Volume 8 Issue 1 (2020) 6-8 ISSN 2347 - 3258
International Journal of Advance Research and Innovation

Face Identification Using HAAR Wavelet Transform

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Article Info

Article history:
Received 5 January 2020
Received in revised form
20 February 2020
Accepted 28 February 2020
Available online 15 March 2020

Keywords: Face identification, Wavelet transform, Correlation coefficient, Euclidean distance, Sum of absolute difference

Abstract: Face identification is the process of matching one or more people by analyzing and comparing the patterns of their faces. Algorithms for face identification typically extract facial features and compare them to a database to find the best match. The Haar wavelet transform has been mainly used for image processing and pattern identification due to its low computing requirements and quality to conserve and to compact the energy of a signal. In discrete wavelet transform, an image signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. Face identification has been performed in terms of correlation coefficient, Euclidean distance and sum of absolute difference.

1. Introduction

Face identification is an important part of many biometric, security, and surveillance systems, as well as image and video indexing systems. Face identification has become a popular area of research in computer vision, it is typically used in network security systems and access control systems but it is also useful in other multimedia information processing areas [1]. The face identification is addressed in wavelet domain using LL sub band image. LL sub-band is used to extract the face features. Matching of features using correlation, Euclidean distance and sum of absolute difference between test and stored database images.

A multiresolution analysis (MRA) is a radically new recursive method for performing discrete wavelet analysis. An MRA introduced by Mallat [2] consists of a sequence $V_j : j \in \mathbb{Z}$ of closed subspaces of $L^2(\mathbb{R})$, a Lebesgue space of square integrable functions, satisfying the following properties:-

(1) $V_{j+1} \subset V_j : j \in \mathbb{Z}$

(2) $\cap_{j\in\mathbb{Z}} V_j = \{0\}$, $\cup_{j\in\mathbb{Z}} W_j = L^2(\mathbb{R})$,

(3) For every, $L^2(\mathbb{R}), f(t) \in V_j \Rightarrow f(2t) \in V_{j+1}, \forall\ j \in \mathbb{Z}$

(4) There exists a function $\phi(t) \in V_j$ such that $\{\phi(t-k): k \in \mathbb{Z}\}$ is orthonormal basis of V_j.

The function $\phi(x)$ is called scaling function of given MRA and property 3) implies a dilation equation as following:-

$$\phi(t) = \sqrt{2}\sum_{k\in\mathbb{Z}} h_k\ \phi(2t-k) \qquad (1)$$

where h_k is low pass filter and is defined as:-

$$h_k = \int_{-\infty}^{\infty} \phi(x)\phi(2t-k)\,dt \qquad (2)$$

The wavelet function ψ is expressed as:-

$$\psi(t) = \sqrt{2}\sum_{k\in\mathbb{Z}} g_k\ \phi(2t-k) \qquad (3)$$

where, $g_k = (-1)^{k+1} h_{1-k}$ We can express a signal in terms of bases of V_j space such that,

$$V_j = V_{j+1} \oplus W_{j+1},\ \forall j \in \mathbb{Z} \qquad (4)$$

where W_{j+1} is the orthogonal complement of V_{j+1} in V_j ($V_{j+1} \perp W_{j+1}$). By iteration, we can write,

$$V_j = W_{j+1} \oplus W_{j+2} \oplus W_{j+2} \dots\dots\dots \qquad (5)$$

Let S=$\{S_n: n \in \mathbb{Z}\}$ be a function sampled at regular time interval, $\Delta t = \tau$ where $\mathbb{Z}$ is an integer. S is split into a "blurred" version a_1 at the coarser interval $\Delta t = 2\tau$ and "detail" d_1 at scale $\Delta t = \tau$. This process is repeated and gives a sequence S, a_1, a_2, a_3, a_4,…..of more and more blurred versions together with the details d_1, d_2, d_3...removed at every scale.

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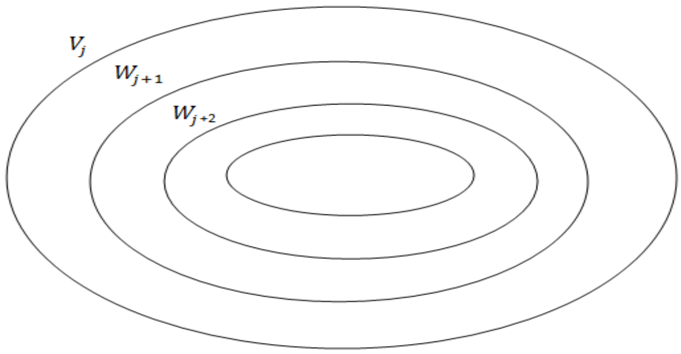

Fig.1: Decomposition of vector space

($\Delta t = 2^m\tau$ in a_m and d_{m-1}) [3, 4]. Here a_m's and d_m's are approximation and details of original signal. After N iteration S can be reconstructed as $S = a_N + d_1 + d_2 + d_3 + d_4 + d_5 + \dots + d_N$. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. Thus the original signal passes through two complementary filters in which one is low pass filter and second one is high pass filter as shown in figure 2.

