Texture-based Image Search of Fashion Designs

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ABSTRACT

In today's world, fashion designers help create billions of dresses, suits, shoes, and other clothing and accessories purchased every year by customers around the world. They study fashion trends, sketch designs of clothing and accessories, select colors and fabrics, and oversee the final production of their designs. With the advent of computers and low storage costs, designers rely on the use of mass computer storage to help them store and manage their designs for future retrievals. The stored designs will be retrieved from time to time so that designers could retrieve them for stimulation of new ideas in their new designs. When the number of stored images grows, searching for a desired piece of design work is likely to be time-consuming and painstaking. Without proper computer-assisted search mechanism, such a search will not be definitely easy. Thus, a huge collection of images containing different designs pattern and textures of certain fashion designs demands for efficient search system. Of all the visual contents identifiable from a design, texture is considered to be the commonest visual attribute that aids in image retrieval. Common approaches for texture-based image retrievals are largely centered around frequency-based models, which are notably suffered from the problem of poor retrieval accuracy. In this paper, a novel approach for texture-based image retrieval has been proposed. This approach, known as Spectral Density Analysis, or SDA for short, is based on the idea of dividing an image into nine equally sized partitions where the spectral density *of each partition is computed to be used to aid in the image retrieval process. Benchmarked using the popular performance measurement technique, Recall and Precision, adopting the SDA technique for retrieving images based on their texture contents has produced remarkable retrieval accuracy, almost three times more accurate over any other frequency-based models.*

Keywords
Spectral Density Analysis, Recall and Precision, Wavelet Filter Bank.

1.0 INTRODUCTION

In the past few decades, we have seen the explosive growth of multimedia applications, computing and communication in all walks of life. Multimedia applications are commonly and popularly used in many areas such as architectural and engineering design, journalism and advertising, education, home entertainment, web searching etc. One of the promising fields is fashion and interior design where a huge collection of fabric designs are produced and saved in digital formats for future references. These stored data are crucial and useful for potential designers to get ideas of their own designs. The designers always reuse images of previous designs as a soruce of inspiration (Yang, 1996; Bird, 1996) It has always become a very tedious process of searching the desired design patterns from a very huge collection of data. Thus, an efficient method is needed to solve this problem. One of the popular techniques in retrieving the desired images is based on the basis of automatically-derived featutres such as colour, tecture and shape, which is more commonly known as *Content-based Image Retrieval* (CBIR). Texture, which is an important visual attribute within a stored image for feature identification purpose, has been widely used for recognizing design patterns in many aspects such as building designs, textiles, weather forecast etc. In this paper, we have proposed a technique for texture analysis and retrieval of fabric images. This technique makes use of signal-based approach, formally known as *Spectral Density Analysis* (SDA), which measures the signal distribution of an image. The rest of the paper is organised as follows. Related works for image retrieval based on the texture content are given in Section 2. Section 3 provides an overview of the proposed technique. Section 4 provides the details of the experimental setup to run the system together with reported results. Some concluding remarks and future works are given in Section 5.

2. 0 PREVIOUS WORKS

Generally, approaches in the analysis of image based on textural contents use either the spatial or frequency-based techniques. Spatial approaches include structural and statistical models such as the co-occurrence matrix and autoregressive models (Abbadeni, 2000). In the frequency-based approach, popular techniques include wavelet-based models such as the Gabor wavelet decomposition model. There is another class of models that can be called perceptual models in which textures are represented by a set of features that have a perceptual meaning such as contrast, linelikeness, regularity, coarseness and directionality(Abbadeni, 2000 ;Tamura, 1978; Amadasun, 1989; Del Bimbo, 1999). Other classical examples include image decomposition by filtering with a subband or wavelet filter bank (Theoharatos, 2006; Laine, 1993; Do, 2002) and appliance of a linear transformation by a Fourier or discrete cosine transform(Randen,1999; Leung, 2001;Mandal,1999;Zhong,2000). In these methods, texture can be modeled by the fusion of marginal densities of subband image coefficients. The samples from the texture distribution can be extracted by utilizing small neighbourhoods of scale-to-scale coefficients. Components of the multivariate texture-distributional vectors can then be formulated using the spatially localized coefficients, at different image decomposition levels.

3.0 PROPOSED TECHNIQUE

Before each image is stored, it will first be divided logically into nine equally-sized non-overlapping partitions. The spectral density, which is a representation of the magnitude of the various frequency components of a 2D image, is then computed for each of the nine partitions. Images including non-periodical or random patterns have a spectral density in which peaks are not easy to detect. Therefore, dividing an image into a fixed number of partitions help eliminate this problem since the focus now is in smaller partitioning area rather than the entire image. The prevalent orientation can be detected by measuring the length of arcs in the spectrum and the change of power in them. A measure of texture regularity can then be derived by the relative value of the highest peak at non-zero frequencies. The maxima of the spectrum can be used as parameters for modeling texture properties. Any periodical pattern in the original spatial domain is represented by the peak in the spectral density. Since the spectral density rotates according to the spatial image's orientation, the orientation of the pattern is given by the direction of the harmonic frequency, closest to the origin. The power at each location in the spectral density is an indication of the frequency and orientation of a particular feature in the image. Evaluating the spectral density is an excellent way to isolate periodic structural features or noise in the image. Since the power can vary by orders of magnitude in an image, the spectral density is usually represented on a log scale. The spectral density is defined as the squared magnitude of the discrete Fourier transform of a signal. Therefore, for the case of 2D signals, we get $P[k_1,k_2] = |X[k_1,k_2]|^2$ where $X[k_1,k_2]$ is the discrete Fourier transform of the 2D signal. A similarity match is then performed by comparing each pair of the corresponding adjacent partitions from both the stored and query images using the following similarity function:

