Wavelet based Feature Extraction of Human Face

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ABSTRACT

Human have a notable ability to recognize faces, which is one of the most common visual feature in our environment. In regarding face pattern, just like other natural object, a geometrical interpretation of face is difficult to achieve. In this paper, we present wavelet based approach to extract the face features. Proposed approach is similar to the feature based scheme, where the feature is derived from the intensity data without detecting any knowledge of the significant feature. Topological graphs are involved to represent some relations between facial features. In our experiments, proposed approach is less sensitive to the intensity variation.

I. Introduction

Facial feature is one of the most useful, powerful means for human being to recognize their emotions and intentions. A number of face recognition system have become available in the laboratory. Unfortunately, automatic face recognition is difficult to achieve because the face image to be recognize may have many variations, including facial expression, scale, orientation, makeup, aging [1][2]. Until now, lots of recognition algorithm have been reported to overcome these variations.

Generally, face recognition methods can be divided two approaches: components based and face based. The main idea of components based approach is to represent face using local features such as eyes, nose and mouth. in addition, this scheme involves two algorithms ,namely, one is based on template matching and another is based on geometrical feature. Experimental results showed that the one is superior to the other. But the scheme based on geometrical features may allow a higher computation speed and smaller memory space. Face-based approach such as, eigenface method, flexible model perform recognition by using global face feature. Eigenface method involved K-L transform to extract the feature of a face at particular facial points (nodes) [3]-[5].

Recently, wavelet based approaches have been reported, which gives better recognition accuracy than typical methods just like component-based as well as face-based[6][7]. Proposed recognition scheme consists of two main stages. In the first stage, to detect the facial feature, orthogonal wavelet is applied to decompose the face image. The low frequency subband of the decomposed is selected to represent its mother image. In the second stage we construct a graph representation of the face based on node in the graph representing feature information, and formulate a graph matching, which involves matching input graph with a data base.

Ⅱ. An Overview of Wavelet Transform

In this section we give an overview of important wavelet theory. Even though most of practical applications of wavelets involve Discrete Wavelet Transformations (DWT), many researchers are likely to insist the insightful graphical displays of Continuos Wavelet Transformations(CWT). Because of understand-ing continuous wavelet transformation is important since many of their properties have analogous discrete counterparts. It is also useful to understand multi-resolution analysis, which is the fundamental concept necessary to construct and understand the wavelet paradigm.

Let $\Psi_{a,b}(x)$, $a \in \mathbf{R}\backslash\{0\}$, $b \in \mathbf{R}$ be a family of functions defined as translations and re-scales of a single function $\Psi(x) \in L_2(\mathbf{R})$,

$$\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{x-b}{a}\right) \tag{1}$$

Such normalization ensures that $\|\psi_{a,b}(x)\|$ is independent of a and b. The function ψ is called the wavelet function or the mother wavelet, and it is assumed to satisfy the admissibility condition,

$$C_\psi = \int_R \frac{|\Psi(\omega)|^2}{w}dw < \infty \tag{2}$$

where $\Psi(w)$ is the Fourier transformation of $\psi(x)$. The admissibility condition (2) implies

$$0 = \Psi(0) = \int \psi(x)dx$$

Also, if

$$\int \psi(x)dx = 0 \text{ and } \int (1 + |x|^a)\psi(x)\,|\,dx < \infty$$

for some $a > 0$, then $C_\psi < \infty$. This property of the function ψ, $\int \psi(x)dx = 0$, motivates the name wavelet.

Consequently, for any L_2 function $f(x)$, the continuous wavelet transformation is defined as a function of two variables

$$\begin{aligned} CWT_f(a,b) &= \langle f, \psi_{a,b}\rangle \\ &= \int f(x)\overline{\psi_{a,b}(x)}dx \end{aligned} \tag{3}$$

In here, the translation and dilation parameters, a and b, respectively, vary continuously over $\mathbf{R}\backslash\{0\}\times\mathbf{R}$.

It is able to express DWT similar to the discrete Fourier transform and discrete short-time Fourier transform. Scale parameter a and the translation parameter b is taken the discrete values in a different way. In here it just mention that we will take a to be of the form 2^{-s} and b to be of the form $k2^{-s}$, where $k, s \in \mathbf{Z}$. With these values of a and b, the integral of (3) becomes

$$\begin{aligned} &W_\psi f(k2^{-s}, 2^{-s}) \\ &= 2^{s/2}\int_{-\infty}^{\infty} f(t)\Psi(2^s t - k)dt \end{aligned} \tag{4}$$

Let us now discretize the function $f(t)$. For simplicity, assume the sampling rate to be 1. In that case, the integral of (4) can be written as

$$W_\phi f(k2^{-s}, 2^{-s}) \approx 2^{s/2} \sum_n f(n) \Psi(2^s n - k) \quad (5)$$

To perform the wavelet transform of a fu nction at some point in the time-scale pla ne, it need not to know the function value s for the entire time axis. It means that evaluation of the wavelet transform can be done almost in real time.

