A Fusion of Trace Transform and Hamming Distance with Multiresolution Technique for Improved Accuracy Approach Face Based Identification

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ABSTRACT – This paper proposes a highly robust method for face recognition with variant illumination, scaling, rotation, blur, reflection and difference emotions (smiling, angry and screaming). Techniques introduced in this work are composed of two parts. The first one is the detection of facial features by using the concept of multi-resolution Trace transform. Then, in the second part, the Hamming distance is employed to measure and determine of similarity between the models and tested images. Finally, our method is evaluated with experiments on the AR and XM2VTS facial databases and compared with other related works (e.g. Eigen face, Enhance-EBGH, Hausdorff ARTMAP and Original Trace-Hamming). The extensive experimental results show that the average of accuracy rate of face recognition with variant pose, illumination, scaling, rotation, blur, reflection and difference expression is very high and it was found that our proposed method performed better than the other related works in all cases.

KEY WORDS – Face Recognition/Authentication, Multi-resolution Trace Transform, Hamming distance, Image Signature.

1. Introduction

Biometric identification [1] system makes use of either physiological characteristics [2-5] (such as a fingerprint, an ear, iris pattern, or face) or behavior patterns [6-8] (such as hand-writing, voice, or key-stroke pattern) to identify a person. Because of human inherent protectiveness of his/her eyes, some people are reluctant to use eye identification systems. However, many biometrics are similar in nature but are deployed in different manners. For example, face recognition [9-13] and face authentication [14-16] use similar identification algorithms, but the former is a passive biometric and the latter is active. Face recognition takes images of people, and returns the possible identity of that person. Face recognition systems are intended for use as a security system to find people in a crowd or deny access to a particular person from a sensitive area. Face authentication typically has a user position themselves in front of a camera, and then they enter their username and have the camera take an image from them. The image is compared to other images of the person. Based on this comparison the user is either granted access or denied. While the uses and procedures for the system are different, the algorithms used to compare the query or inputted images to the training images are similar. Face recognition methods use statistical methods like Eigen faces and Fisher faces [17-22] to associate an identity with a face when it falls within a threshold to a training number associated with a person in the training set. Support vector machine (SVM) based face recognition [23-27] use multiclass decision functions to recognize faces. Hausdorff ARTMAP (A-ARTMAP) [28,29] use Neuron network and

Hausdorff distance to classify and recognize faces. Statistical face recognition uses methods like principal component analysis (PCA), independent component analysis (ICA), and linear discrete analysis (LDA) to find the closest match in a face database. Like with face authentication, face recognition has two phases: a training phase and a classification phase. During the training phase, a database of identified images, called gallery images are converted from image matrices into vectors, where all the images have the same dimensions. These vectors of all the gallery images are combined into a matrix, where each column is a vector of the images. This matrix then has the dimension reduction tool applied to it; whether, it is PCA, ICA, or LDA, or a combination of them. This paper presents a face feature extraction and recognition method that employs the texture representation derived from the Trace transform.

The organization of this paper is as follows. An introduction to the multi-resolution Trace transform, its properties and how it can be used to extract invariant features is given and the extraction of the string identifier from a facial image in Section 2. The method of similarity measure is described in Section 3. Section 4 presents the experimental results and then conclusions and references in order of Section 5 and 6.

2. Features Extraction

In this work, we use a trace transform with multi-resolution technique for extracting features from clustered segments. The multi-resolution trace transform method able to produce feature values of an input image, invariant to translation, rotation and even reflection of an input image. Accordingly, it is suitable to extract feature values from various shapes of facial segments, even if deformed by translation, rotation, or reflection.

2.1 Pre-processing

The pre-processing phase that helps to improve the robustness of features extraction by removing possible artifacts due to resampling when trace transform is computed. Following [30], we represent each extracted face inside an ellipse. Therefore, all faces have a shape that is not intrinsic to the face. So, we describe the algorithm for face detection. This algorithm will search only the human skin areas, not the entire image. The whole algorithm can be described as shown in table 1.