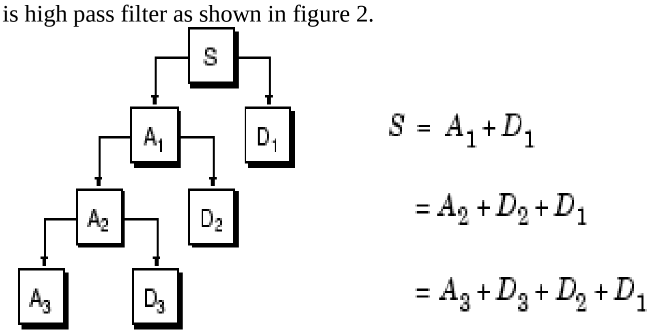

Fig. 2 Decomposition of 1D signal

2. Haar Wavelet transform

The Haar transform is one of the oldest transform functions, proposed in 1910 by the Hungarian mathematician Alfred Haar. Haar wavelet is discontinuous, and resembles a step function. The Haar wavelet's mother wavelet function ψ(t) can be described as [5]:

$$\psi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2} \\ -1 & \frac{1}{2} \le t < 1 \\ 0 & \text{otherwise} \end{cases}$$

Its scaling function ϕ(t) can be described as:

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1 \\ 0 & \text{otherwise} \end{cases}$$

It conserves the energy of signal and compaction of the energy of signals. In discrete form, Haar wavelets are related to a mathematical operation called the Haar transform. Due to its low computing requirements, the Haar transform has been mainly used for image processing and pattern identification. From this reason two dimensional signal processing is an area of efficient applications of Haar transform due their wavelet like structure. It is found effective in applications such as signal and image compression in electrical and computer engineering as it provides a simple and computationally efficient approach for analysing the local aspects of a signal. It shows orthogonal, biorthogonal and compact support. Its wavelet and scaling functions are shown below in figure 3.

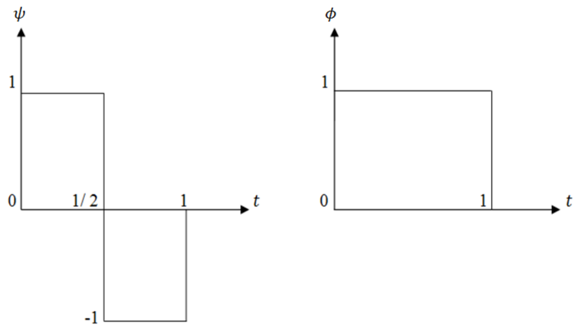

Fig. 3: Haar wavelet and scaling function

This transform decomposes the signal into mutually orthogonal set of wavelets. The discrete wavelet transform provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time. In the discrete wavelet transform, an image signal can be analysed by passing it through an analysis filter bank followed by a decimation operation. This analysis filter bank, which consists of a low pass and a high pass filter at each decomposition stage, is commonly used in image compression. When a signal passes through these filters, it is split into two bands. The low pass filter, which corresponds to an averaging operation, extracts the coarse information of the signal. The high pass filter, which corresponds to a differencing operation, extracts the detail information of the signal. The output of the filtering operations is then decimated by two. A two level decomposition of image signal is shown in figure 4 [6].

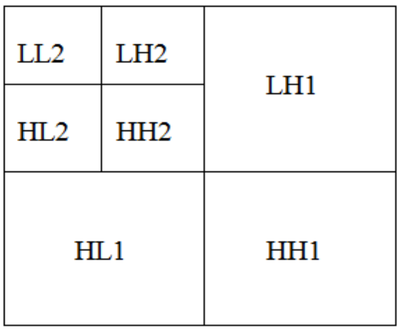

Fig. 4 Decomposition of 2D signal

3. Experimental analysis

We are developing a face identification system, in which we are using seven images out of which two images are of same person. In this system, we take one image as test image that is compared with six images that are stored in image database.

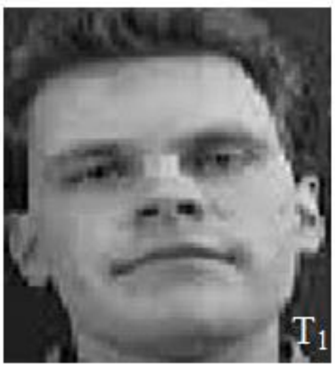

Fig. 5 Test image T_1

Fig. 6 Database image (D1- D6)

We select original image as a test image T_1 for experiment analysis. We take Haar wavelet and at level 2 and retrieve LL subband. Euclidean distance examines the root of square differences between the coordinates of a pair of objects. For testing we used the Euclidean distance classifier, for calculating the minimum distance between the test image and image to be recognized from the database [7]. In signal processing, correlation is a measure of similarity of two series as a function of the displacement of one relative to the other. Sum of absolute difference (SAD) is used for measuring the similarities between the images by calculating the absolute differences between the pixels of the image. The SAD algorithm is the simplest metric which considers all the pixels in the block for computation and also separately, which makes its implementation easier and parallel [8].

Table 1 Wavelet statistical analysis of test image and database images

S. No.	Test image and database image	Correlation Coefficient	Euclidean distance	S.A.D.
1.	T_1-D_1	0.64633205	7.1719×10^3	2398080
2.	T_1-D_2	0.449733361	1.0643×10^4	3185200
3.	T_1-D_3	0.5263451501	1.0828×10^4	2708816
4.	T_1-D_4	0.51404803142	1.1807×10^4	3232144
5.	T_1-D_5	0.3001736427	1.2257×10^4	3394368
6.	T_1-D_6	0.5410996575	1.0968×10^4	3061184

4. Results and Conclusions

From table 1, it is obvious that correlation coefficient between test image and database image 1 is larger compared to the correlation coefficient between test image and rest database image (D2-D6) for level 2. Also the Euclidean distance and sum of absolute difference between test image and database image 1 is smaller compared to the Euclidean distance and sum of absolute difference between test image and rest database image (D2-D6). By virtue of these results, we can say that wavelet transform technique provides a simple and accurate framework to investigate the images for the face identification.

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