219	0.282	0.090
cprom	0.101	0.014	0.023	0.043	0.033	0.014
cshad	0.674	0.708	0.694	0.676	0.685	0.013
dissi	0.714	0.350	0.295	0.438	0.366	0.100
energ	0.128	0.244	0.260	0.170	0.215	0.064
entro	0.591	0.420	0.396	0.554	0.475	0.112
homom	0.145	0.430	0.512	0.353	0.432	0.112
homop	0.143	0.465	0.544	0.380	0.462	0.116
maxpr	0.133	0.294	0.319	0.225	0.272	0.066
sosvh	0.343	0.140	0.120	0.118	0.119	0.001
savgh	0.684	0.833	0.794	0.594	0.694	0.142
svarh	0.536	0.654	0.620	0.463	0.542	0.111
senth	0.432	0.314	0.344	0.460	0.402	0.082
dvarh	0.541	0.176	0.145	0.257	0.201	0.080
denth	0.591	0.406	0.349	0.524	0.437	0.123
inf1h	0.000	0.825	0.696	0.875	0.786	0.127
inf2h	1.000	0.379	0.518	0.343	0.431	0.124
indnc	0.232	0.587	0.650	0.499	0.575	0.107
idmnc	0.398	0.791	0.828	0.703	0.765	0.088

most changing	
least changing	
our selection	
features selected in the PCA	

Table app5.5: 22 features for the samples in group 5 and their mean and standard deviation