THE EFFECT OF MOTHER WAVELET AND SUBBAND CHOICE ON CLUSTERING OF IMAGES DATABASE

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ABSTRACT

Clustering is used in content-based multimedia retrieval to reduce the size of the search space and make user navigation through the database easier. In retrieval by example systems, clusters are selected and presented to the user before starting a search in order to give him an overview of the database contents. The discrete wavelet transform with specific mother functions is widely adopted to extract features to perform clustering of images in a given database. The main purpose of this work is to investigate the incidence of mother wavelet and frequency channel features on the obtained clustering. The results show that clustering trees vary largely with mother wavelet function and subbands.

KEYWORDS

Digital Image Processing, Wavelet Transform, Subbands, Clustering

1. INTRODUCTION

Content-based image retrieval (CBIR) is a very active research field. A typical CBIR system is based on tow major steps. In the first step, a set of features is extracted to accurately represent the content of each image in the database. In the second step, a similarity distance between the query image and each image in the database is computed using their features to retrieve the closest images. In general, colour, texture, and shape are common features used to develop a content-based retrieval system. Color features are obtained directly from the pixel intensities using; for instance; color histogram. Textural features are spatial patterns with some properties of homogeneity. Shape features are a geometrical representation derived from color patterns or texture. In practice, textural features are the most employed in computer vision and pattern recognition to retrieve an image in a database. Indeed, an image can be viewed as a mosaic of different texture segments from which features can be extracted and used by a search and retrieval system.

Image clustering is very useful for the construction of databases that will be used by browsers to retrieve and identify a query image. For example, photos databases are organized for browsing, retrieval, and for sharing selected photos with others. Typically, a set of features is used to describe each image, and content-based categorization is performed by clustering these features into an a priori unknown number of clusters. The relationship among the objects of the image database is described by multiple (dis)similarity matrices to categorize images. For instance, a similarity matrix contains color information, texture or structure information. Currently, there is a need for automatic organization, and browsing of these image databases [1].

In many collections, images are arranged in a default order to be presented to the user for browsing. According to the authors in [2] ‘’automatically arranging a set of thumbnail images

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according to their similarity does indeed seem to be useful to designers… An arrangement based on visual similarity helps to divide the set into simple genres,…''. However, there is a need for an automatic arrangement of the image set using clustering techniques. Indeed, clustering algorithms help grouping similar people, places, or objects. Database clustering is needed to discover summarized knowledge at the database level [3]. Moreover, clustering is an essential tool for knowledge discovery in large data sets [4].

Wavelet analysis is widely used to explore an image database for its usefulness to detect spatial scales and clusters in images [5]. Moreover, wavelet analysis is able to preserve and display hierarchical information while allowing for pattern decomposition [6]. Features computed from the wavelet decomposed images are used for texture categorization to perform visual searching.
This paper investigates the effect on the hierarchical clustering trees of wavelet-derived features types as image texture descriptors. Indeed, the effectiveness of wavelet transform in clustering or categorization of images could depend on the choice of the mother wavelet (basis function) and also on the frequency channel from which images features are computed. The main purpose of this work is to shed light on the effect of choosing different mother wavelets and frequency channel on the clustering of digital images.
The rest of this paper is organized as follows. Section 2 presents the related works. Section 3 describes our methodology. Section 4 presents the database and provides the results. Finally, the conclusion is given in Section 5.

2. RELATED WORKS

The texture image annotations were evaluated by various wavelet transform representations, and the Gabor transform was found to match the human vision much better than orthogonal, bi-orthogonal, and tree-structured wavelet transform [7]. Based on date and time of capture and content similarity between pictures, an event-clustering algorithm was introduced to organize pictures into events and sub-events [8]. The authors in [9] investigated whether the properties of decomposition filters play an important role in texture description, and which feature was dominant in the selection of an optimal filter bank. An unsupervised and adaptive clustering algorithm (Adaptive Robust Competition) was introduced to categorize image databases where prototypes of all categories, once grouped, provide a summary of the image database [10]. Two photo browsers were developed for collections of time-stamped digital images where the users exploit the timing information to structure and automatically generate summaries; they use cluster analysis of the times to summarize photos [11]. A semantic-related image retrieval, categorization and browsing method was proposed for image indexing scheme. The user introduces a cognitive dimension to the search based on low-level image descriptors derived from perceptual experiments [12]. A photo image clustering method based on automatic event clustering was proposed to create clusters which minimize the search time for a user to locate a photo of interest using both temporal and content based features [1]. A similarity measure based on interest points (IP) - where regions with an increased probability to yield relevant information are evaluated - was proposed to categorize image databases using a combination of color and shape features [13].

