# NEW WAVELETS BASED FEATURES FOR NATURAL SURFACE INDEXING

H. Alexandre, J. Caldas Pinto
*IDMEC, Instituto Superior Técnico, Av. Rovisco Pais, 1049-001 Lisboa, Portugal*

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Abstract: Natural Surfaces Indexing based on their visual appearance is an important industrial issue for example in inspection and automatic goods retrieval problems. However due to the presence of randomly distributed high number of different colours and its subjective evaluation by human experts, the problem remains practically unsolved. In this paper it is presented some new features derived from a wavelet decomposition of the original images. This decomposition was applied to different models of colour representation and they were used different wavelet families and resolution levels. It will be shown that promising indexing results applied to marble surfaces can be obtained with a suitable combination of those parameters and using our proposed new features for indexing with very simple Euclidian distances.

## 1 INTRODUCTION

The problem of automatic indexation of natural surfaces has been tackled in the literature based on different techniques. They have been applied to ornamental stones (Larabi, 2003), fabrics (Sobral, 2005) and generic images in database image retrieval problems (Park, 2004). However, it is not yet a solved problem. Indeed the appearance of a natural surface depends on the subjective evaluation of the expert that however in general do not corresponds to a reliable measurement of the visual properties, such as colour, texture and shape. This situation is not affordable when currently industry demands high level quality control.

Visual feature extraction applied to content-based image retrieval has been thoroughly studied for the last years. Most work concentrates on low level visual features such as colour, shape, texture, etc. When we are dealing with a very broad variety of images a previous classification operation will generate a more homogeneous set of images and hence facilitate the indexation. In this paper we will avoid classification using a given category of objects, marbles in this paper, despite its quite large variety.

In order to perform content-based image operations, features which are representative of image content, should be extracted. Generally, colour, texture, shape, and spatial relations of objects are used. Colour histogram is a common colour feature (Cinque, 2001). Other colour based features were introduced by Caldas Pinto et al. (Pinto, 2000), Ioka, Niblack and others. A good survey on the subject is presented by Yong and Huang in (Yong Rui, 1999) Shape representation invariant to translation, rotation, and scaling have also been used. In general, it can be divided into two categories, boundary-based and region-based. (Haralick, 1992). The most successful representatives for these two categories are Fourier descriptor and moment invariants. Texture information along with the colour information can well describe the image content such as roughness, regularity, directionality, correlation, etc. Co-occurrence features (Park, 2004) Gabor filters (Idrissa, 2002), modified Tamura, Markov random field features (Bouman, 1995), and fractal features (Harsh, 1998), and morphological operators (Serra, 1982) are generally used for describing texture information.

This paper is organized as follows. In Section 2 a brief revision of colour models are presented. Section 3 presents a short description of the one and two dimensional wavelets decomposition and in section 4 the proposed new features derived from the resulting detailed images are described. Finally in section 5 results are presented and discussed and section 6 concludes the paper, giving guidelines for futures developments in this important area.



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## 2 COLOR MODELS

Since long researchers and practitioners have proposed colour models to better match quantitative description of color with the application. Areas related to scanners, printers, virtual reality, industrial inspection, color classification, amongst others, all need different color models. The most popular color space corresponds to the RGB tristimulus values. It is intensively used in hardware settings but unfortunately it is not well suited for a human interaction and interpretation. Indeed human beings do not refer an image appearance through its primary colours percentages, but mainly though the notion of hue, saturation and brightness. Because this last parameter is difficult to measure it was replaced by the intensity in the definition of an alternative colour space, the HSI.

Another space colour tested in this work was the YIQ. It works directly with the chromatic light properties, what means that colour is classified through its luminance and chrominance. Another space reported as providing good results in different applications (Schwardt, 2005) is the so-called K-L space based on the Karhunen-Loève transform. It is a orthogonal space and it corresponds to a linear representation based on the statistical properties of the image.

Finally two other spaces tested in this work were the CIE L*a*b* and CIE L*C*H*. These representations have their origin in the experiences carried on by the International Commission on Illumination (CIE) with human observers and that led to the CIE XYZ space. Because the bases of these spaces correspond to the answer of human observers to stimulus originated in their colour observation, they are very adequated for textures description (Westlend, 2000).

