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Discriminant Waveletfaces and Nearest Feature Classifiers for Face Recognition

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In general, the feature extraction, discriminant analysis and classification rule are three basic elements in face recognition systems [2][3]. This study aims to build the hybrid approaches to handle these three issues together. The overall face recognition system is shown in Figure 1. First, we perform the multiresolution wavelet transform to extract *waveletface* and apply the *linear discriminant analysis* on waveletfaces to reinforce discriminant power. Finally, the *nearest feature plane* (NFP) and *nearest feature space* (NFS) classifiers are explored for robust classification addressing the facial variations.

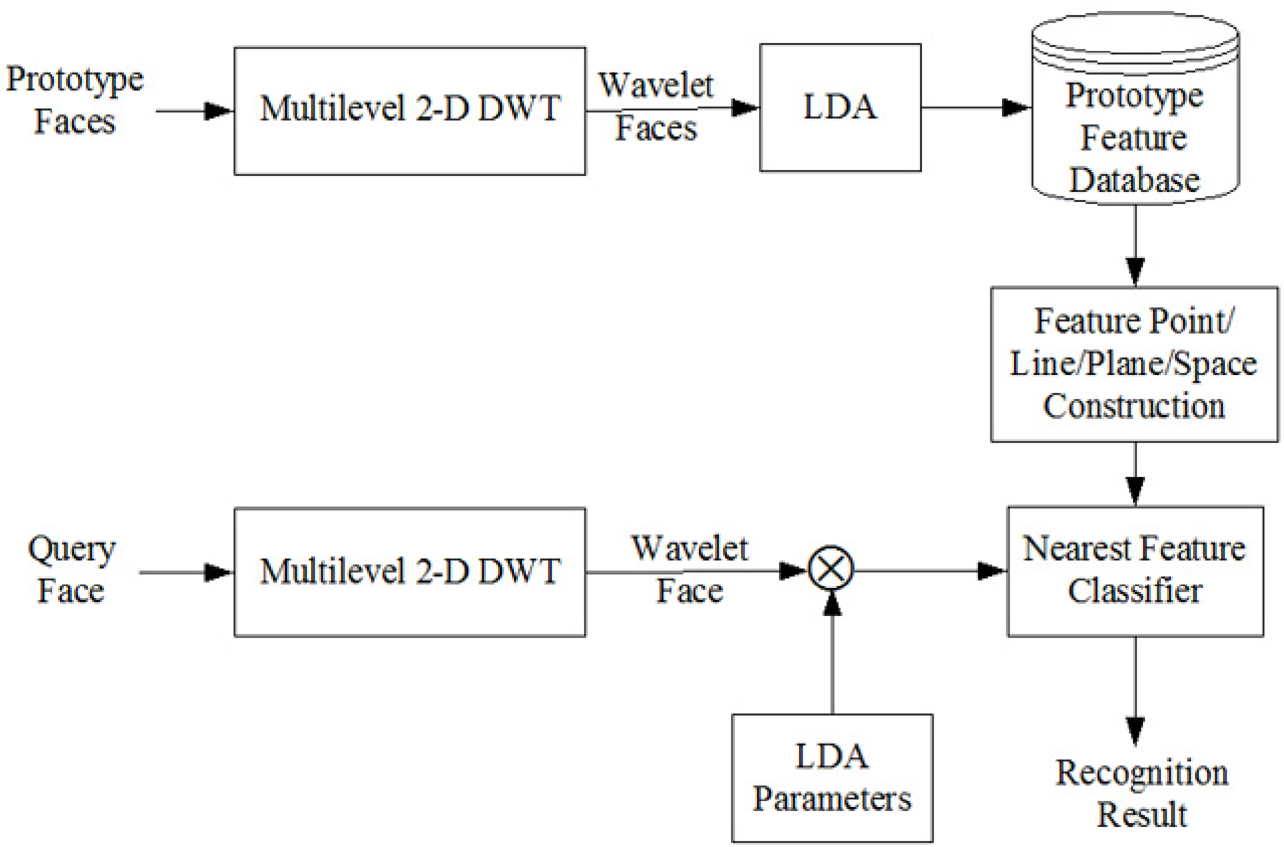

Figure 1: Overall system architecture of waveletface recognition.

Waveletface

The wavelet decomposition technique has been successfully used to extract the intrinsic features for face recognition [4]. We employ the multilevel 2-dimensional (2-D) wavelet transform to extract the facial features. Using 2-D wavelet transform [5], we decompose the image data into four sub-images via the high-pass and low-pass filtering with respect to the column vectors and the row vectors of array pixels. It is an extended technique of one-dimensional wavelet transform, where the decomposition is done along the vertical followed by the horizontal directions.