Ⅲ. Feature Detection by Wavelet sub-pattern

One of the main goal of transform coding is to make as many transform coefficients as possible small enough so that they are insignificant and need not be coded for transmission and consequently, wavelet transform also has the potential of reducing redundancy. In this view point, we invoke the idea that taking the WT as a preprocessor, which can be directly obtained the feature parameters by utilizing transformed coefficients matrix [7]. The DWT is a particular kind of this family that operates on discrete sequences. It is also closely related to and in some cases identical to subband codes, and quadrature mirror filters.

In a typical application, an image is subjected to a two-dimensional (2-D) DWT whose coefficients are then quantized and may be used as a feature parameters. Since the extracting operation computes for each group of pixels a list of its properties, the coefficients matrix guarantees that the output of the DWT have some properties might include its centroid, its area, its circumscribing portion, its orientation, its spatial moments, and so on.

Consider a two-channel orthogonal filter bank, the usual wavelet decomposition for 2-D images can be expressed as Eq. (6).

$$\begin{aligned} A_{2^{j-1}}f &= \sum_k\sum_l h(2m-k)\,h(2n-l)\,A_{2^j}f \\ H_{2^{j-1}}f &= \sum_k\sum_l h(2m-k)\,g(2n-l)\,A_{2^j}f \\ V_{2^{j-1}}f &= \sum_k\sum_l g(2m-k)\,h(2n-l)\,A_{2^j}f \\ D_{2^{j-1}}f &= \sum_k\sum_l g(2m-k)\,g(2n-l)\,A_{2^j}f \end{aligned} \quad (6)$$

Where $\{h_i\}$ and $\{g_i\}$ are the filter coefficients corresponding to the scaling and wavelet function. It is important to observe that the DWT performs down-sampling of the coefficients at the finer scales since the filters (h and g) are moved in a step size of 2. Although different type of wavelet functions are exist, orthogonal wavelet filter banks have lots of good features -conservation of energy, identical analysis and synthesis- but also some constraints. In addition two main types of filter bank trees: the full-grown tree and the octave-band tree are commonly used. In this research, it is necessary to choose a particular DWT, that is, we selected the Daubechies' family of orthogonal wavelets.

After detecting feature, the next step is to construct a information graph about the face using the available information at the feature points. topological graphs are used in this scheme to represent relationship between features. The nodes N_i for the graph correspond to the feature points. These are also characterized by {S, f }. In here S stands for information about the spatial location, and $f_i = [Q_i(x, y, k_1), \ldots. Q_i(x, y, K_n)]$ is the feature vector corresponding to the i'th feature. If N_i denote the set of neighbors of i'th node, a search is performed to find the best matching feature node $V_{i'}$ in the stored graph, such that

$$S_{ii'} = 1 - \frac{f_i \cdot f_{i'}}{\| f_i \| \, \| f_{i'} \|} = \min_{m' \in N^i} S_{im'} \quad (7)$$

And also, the orientation matching process can be described as a convolution-like operation as

$$C(x, y) = \sum_n \sum_m dist(V_M(m, n), \; V_I(x+m, y+n)) \quad (8)$$

where C (x, y) is an image like structure containing the similarity score between sub-image of size $m \times n$ and the model which is of the same size for each possible model position within the image. In here, the function dist( ) calculates the local distance between two single orientation vectors [9]. After all the individual features are matched, total cost is computed by taking into account the topology of the matched graphs. The total cost of matching input graph I_g to a stored graph O_g is then given by Eq. (9)

$$C_1(I_g, O_g) = \sum_i S_{ii'} + \lambda_t \sum_i \sum_{j \in N^i} T_{ii'jj'} \quad (9)$$

where λ_t is a scaling parameter which controls the relative importance of the two cost functions.

Ⅳ. Experimental Consideration

The procedure of facial feature extraction we addressed consist of two main stage. In the first stage we address a scheme of the DWT based feature extraction. A feature based approach is less sensitive to such variation as intensity. In the second stage we utilize the topological graph based on feature information.

Feature extraction is the core of a pattern recognition system. Because some features are utilized to identify one class of pattern from another. this process can be view s a mapping, which maps a pattern space into a feature space. Pattern space P may be described by a vector of m pattern vectors such that

$$P = \begin{vmatrix} P_1^T \\ P_2^T \\ \cdot \\ \cdot \\ \cdot \\ P_m^T \end{vmatrix} = \begin{vmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{vmatrix},$$

where the superscript T for each vector stands for its transpose, the $P_i^T =$ $(x_{i1}, x_{i2}, \cdots, { x}_{i n }),i=1, \cdots$,m represent pattern vectors. In here the objective of the feature extraction function (DWT) as the dimensionality reduction. It maps the pattern space (i.e. input facial images) into the feature space (i.e. DWT coefficients vectors).