## 3 WAVELETS TRANSFORM

A multiresolution analysis of a function $f(t)$ is performed by projecting $f(t)$ on successive lower resolution approximations. Let $L^2(\Re)$ the space of squared integrable functions that contains $f(t)$. A multiresolution approximation of this space consists of a series of nested subspaces such that $\cdots \subset V_{-1} \subset V_0 \subset \cdots \subset L^2(\Re)$, that should obey to the following rules:

$$\bigcap_j V_j = \{0\}, \quad \overline{\bigcup_j V_j} = L^2(\Re), \tag{1}$$

where $\overline{A}$ represented the space generated by $A$

$$f(t) \in V_j \Leftrightarrow f(2t) \in V_{j+1} \tag{2}$$

$$f(t) \in V_0 \Leftrightarrow f(t-k) \in V_0 \tag{3}$$

There exist a function $\phi(t)$, called scale function, such that $\{\phi(t-k)\}$ is an orthogonal basis of $V_0$. This last statement together statement (3) leads to the important result:

$$\phi_{j,k}(t) = 2^{j/2}\phi\left(2^j t - k\right) \tag{4}$$

and $\{\phi_{j,k}(t)\}$ constitutes an orthogonal basis for $V_j$.

The process of projecting $f(t)$ from $V_{m+1}$ to $V_m$ results in loss of signal information. This can be interpreted as a decomposition of the signal $f_{m+1}(t)$ into two components one corresponding to its m resolution version, the other to the lost detail. If we define $W_m$ as a space orthogonal to $V_m$ we can write:

$$V_{m+1} = V_m \oplus W_m \tag{5}$$

$W_m$ is called the detail space at scale *m*. Generalizing this result we have:

$$V_{j+1} = W_j \oplus V_j = W_j \oplus W_{j-1} \oplus V_{j-1} = \cdots = W_j \oplus \oplus W_{j-1} \oplus W_{j-2} \oplus \cdots \oplus W_{j-J} \oplus V_{j-J}.$$

In practical (computer) applications, signals to be analyzed are given in sampled form, i.e. $f(t)$ is known at certain time positions $f(n)$ with n in some finite interval of Z. Since every physical recording device has a finite resolution, the samples $f(n)$ represent $f(t)$ at the highest possible scale. Let us arbitrarily set this scale to $j$ = 0 (we thus assume that $f(t) \in V_0$). From the above expression we have for any negative $j$:

$$f(t) = f_j(t) + \sum_{k=j}^{-1} d_k(t). \tag{6}$$

where $d_k(t)$ represent the details of the representation at each level of resolution.

Wavelets families provide basis functions for these spaces. Each family is constituted by a mother wavelet function $\psi(t)$ from which it is defined the basis function for each $W_k$ and the scalar function (sometimes referred as wavelet father) that generates the basis for each $V_k$. One of the most used families is the Haar wavelets. The corresponding scale and mother wavelet functions are:

$$\begin{cases} \phi(t)=1 & \text{if} \quad t\in[0,1] \\ \phi(t)=0 & \text{if} \quad t\notin[0,1] \end{cases}$$

$$\begin{cases} \psi(t)=1 & \text{if} \quad 0\le t<\frac{1}{2} \\ \psi(t)=-1 & \text{if} \quad \frac{1}{2}\le t<1 \\ \psi(t)=0 & \text{if} \quad t\notin [0,1[ \end{cases} \qquad (7)$$

Another families tested in this paper are the Daubechies and Biorthogonal wavelets. The Haar wavelet corresponds to the Daubechies of order one (Daubechies, 1992).

The wavelet transform is carried out in practice in a very simple way due to the existing connection of this decomposition with subband filtering schemes, which were frequently used for signal compression. It turns out that the wavelet coefficients can be computed by iterative filtering of the signal (Gonzalez, 2002). To this end, a set of quadrature mirror filters are employed. They consist of a lowpass filter $h(t)$ and a highpass filter $g(t)$ which are related to the bases of $V_m$ and $W_m$ respectively. This is followed by downsampling operations that allow to keep the same number of points in each iteration. (Van de Vower, 1999).

*Two dimension wavelets transform*

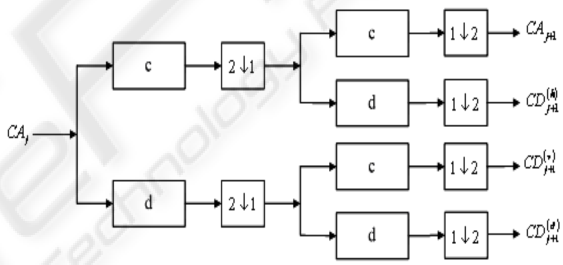
The bidimensional scale function is obtained through the product of the one-dimensional scale functions for each one of the directions:

$$\phi(x,y)=\phi(x)\phi(y) \qquad (8)$$

The same reasoning is applied to the mother wavelet. However in this case we will have three equations:

$$\begin{aligned} \psi^{(I)}(x,y)&=\phi(x)\psi(y), \\ \psi^{(II)}(x,y)&=\psi(x)\phi(y), \qquad (9) \\ \psi^{(III)}(x,y)&=\psi(x)\psi(y). \end{aligned}$$