Linear Discriminant Analysis (LDA)

After extracting waveletface, we further reduce the feature dimensionality and enhance the class discriminability by applying LDA [1]. The discriminant waveletface is accordingly produced to optimally discriminate classes of prototype data. It is advantageous to attain relatively small dimensionality using the discriminant waveletface. The "curse of dimensionality" could be alleviated.

Nearest Feature Classifier

This study proposes two nearest feature classifiers, nearest feature plane (NFP) and nearest feature space (NFS). In NFP, we calculate the distance between query and feature plane by $d(\mathbf{z}, F_{lkg}^{c}) = \|\mathbf{z} - \mathbf{p}_{lkg}^{c}\|$ where $\mathbf{p}_{lkg}^{c}$ is the projection of the query z on plane F_{lkg}^{c} spanned by three feature points *l*, *k*, *g* of class *c*. The class label is determined by

$$(\hat{c}, \hat{l}, \hat{k}, \hat{g}) = \mathop{\arg\min}_{\substack{1 \le c \le C, 1 \le l, k, g \le n_c \\ l \ne k \ne g}} d(\mathbf{z}, F_{lkg}^{c})$$

.

Furthermore, the NFS is proposed to cover sufficient facial variations without much computation overhead. Let $\{Z_{c1}, z_{C2}, \ldots, Z_{cn_c}\}$ denote the independent prototype features associated with class *c*. The subspace spanned by

$S^c = SP(Z_{c1}, z_{C2}, \ldots, Z_{cn_c})$ represents the *feature space* for a person *c*. This feature space contains large scale of

variations. The NFS is intended to classify the query z by finding the nearest feature space among all classes

$$\hat{c} = \mathop{\arg\min}_{1 \le c \le C} d(\mathbf{z}, S^{c}) = \mathop{\arg\min}_{1 \le c \le C} \|\mathbf{z} - \mathbf{p}^{c}\|$$

.

No matter how many prototypes are collected, the number of distance calculation always equals to the number of classes. Such classifier is efficient for face recognition.

Experimental Results

In the experiments, the proposed methods were implemented on the IIS face database accessible at http://smart.iis.sinica.edu.tw/ and the public-domain ORL database accessible at http://www.cam-orl.co.uk/facedatabase.html . In this study, we performed the multilevel 2-D wavelet decomposition and select the lowest frequency image as the feature vector. Our face recognition system was implemented in a personal computer with Pentium III 733 CPU and 256 MB RAM. Table I lists the results of feature representation by using eigenface and waveletface involving two-level, three-level and four-level wavelet decomposition. The nearest neighbor (NN) classifier is employed.

Table I. Recognition rates (%) and training times for eigenface and waveletface under different levels of wavelet decomposition

	Eigenface	Two-Level Waveletface	Three-Level Waveletface	Four-Level Waveletface
Recognition Rate	91.2	N/A	91.9	88.9
Training Time	14.8 min	N/A	6.7 min	3.1 min

When evaluating the effect of LDA on eigenface and waveletface, we report the recognition rates and times in Table II. The recognition time per image using waveletface is shown to be 0.202 sec, which is efficient compared to 0.337 sec using eigenface. Furthermore, we evaluated the recognition performances using four nearest feature classifiers, NN, NFL, NFP and NFS. We find that NFL outperforms NN. NFP attains better performance than NFL. The proposed NFS achieves the best recognition accuracy on both IIS and ORL corpora. Finally, we evaluated different classification rules using different numbers of prototype images of each class. As shown in Table III, in case of six prototype images, it is found that the recognition rate 96.4% using NFS are improved compared to 95.7% using NFP. The NFS outperforms the other methods.

Table II. Comparison of recognition rates (%) and recognition times (sec) for different discriminant features and classification rules using IIS and ORL face databases.

Methods	Recognition Rates (IIS)	Recognition Times (IIS)	Recognition Rates (ORL)
Eigenface + NN	91.2	0.337	92
Discriminant Eigenface + NN	91.4	0.339	93.5
Waveletface + NN	91.9	0.202	92.5
Discriminant Waveletface + NN	93.1	0.208	94.5
Discriminant Waveletface + MLP	N/A	N/A	94.9
Discriminant Waveletface + NFL	95.4	0.212	95
Discriminant Waveletface + NFP	95.7	0.219	95.8
Discriminant Waveletface + NFS	96.4	0.285	96.1

Table II. Comparison of recognition rates (%) and recognition times (sec) for different discriminant features and classification rules using IIS and ORL face databases.

	Number of distinct prototype images in each class		
	3	4	6
NN	75.4	76	93.1
NFL	82.6	88.4	95.4
NFP	85.5	90.5	95.7
NFS	N/A	90.6	96.4

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