2.2 The Original Trace Transform

The Trace transform [31,32] projects all lines over an image and applies functional over these lines. A further functional, known as the diametrical functional, is applied to the Trace transform to obtain a one-dimension function known as the circus function. A facial image identifier is developed using the trace and diametrical functionals. A line is parameterized in a co-ordinate system C_1 by (θ_1, d_1, t_1), where θ_1 the angle of the normal to the line is, d_1 is the distance between the origin and line and t_1 is the distance along the line. The values of the image function along a particular line are $F_1(\theta_1, d_1, t_1) = F(C_1; \theta_1, d_1, t_1)$. And then, the Trace transform T applies some functional over the image function that results in the diametrical function $d(C_1; \emptyset_1, \rho_1) = T\big(F(C_1; \emptyset_1, \rho_1, t_1)\big)$. The diametrical functional D operates on the diametrical function to give the circus function as shown below:

$$c(C_1; \emptyset_1) = D\left(T\left(F\left(C_1; \emptyset_1, \rho_1, t_1\right)\right)\right). \qquad (1)$$

Table 1. The face detection algorithm [30]

Algorithm-I	
Step 1:	RGB to HSV Color Model Conversion.
Step 2:	Human Skin Detection.
Step 3:	The Region of Human Skin.
Step 4:	RGB to Gray scale Conversion.
Step 5:	Edge Detection.
Step 6:	Face Region Searching and Snipping by using an Elliptical Model.

Table 2.Invariant functionals and their properties are used in this work.

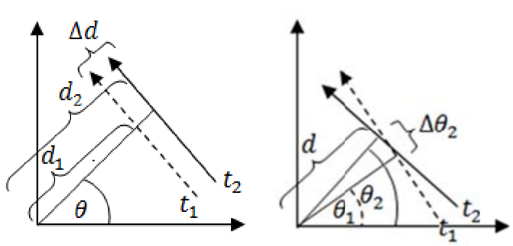
No	Functional	k	λ	Properties
IF_1	$\int \xi(t)dt$	-1	1	I_1, i_1 and i_2
IF_3	$\int \lvert\xi(t)'\rvert dt$	0	1	I_1, i_1 and i_2
IF_6	$\max(\xi(t))$	0	1	I_1, i_1 and i_2

2.2.1 Invariant Functional

Shift invariance means that the value of the functional does not change if the function shifts. Examples are the integral, the median value, the maximal value of a function, etc. One might say that an invariant functional chooses an ordinate independently of the shift. A functional Ξ is called shift invariant if for any admissible function $\xi(x)$ is invariant if $\Xi(\xi(x+b)) = \Xi(\xi(x))$ for all $b \in \mathbb{R}$ (Property I_1). The invariant functionals can have two further properties $\Xi(\xi(ax)) = \alpha(a)\Xi(\xi(x))$ for all $a > 0$ (Property i_1), and $\Xi(d\xi(x)) = \gamma(a)\Xi(\xi(x))$ for all $d > 0$ (Property i_2). It can be shown that $\alpha(a) = a^{k_\Xi}$ and $\gamma(d) = d^{\lambda_\Xi}$, where the constants k_Ξ and λ_Ξ are called homogeneity constants of functional Ξ . The used invariant functionals and their properties are shown in table 2.

2.3 Multi-Resolution Trace Transform

Multi-resolution representations are popular technique for their powerful ability to describe signals at varying levels of detail from coarse gain to fine gain. Here a multi-resolution Trace transform is introduced that is quickly and efficiently generated from the original Trace transform. A Trace transform T with a specific functional provides one representation of an image. From this one abstraction a multi-resolution representation of the image can be generated which captures information at different scales. The Trace transform multi-resolution decomposition is performed by sub-sampling the original Trace transform of the image in either of its two dimensions, d or θ, or in both dimensions.



(a) (b)

Fig. 1. The multi-resolution Trace transform **(a)** with difference *d* **(b)** with difference *θ*.