Again the evaluation of the wavelet coefficients are obtained through subband filtering according to the scheme presented in Figure 1. It corresponds to decompose image in its low and high components (respectively smooth and detail images). After that the images columns are downsampled and new high and low pass filters are applied to these images that are again downsampled but now according to the lines. This process originates four images that defines respectively an approximation of the original image and horizontal, vertical and diagonal components details.




where

c and d are a low and high pass filter

$2\downarrow 1$ and $1\downarrow 2$ are the columns and rows downsample

$CA_j$ is the image to decompose

$CA_{j+1}$ is the approximation of the original image

$CD^h_{j+1}$ is the horizontal component detail

$CD^v_{j+1}$ is the vertical component detail

$CD^d_{j+1}$ is the diagonal component detail

Figure 1: Bi-dimensional filtering scheme.

# 4 NEW FEATURES

A good algorithm to extract marbles features should manage the color and texture information simultaneously. Such algorithm was proposed by (Van de Wower, 1999) who proposed the following set of features for color texture characterization:

$$E^i_{j,k} = \sum_{I(r,s)} {CD^i_{j,k}}^2$$
$$E^i_{j,k,l} = \frac{\sum_{I(r,s)} CD^i_{j,k} \cdot CD^i_{j,l}}{E^i_{j,k} \cdot E^i_{j,l}} \quad (10)$$

where:

$CD$: Wavelet decomposition detail images.

$i = h, v, d$ (horizontal, vertical e diagonal detail components).

$j$ : Decomposition level

$k, l$ : Colour space components (1, 2, 3).

These features are known as Wavelet Correlation Signatures (WCS). Analysing these features we see that $E^i_{j,k,l}$ has a very small value because the numerator has order degree of $CD^2$ and the denominator has order degree of $CD^2 \cdot CD^2$ . In order to minimise this problem two new set of features were proposed:

- WCS_1
$$E^i_{j,k} = \sum_{I(r,s)} {CD^i_{j,k}}^2, \qquad E^i_{j,k,l} = \sum_{I(r,s)} CD^i_{j,k} \cdot CD^i_{j,l}. \quad (11)$$

- WCS_2
$$E^i_{j,k} = \sum_{I(r,s)} {CD^i_{j,k}}^2, \quad (12)$$
$$E^i_{j,k,l} = \frac{\sum_{I(r,s)} \left[\left(CD^i_{j,k} \cdot CD^i_{j,l}\right)^2\right]}{E^i_{j,k} \cdot E^i_{j,l}}.$$

Each set of features defined above leads to a general feature vector given in (13). This vector will be referred to WCS, WCS_1 or WCS_2 according to the considered set of features.

$$WCS(x) = \begin{bmatrix} E^h_{j,1} \middle| E^h_{j,2} \middle| E^h_{j,3} \middle| E^v_{j,1} \middle| E^v_{j,2} \middle| E^v_{j,3} \middle| E^d_{j,1} \middle| \\ E^d_{j,2} \middle| E^d_{j,3} \middle| E^h_{j,1,2} \middle| E^h_{j,1,3} \middle| E^h_{j,2,3} \middle| E^v_{j,1,2} \middle| \\ E^v_{j,1,3} \middle| E^v_{j,2,3} \middle| E^d_{j,1,2} \middle| E^d_{j,1,3} \middle| E^d_{j,2,3} \end{bmatrix} \quad (13)$$

where:

$j = 1, \ldots, n$

$n$ = wavelet decomposition level.

# 5 RESULTS

The features and the indexing algorithm created were applied in a sample of 112 marbles. Previously for each one of these marbles, human experts had defined the most similar marbles, creating a similarity matrix for this sample of marbles. To measure the performance of the developed features we used the *Recall*/*Precision curves* (Bucland, 1994). Where *Recall* and *Precision* are given by the following equations.

$$Recall = \frac{r}{n} \quad (14)$$

with

$r$ = number of relevant retrieved marbles

$n$ = Total number of relevant marbles in DB

$$Precision = \frac{r}{N} \quad (15)$$

with

$N$ = Number of retrieved marbles .

In order to test our indexing algorithm a large set of features were derived combining different wavelet families, colour spaces and one of the three features (*WCS*, *WCS*_1, *WCS*_2). Two different families were used, the Daubchies and Biorthogonal. From the first family the wavelets used had one order degree (*DB*1), two order degree (*DB*2) and three order degree (*DB*3). About Biorthogonal family the wavelets had the following decomposition and reconstruction pairs of functions: [1-3 (*bior*1.3)]; [3-5 (*bior*3.5)] and [6-8 (*bior*6.8)]. The colours spaces tested were RGB, HSI, YIQ, KL, CIE LCH e CIE L*a*b*. All these features were finally normalized. For indexing we only use the Euclidian distance between the candidate marble and the remaining ones.