In most of previous works, specific mother wavelets have been adopted to cluster images. As a result, the effect of function basis choice on clustering is unknown. The main purpose of this work is to shed light on the effect of mother wavelet type on image clustering. In addition, we compare the effect of frequency subband or channel (high versus low) from which features that characterize images are computed. Indeed, high frequency and low frequency features may have different and significant impacts on automatic clustering of images database.

2. METHODOLOGY

The discrete wavelet transform (DWT) decomposes an image into several sub-bands according to a recursive process (Fig. 1). These include LH1, HL1 and HH1 which represent detail images and

LL1 which corresponds to the approximation image. The approximation and detail images are then decomposed into second-level approximation and detail images, and the process is repeated to achieve the desired level of the multi-resolution analysis. The obtained coefficients values for the approximation and detail sub-band images are useful features for texture categorization [14][15].

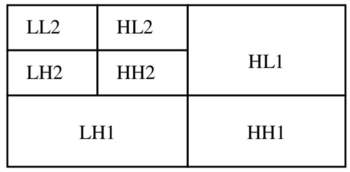


Figure 1: Two level decomposition of an image

Mathematically, a one dimension DWT is defined as follows:

$$f(x) = \sum_{i,j} c_{i,j} \psi_{i,j}(x)$$

where $\psi_{i,j}(x)$ are the wavelet functions and and $c_{i,j}$ are the coefficients of $f(x)$. They are defined by:

$$c_{i,j} = \int_{-\infty}^{+\infty} f(x) \psi_{i,j}(x)$$

A mother wavelet $\psi(x)$ is used to generate the wavelet basis functions by using translation and dilation operations:

$$\psi_{i,j}(x) = 2^{-i/2} \psi\left(2^{-i} x - j\right)$$

where j and i are respectively the translation and dilation parameters. The two dimension (2D) DWT of a digital image is implemented by a low-pass filter which is convolved with the image rows, and a high pass filter which is convolved with the image columns. The convolutions are followed by down sampling by a factor of two. As a result, the 2D-DWT hierarchically decomposes a digital image into a series of successively lower resolution images and their associated detail images as shown in Figure 1. In our work, four types of mother wavelets are compared; namely the Haar, Daubechies-3, Coiflet-3, and Symlet-3.

In addition, a third level decomposition is considered in this study as it provides good analysis [16]. For each obtained HH3 and LL3 texture, the following statistics [17] are computed:

$$Mean = m = \sum_{i=0}^{L-1} z_i \, p(z_i)$$

$$St.Dev = \delta = \sqrt{\mu_2(z)} = \sqrt{\delta^2}$$

$$Smoothness = R = 1 - \frac{1}{1/\left(1+\delta^2\right)}$$

$$3th.Moment = \mu_3 = \sum_{i=0}^{L-1} (z_i - m)^3 \, p(z_i)$$

$$Uniformity = U = \sum_{i=0}^{L-1} p^2(z_i)$$

$$Entropy = e = -\sum_{i=0}^{L-1} p(z_i)\log_2 p(z_i)$$

Then, 12 features – 6 for HH3 and 6 for LL3 – are constructed with these statistics as feature components. The goal is to construct two matrices X_{LL} and X_{HH} to be used in the clustering algorithm. The generic matrix form is given as:

$$X = \begin{bmatrix} m_1\delta_1 R_1 \mu_{3,1} U_1 e_1 \\ m_2\delta_2 R_2 \mu_{3,2} U_2 e_2 \\ \vdots \\ m_{10}\delta_{10} R_{10} \mu_{3,10} U_{10} e_{10} \end{bmatrix}$$

