NOVEL PATTERN REPRESENTATION BASED ON WAVELET TRANSFORMS

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ABSTRACT:
Visual features are used extensively to compose image signatures in content based image retrieval systems. Although the retrieval quality is sufficient for some tasks and the automatic extraction of visual features is rather convenient, there is still a semantic gap between the low-level visual features (textures, shapes, colors) automatically extracted and the high-level concepts that users normally search for (tumors, abnormal tissues). We propose a new pattern representation scheme based on wavelet transforms that represents visual features efficiently.

1. INTRODUCTION:

With the advent of the World Wide Web (WWW), large volume of image data are now made available over the web for information sharing and it is possible to access such large image repositories distributed throughout the world. As large web-based image databases are being built, organizing the image databases for efficient retrieval is a non-trivial problem. To support content-based image retrieval, the existing approaches extract features from images, and then perform similarity search between the features of the query image and database images.

Texture features using wavelet transforms in image processing is often employed to overcome the generalization of features. In wavelet transforms, the image is represented in terms of the frequency of content of local regions over a range of scales. This representation provides a framework for the analysis of image features, which are independent in size and can often be characterized by their frequency domain properties.

Wavelet-Fourier analysis (WFA) is used as a mathematical model to analyze and parameterize the temporal, superior nasal, inferior, and temporal shapes. In this approach, discrete wavelet transform is used to extract features and analyze discontinuities and abrupt changes contained in signals.

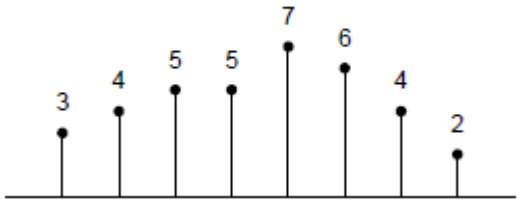
Discrete Wavelet Transform is a multi-scale analysis method, in which analysis can be performed on various scales. Each level of the transformation provides an analysis of the source image at a different resolution, resulting in its independent approximation and detailed coefficients. In the WFA, the fast Fourier transform is applied to the detailed coefficients. The resultant Fourier amplitudes are combined with the normalized approximation coefficients of the Discrete Wavelet Transforms [2] to create a set of features. Though providing valuable insight to the analysis of images using mathematical generalization techniques with

Discrete Wavelet Transform [1] and Fast Fourier Transforms, it is yet uncertain which Discrete Wavelet Transform features need to be extracted to represent an image that is as discriminative as possible in the transform domain.

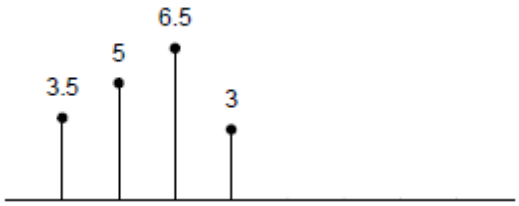
2. WAVELET TRANSFORMS:

The most basic wavelet transform [1] is the Haar transform described by Alfred Haar in 1910. It serves as the prototypical

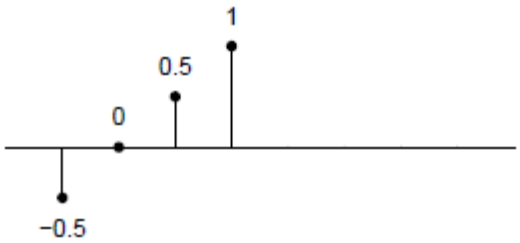
wavelet transform. We will describe the (discrete) Haar transform, as it encapsulates the basic concepts of wavelet transforms used today. We will also see its limitation, which the newer wavelet transform [1] (in 1998 by Ingrid Daubechies) resolves. The basis of the Haar transform is the decomposition of a signal, say the eight-point signal x(n),



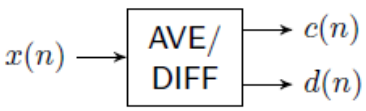
into two four-point signals. One being the average of pairs of signal values, c(n):



The other signal being their differences, d(n):



This decomposition can be written as
c(n) = 0:5 x(2n) + 0:5 x(2n + 1)
d(n) = 0:5 x(2n) □ 0:5 x(2n + 1)
and represented by a block diagram:

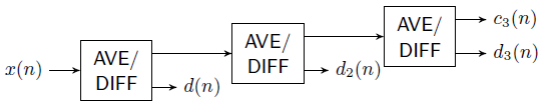


It should be clear that this decomposition can be reversed. The original signal x(n) can be reconstitituted from the two shorter signals using

y(2n) = c(n) + d(n)
y(2n + 1) = c(n) □ d(n)
which we represent by a block diagram



When we repeat the simple AVE/DIFF signal decomposition procedure a number of times, each time on the average signal c(n), we get the Haar transform. For our toy example eight-point signal,the AVE/DIFF decomposition can be repeated up to three times. In this case the Haar transform can be expressed clearly in block diagram form as