As we said earlier we used the graphics *Recall*/*Precision* to measure features performance, so to find best Colour Space we generate those graphics for all Colour Spaces, where the family wavelet used was *DB*3 and the features set was *WCS*_1. We have tested other families of wavelets and set of features but the results were similar. The result produced is showed on Figure 2, the curves presented in this figure confirm that CIE Color Spaces are good for color description accordingly human perception. As previewed the RGB model is not very suitable for describing color accordingly human perception. Finally the space based on KL transform gave also poor results. This can be explained by the strong variation of the texture between marbles of different species and such variation conduct to a big variation on the transform coefficients.

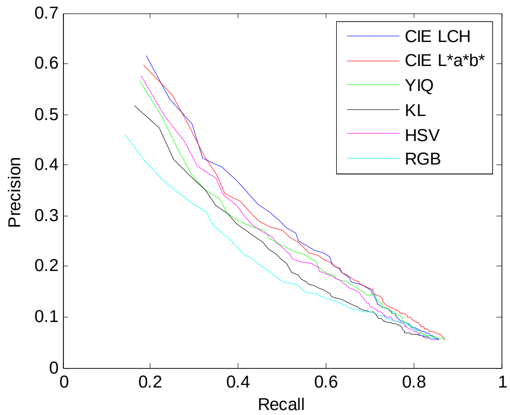



Figure 2 *Recall*/*Precision* curves for all Colour Spaces.

Having chosen the best color space we have tested marble indexation for each wavelet family and the different features. Figure 3 shows the *Recall*/*Precision* curves achieved.

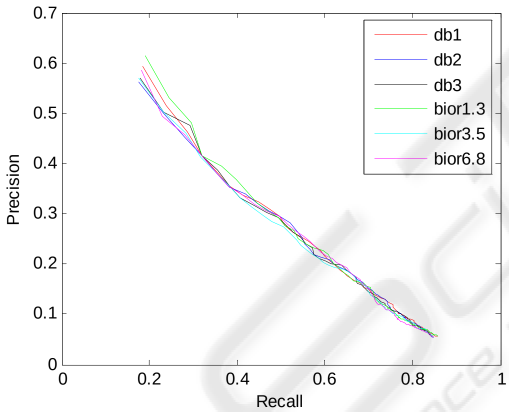



Figure 3 *Recall*/*Precision* curves for all the wavelet families.

These curves show that all the families perform in a similar way. Although wavelet *bior*1.3 performs a little better.

Finally for the same pair color space/wavelet family (CIE LCH/*db*3) we compared the *Recall*/*Precision* curves for the different set of features. Results presented in Figure 4 clearly shows that our proposed features perform better than that proposed in (Van de Vower, 1999).

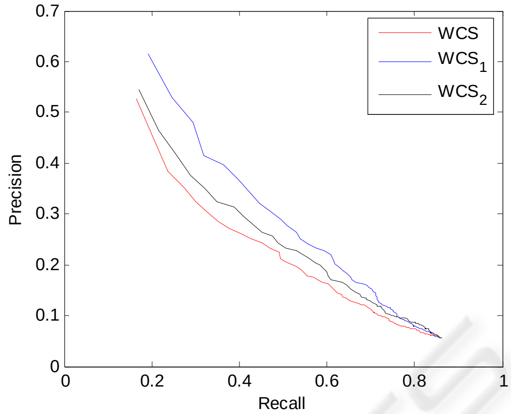



Figure 4 *Recall*/*Precision* curves for all the features.

An illustrative example of an indexation operation is presented in Figure 5.

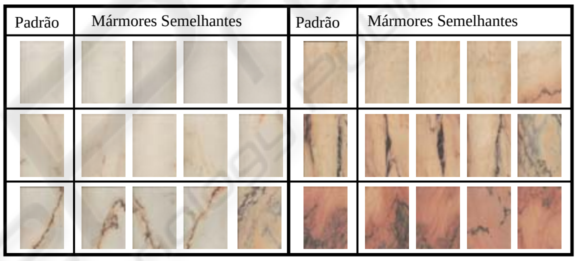



Figure 5 Indexation example applied to marbles.

## 6 CONCLUSIONS

This paper deals with the problem of indexing natural surfaces based on their visual appearance. Based on a wavelet decomposition of the different colour components of the images for a given colour space, extensions of the features presented in (Van de Vower, 1999) were tested for indexing using a simple Euclidian distance. An exhaustive test of different wavelets families and colour spaces allows us to conclude that wavelet based features are quite suitable for natural surfaces characterization mainly when combined with proper colour spaces as the CIE Colour Spaces. It was also shown that our modification of the features set proposed in (Van de Vower, 1999) clearly results in better indexing.

Future work includes research in new features and test of more complex distances as heterogeneous distances. (Wilson, 1997).

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