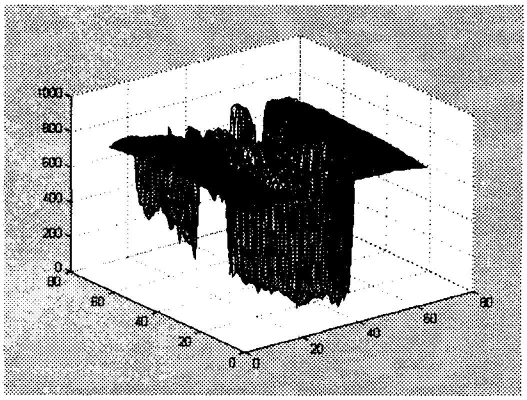
This approach focuses on the recognition of frontal-view face image and each with two images. In the first orthogonal wave let is applied to decompose the image. The low-frequency subband of the decomposed is selected to represent its mother image, which is an optimal approximate image of mother image in lower dimension. The global procedure for extracting facial features is embodied in the following algorithm 1 which list the basic traversal of this approach.

Algorithm 1

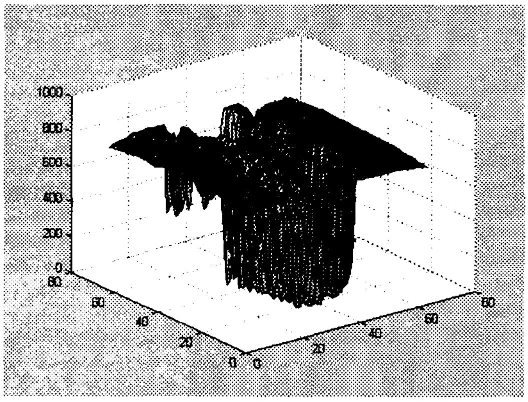
Notation: N is the number of facial image and input array of it's image is I(x,y). Co-Matrix denotes the coefficient matrix of DWT. Fp express the feature parameter. NoF is the total number of Fp. The while condition in step 9 assume that the graph matching is only allowed by threshold value.

1. **For** each image of t from 0 to N by Δt **do**:
   Begin.
2. Perform 3-level DWT.
3. Extract the Fp from Co-Matrix.
   End.
4. **While** Fp is not equals NoF **do**:
   Begin.
5. Link Fp into Fp+1.
   End.
6. **If** link is complete **then do**:
   Begin.
7. Construct the graph matching with database.
8. Calculate the recognition accuracy.
   End.
   Else Set NoL=NoL+Fp.
9. **While** graph matching is false **do**:
   Begin.
10. Perform 2-level DWT.
11. Repeat steps 3 - 8, at most three times.
    End.
12. **End of algorithm.**

Fig.1 shows the magnitude of facial images. The performance of recognition accuracy in Fig .2 is satisfactory. The number of feature parameter for individual image as shown in Fig. 3



a) model 1



b) model 2

Fig. 1. Example of facial images

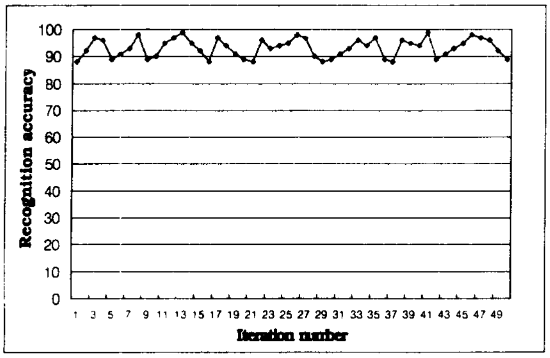


Fig. 2. Recognition accuracy.

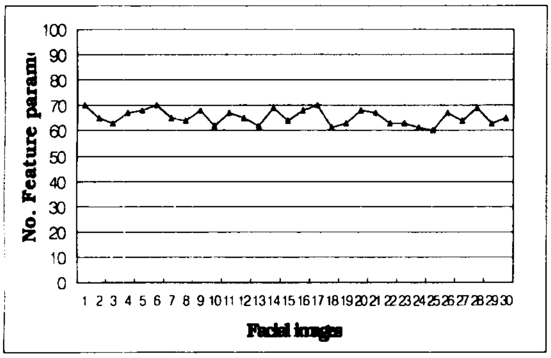


Fig. 3. Extracted facial feature.

V. Conclusion

We have presented a wavelet-based feature extraction of facial images. In the preprocessing, wavelet decomposition is involved to extract the facial feature. After extracting feature parameter, the information graph obtained using our method is matching with that of stored database.

The performance of proposed approach is demonstrated by simulation and experimental results. Simulation results show that this approach have a recognition accuracy of 92%. This approach is relatively simple but robust than [8] in extracting facial features. Future work for proposed scheme will center around finding the resonable nodes, optimizing its link process. And than it is expected that this approach will be applicable to Spcetroface.

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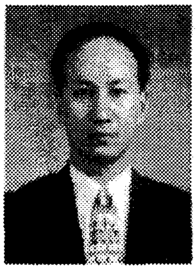

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