Finally, "Hierarchical Clustering" is used to group data over a variety of scales by creating a cluster tree (dendrogram). Consider an m-by-n data matrix X such as the one defined previously, which is treated as m 1-*by*-n row vectors $x_1, x_2, \ldots, x_m$, each containing n features values. In our case, $n = 6$ from the above statistical measures. Then, the Euclidean distance between two vectors x_r and x_s is defined as follows:

$$d_{rs}^2 = (x_r - x_s)(x_r - x_s)'$$

a) The information regarding how pairs of objects in the data set are related is stored in an $N \times N$ matrix called the (dis)similarity matrix. The algorithm of hierarchical cluster analysis on the feature data is as follows:

b) Find the similarity or dissimilarity between every pair of objects in the data. The distance between objects is calculated using the Euclidian distance defined above.

c) Group the objects into a binary hierarchical cluster tree. Pairs of objects that are in close proximity are linked using the distance information generated in step 1. As objects are paired into binary clusters, the newly formed clusters are grouped into larger clusters until a hierarchical tree is formed.

d) Determine where to cut the hierarchical tree into clusters. Data is partitioned by pruning branches off the bottom of the hierarchical tree, and assign all the objects below each cut to a single cluster.

3. DATA AND RESULTS

Hierarchical clustering experiments are performed with 10 (512×512 pixels) Brodatz textures [14][15] shown in Figure 2. Experiments are conducted to compare the hierarchical clustering trees generated from extracted wavelet analysis coefficients in regions of the LL3 and HH3 separately with various mother wavelets; including Haar, Daubechies, Coiflet, and Symlet.

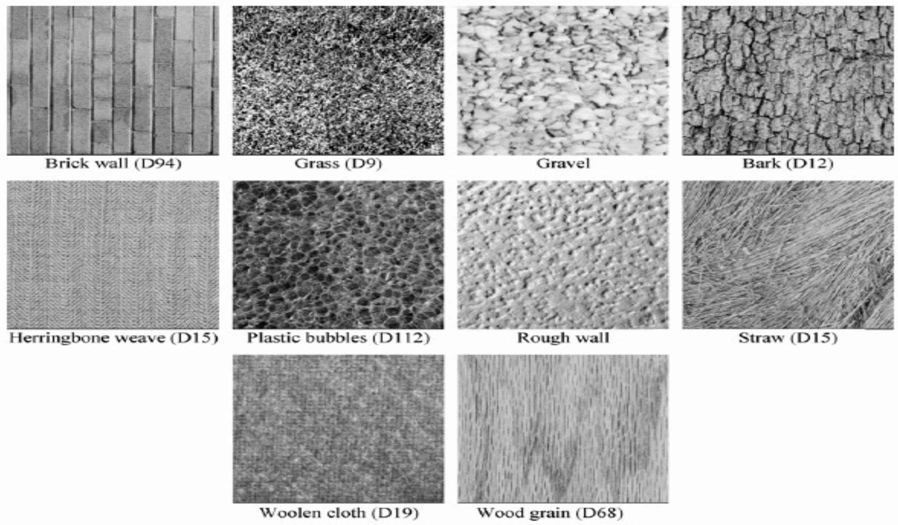


Figure 2: Textures used in the study

The clustering trees are given in Figures 3, 4 and 5. The results show that modifying the wavelet function leads to different hierarchical trees for the LL3 and HH3 textural features. Moreover, the clustering trees using the HH3 textures are different from those for LL3 (figure 5). The differences are strongly significant. Thus, the results indicated that the selection of the decomposition filters has a significant influence on the result of texture characterization and categorization. This finding suggests that the choice of type for image database organization belongs to the preferences of the designer or the user. Indeed, according to [2], having access to different arrangements of the same set of images is useful for some people.

In addition, human database designer has to decide only whether a category is useful or too inhomogeneous from a high level point of view [2]. In sum, the obtained results suggest that automation of the process of image database clustering using wavelets highly depends on the choice of mother wavelet and on the choice of the frequency subband used to compute textural features for clustering task. Thus, human intervention may always be needed for database automatic organization.