This corresponds to projecting strips of width d over the image during the Trace transform, as shown in Fig. 1(a). Sub-sampling also takes place by integrating over intervals in the θ parameter as shown in Fig. 1(b).

2.4 Facial Image Identifier Extraction Algorithm

An image $f(x, y)$can be viewed from two different co-ordinate systems C_1 and C_2.The coordinate system, C_2, is obtained from the C_1 by a rotation of angle $-\phi$, scaling the axis by parameter *v* and by translating with the vector $(-S_0 \cos\varphi_0, -S_0 \sin\varphi_0)$. The image $f_2(\tilde{x}, \tilde{y})$ viewed from C_2 can be seen as the image $f_1(x, y)$ having undergone rotation by ϕ, scaling by v-1and shifting by$(-S_0 \cos\varphi_0, S_0 \sin\varphi_0)$. These linear transformations a line in f_1 will still be a line in f_2; the transformations are line preserving. The parameters of an image line in co-ordinate system C_1 in terms of the parameters of the line in C_2 are$\theta_1 = \theta_2 - \phi, d_1 = v\,[d_2 - S_0 \cos(\varphi_0 - \theta_2)]$ and $t_1 = v\,[t_2 - S_0 \sin(\varphi_0 - \theta_2)]$. From equation (1); it can be seen that the relationship of the circus function of an image in co-ordinate system C_2 to the image in coordinate system C_1 is given as:

$$c(C_2;\phi_1) = D\left(T\left(F_1\left(\begin{matrix}\phi_1-\theta,\\ v[\rho_1 - S_0\cos(\varphi_0-\phi_1)],\\ v[t_1 - S_0\sin(\varphi_0-\phi_1)]\end{matrix}\right)\right)\right). \quad (2)$$

The Trace functional T is chosen to obey I_1 and i_1

$$c(C_2;\phi_1) = D\left(\alpha_T(v)\left(F_1\left(\begin{matrix}\phi_1-\theta,\\ v[\rho_1 - S_0\cos(\varphi_0-\phi_1)],\\ t_1\end{matrix}\right)\right)\right). \quad (3)$$

Furthermore, the diametrical functional T can be chosen to obey I_1, $i_1$and i_2 such that $c(C_2;\phi_2) = \gamma\, D\,(\alpha_T\,(v)\,)\, D\left(T\left(F_1(\phi_1 - \theta, v[\rho_1 - S_0\cos(\varphi_0 - \phi_1)], t_1)\right)\right)$, we obtain $(C_2;\phi_2) = \gamma D(\alpha_T(v))\alpha_D(v) D\left(T\left(F_1(\phi_1 - \theta, \rho_1, t_1)\right)\right)$, and it can then be define as

$$(C_2;\phi_2) = kD\left(T\big(F_1(\phi_1-\theta,\ \rho_1,t_1)\big)\right), \quad (4)$$

where $k=\gamma D\big(\alpha_T(v)\big)\alpha_D(v)$. From equation (4) it can be seen that the one-dimension circus function in C_2 is a scaled and shifted version of the circus function in C_1. From equation (4) we taking the Fourier transform gives $F(\Phi)=\mathcal{F}\left[kD\left(T\big(F_1(\emptyset_1-\theta,\rho_1,t_1)\big)\right)\right]$, then exploiting the linearity identity and translation property of the Fourier Transform gives $F(\Phi)= kexp^{-j\theta\Phi}\mathcal{F}\left[D\left(T\big(F_1(\emptyset_1-\theta,\rho_1,t_1)\big)\right)\right]$. Taking the magnitude of $F(\Phi)$ gives

$$F(\Phi)=\left|k\mathcal{F}\left[D\left(T\big(F_1(\emptyset_1-\theta,\rho_1,t_1)\big)\right)\right]\right|. \quad (5)$$

By the properties of the circus function and the magnitude of the Fourier transform an identifier can be extracted from an image. An algorithm to extract the binary identifier is given in Table 3. The identifier is robust under similarity transform, which is scaling, rotation and translation.