$$S_{ff}(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} R_{ff\,(a,b,w_i)}\, e^{-2pi(au+bv)}\, da\; db$$

where u, v are spatial frequencies of an image, R_{ff} is the autocorrelation function of the random process f, which is defined as a mean of the product of the image coordinate values of random variables a and b.

4.0 EXPERIMENTATION

A total of 70 fabric images have been carefully selected from the standard fabric image database, which consists of a total of 2550 fabric images, for benchmarking tests with the frequency-based approach. The selected query images comprise textured proportions in different locations within the images. These queries are fed into both the systems, i.e. the proposed technique and the frequency-based approach. To measure their retrieval performance in term of retrieval accuracy, the *Recall* and *Precision* measures will be used. To measure the performance of the system, a common and popular technique, known as Recall and Precision measures will be used for the benchmarking test run.

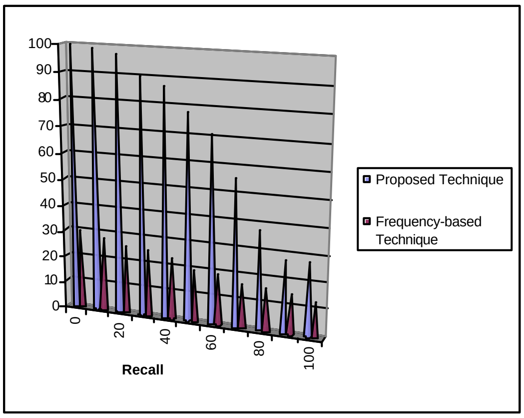

Figure 1. Summary of Results

From the graphed data above, it's obvious that the proposed technique for texture-based image search of fabric designs has given superior result as compared to the frequency-based approach.

5.0 CONCLUSION AND FUTURE WORK

A new approach, which is based on the measure of signal energy of an image to analyze the texture distribution of an image has been proposed for image matching based on the textured patterns in fabric images. Benchmarked against the frequency-based technique for the same purpose, the proposed technique has given a superior performance in term of retrieval accuracy against the frequency-based approach. The authors intend to capture additional visual attributes, i.e. both colours and shape features from the image, hoping the retrieval accuracy can be further improved.

REFERENCES

Abbadeni, D. Ziou, and S. Wang (2000). Autocovariance-based Perceptual Textural Features Corresponding to Human Visual Perception. Proceedings of the 15th IAPR/IEEE International Conference on Pattern Recognition, Barcelona, Spain, September 3-8.

Amadasun and R. King. (1989) Textural Features corresponding to textural properties. IEEE Transactions on Systems, Man and Cybernetics, 19(5):1264-1274, September/October 1989.

Bird, C., Elliott, P., And Griffiths, E. (1996). User Interface for content-based Image Retrieval. In Proceedings fo the IEE Colloquium on Intelligent Image Databases (London, U.K).

Del Bimbo. Visual Information Retrieval (1999). Morgan Kaufmann Publishers, San Francisco, CA.

Do M.N., and Vetterli M. (2002)Wavelet-based texture retrieval using generalized Gaussian density and Kullback-Leibler distance. *IEEE Trans Image Process 11,* 2, 146-158.

Laine A., and Fan J. (1993) Texture classification by wavelet packet signatures. *IEEE Trans Pattern Anal Mach Intell 15,* 11, 1186–1190.

Leung T., and Malik J. (2001), Representing and Recognizing the Visual Appearance of Materials using Three-dimensional Textons. *Int J Comput Vis, 43,* 1 29-44.

Mandal M.K., Idris F., and Panchanathan S. (1999), A critical evaluation of image and video indexing techniques in the compressed domain. *Image Vision Comput, 17,* 7 513-529.

Randen T., and Husoy J.H. (1999), Filtering for Texture Classification: A Comparative Study. *IEEE Trans Pattern Anal Mach Intell, 21,* 4 291-310.

Tamura, S. Mori and T. Yamawaki. (1978) Textural Features Corresponding to Visual Perception. IEEE Transactions on Systems, Man and Cybernetics, Vol. SMC-8, N. 6.

Theoharatos C., Pothos V.K., Laskaris N.A., Economou G., and Fotopoulos (2006). S. Multivariate Image Similarity in the Compressed Domain using Statistical Graph Matching. *Pattern Recognit, 39,* 10, 1892-1904.

Yang, D.S., Garrett, J.H,Shaw, D.S., And Rendell L.A. (1996) An Intelligent Symbol Usage Assistanf for CAD Systems. IEEE Exp. 10, 3, 32-41.

Zhong Y., and Jain A.K. (2000), Object localization using color, texture and shape. *Pattern Recognit 33,* 671-684.