The Haar wavelet [2] representation of the eight-point signal x(n) is simply the set of four output signals produced by this three-level operation. Four our example, the four signals (or vectors) have lengths 1, 1, 2, and 4. Specifically,
c3 = [4:5]
d3 = [□0:25]
d2 = [□0:75; 1:75]
d = [□0:5; 0; 0:5; 1]

These values, taken together, are called the `wavelet representation' of the signal x. Note that the single value c3 is simply the average value of the original signal values, x(n). In general, if the original signal is of length 2M, then the decomposition can be repeated up to M times. (In case the length of the original signal is not a power of two, there are several way to accommodate that.) The Haar transform can be very easily reversed by successive use of the INV block. If we take the three-level Haar transform of the 128-point signal:

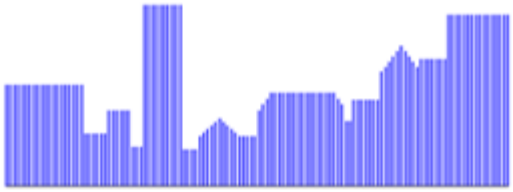


Fig: Haar Transform of 128 points signal

Consider a periodic function x(t) with period T

$$x(t) = 1 - \frac{2|t|}{T}, |t| < T$$

Find its Fourier series coefficient. Recall the relationship of Fourier series expansion. We can decompose a periodic signal with period T into the superposition of its high order harmonics, which is the synthesis equation

$$x(t) = \sum_{k=\infty}^{\infty} a_k \exp(j\frac{2\pi kt}{T})$$

According to the orthogonal property of complex exponential function, we have the analysis equation

$$a_k = \frac{1}{T}\int_{-T/2}^{T/2} x(t)\exp\left(-j\frac{2\pi kt}{T}\right)dt$$

In this example the Fourier series coefficients are

$$a_k = \frac{sin^2\left(\frac{\pi k}{2}\right)}{2\left(\frac{\pi k}{2}\right)^2} = \frac{1}{2}\,sinc^2(\frac{k}{2})$$

What's the physical meaning of the result? The Fourier series coefficient indicates the amplitude and phase of the high order harmonics, indexing by the variable k. The higher k is, the higher frequency refers to. In general, the power of a signal concentrates more likely in the low frequency components. If we truncate the Fourier series coefficient in the range of [□K;K] and set ak = 0 outside this range, we expect the synthesis version of the truncated coefficients be

$$\bar{x}k(t) = \sum_{k=-K}^{k} a_k \exp(j\frac{2\pi kt}{T})$$

Intuitively, as K approaches infinity, the reconstructed signal is close to the original one.

3. PATTERN REPRESENTATION:

Wavelet Analysis [4] have been introduced to override the problems of the Fourier transform and provide a time-scale analyzing tool able to represent the local variations of a signal and operate on non-stationary ones. Haar Basis [4] is replaced with wavelets of vanishing moments [5] and assuming that the coefficients $s_k^0, k = 1,2,3\ldots.,N$ are given, we replace the haar basis with formulae

$$s_k^j = \sum_{n=1}^{n-2M} h_n s_{n+2k-2}^{j-1}$$

$$d_k^j = \sum_{n=1}^{n-2M} g_n s_{n+2k-2}^{j-1}$$

Where s_k^j and d_k^j are viewed as periodic sequences with period 2^{n-j}. These coefficients create a two dimensional signal giving information on the energy at a given time b and a given scale a. If we consider an adapted wavelet, when searching for maximal surfaces on this two dimensional signals, we can localize in time and scale the apparition of the pattern. To do so, we will create patterns adapted to each postural transition that we are looking for and we will look for each pattern in the windows determined by the segmentation algorithm.

Feature Matching:

Feature of query image is calculated and is matched with existing feature vectors in the database. Euclidean distance is used for comparison. Euclidean distance is zero for exact image and it increases as similarity between query image and database image decreases. Euclidean distance is given by

$$D_{x,y} = \sqrt{\sum_{i=0}^{N}(x_i - y_i)^2}$$

4. CONCLUSION

We have presented an approach, novel pattern representation using wavelet transforms, for efficiently retrieving images from large Image database. We then described a detailed technique to accumulatively apply wavelet transform on the hashed feature space. This approach also reduces the cost of image retrieval dramatically yet maintaining all the advantages of wavelet-based pattern recognition.

5. References:

1. "Wavelet Transforms | A Quick Study"
Ivan W. Selesnick, Polytechnic University
Brooklyn, NY , September 27, 2007.
2 . "A Tutorial of the Wavelet Transform"
Chun-Lin, Liu. February 23, 2010.
3. "Application of Wavelet Transform and its Advantages Compared to Fourier Transform", M. Sifuzzaman , M.R. Islam and M.Z. Ali , Journal of Physical Sciences, Vol. 13, 2009, 121-134
4. "Wavelet Theory and its Application to Pattern Recognition". Y. Y. Tang, L. H. Yang, J. Liu, and H. Ma World Scientific, 2000.
5. "A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity". C. V. C. Bouten, K. T. M. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen. IEEE Trans. Biomed. Eng.,
44(3):136–147, 1997.