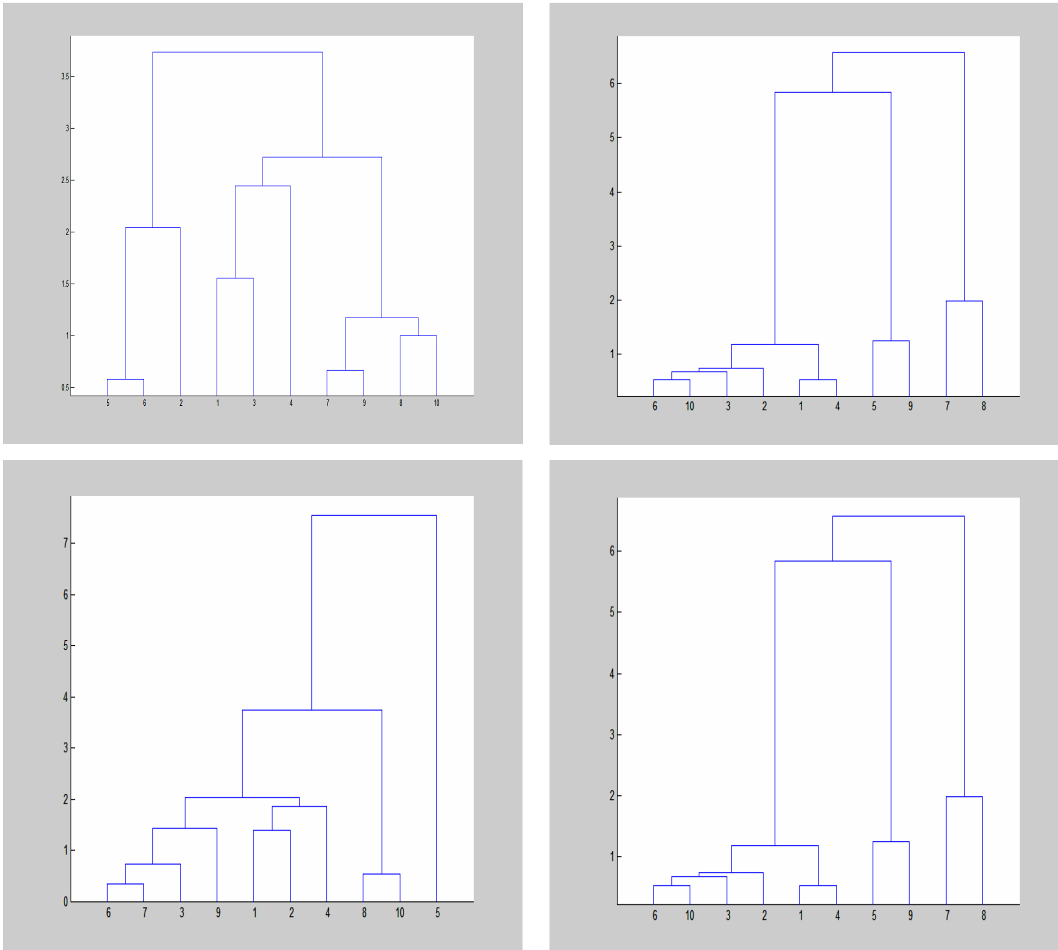
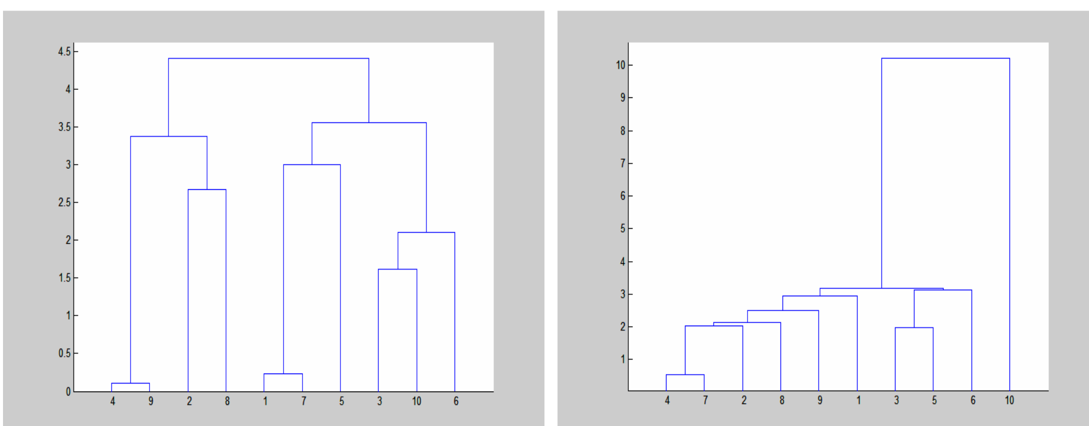


Figure 3: Up left: Haar(LL3), Up right: db3(LL3), Down left: Coiflet3(LL3), Up right: Symlet3(LL3)



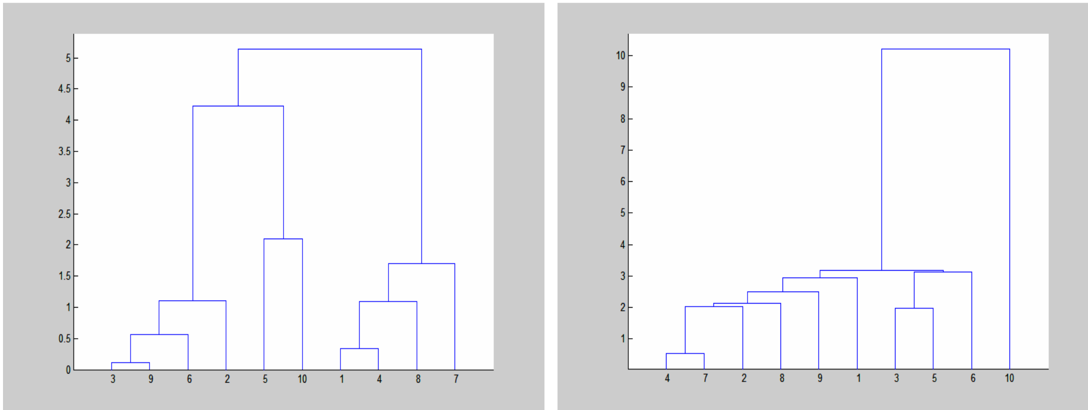


Figure 4: Up left: Haar(HH3), Up right: db3(HH3), Down left: Coiflet3(HH3), Up right: Symlet3(HH3)

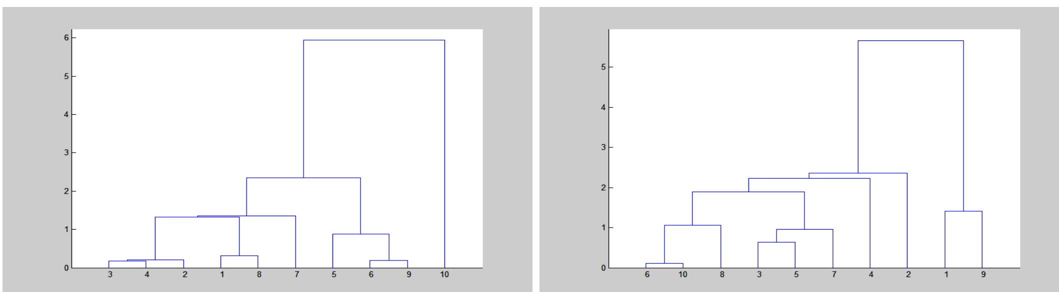


Figure 5: Up left: Biorthogonal 3.3(LL), Up right: Biorthogonal 3.3(HH)

4. CONCLUSION

Clustering is useful to improve the structure and usage of multimedia data. After clustering is performed, similar images are grouped together and the search, browsing and navigation spaces are well delimited to find accurate target images. This brief research attempts to offer some insight relative to the effect of mother wavelet and subband choice for textural features extraction on the result of images clustering. In order to obtain the set of features that characterize a given texture image, the 2D-DWT wavelet transform is used to find its spectral components. In particular, the original image is decomposed using three levels of DWT and textural features are computed by means of statistical measures that describe LL and HH sub-bands coefficients at level three of decomposition; for instance LL3 and HH3. These textural features are computed from all images of the collection. Then, categories are formed to represent the images database. The categories are not pre-defined but found by unsupervised learning using the hierarchical clustering algorithm. In particular, hierarchical clustering method is employed to compute a representative data set based on hierarchical structures of its objects content. The main purpose is to investigate the effect of changing wavelet functions and the use statistical information from LL and HH coefficients on the clustering results. The experimental results indicate that the selection of the decomposition filters has a significant influence on the result of texture characterization and categorization. In other words, we may have as many clustering trees (images database organization/categorization) as wavelet functions used to analyse and characterize textures. Therefore, it is important to determine the appropriate mother wavelet and subband to perform clustering.

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