Table 3. The binary identifier extraction algorithm.

Algorithm-II	
Step 1:	Take the Trace transform of the image using the functional $\int \xi(t)dt$ i.e., integrating over all lines in the image.
Step 2:	Find the first two circus functions by applying the following diametrical functionals to the columns of the two dimensions matrix resulting from step 1, $\int \lvert\xi(t)'\rvert dt$ where $'$ is the gradient $\max\big(\xi(t)\big)$.
Step 3:	Get the magnitude of two circus functions by taking the Fourier transform.
Step 4:	Obtain the binary strings from each circus function that comes from taking the difference of neighboring coefficients $i_\omega=\begin{cases}0 & c(\omega)<0\\ 1 & othrwise\end{cases}$, (6) where $c(\omega)$ is defined by $c(\omega)=\lvert F(\omega)\rvert-\lvert F(\omega+1)\rvert$.
Step 5:	The first bit $i_1$corresponding to the different-combinations component is discarded and the identifier is made up of the subsequent *N* bits, $I==\{i_1,i_2,\ldots,i_n\}$.
Step 6:	For each diametrical functional perform steps (2) to step (5).
Step 7:	Concatenate each of the identifiers to obtain the complete identifier.

The multi-resolution Trace transform provides more identifiers. One-dimension decomposition over the distance (d) parameter is performed. The extraction process shown in table 2, steps 2 to 5, are used for each level of the multi-resolution Trace transform. Significant performance improvements are obtained by extracting multiple identifiers from each image. Firstly different identifiers are extracted by making different choices for the diametrical functionals in steps 1 and 2 of Algorithm-II (see in Table 3).

From algorithm in table 3, the results are further improved by using different diametrical functionals to extract multiple component identifiers and concatenating them to obtain a complete identifier as shown in Fig. 2.

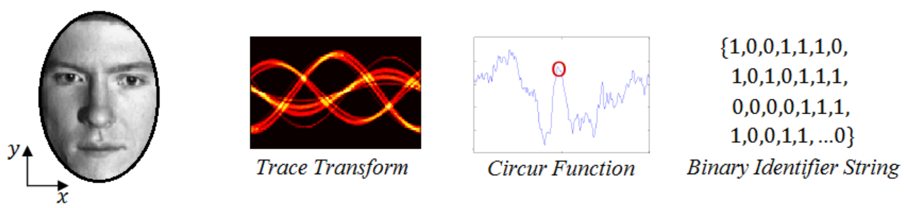
3. Similarity Measure

3.1 The Hamming Distance

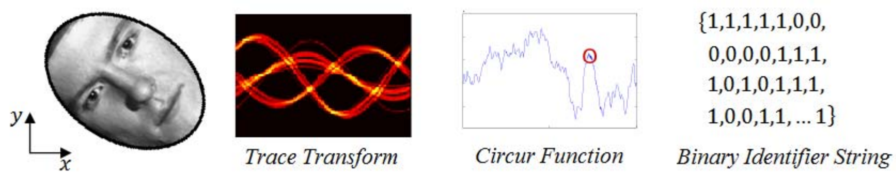
To perform identifier matching between two different identifiers B_1 and B_2, the length of each identifier denotes N and the normalized Hamming distance [33] is defined by:

$$\mathrm{H}(\mathrm{B}_1,\mathrm{B}_2)=\frac{1}{\mathrm{N}}\sum_{\mathrm{N}}\mathrm{B}_1\otimes\mathrm{B}_2, \quad (7)$$

where $\otimes$ denote the exclusive OR (XOR) operator. If the $\mathrm{H}(\mathrm{B}_1,\mathrm{B}_2)$ is less than some predefined threshold the images are classified as “accept”, if the distance value is above the threshold then the images are classified as “reject”.



(a)



(b)

Fig. 2. The binary identifier for a facial image (a) and its distortion version (b).

Fig. 3. Some example of facial images in AR and XM2VTS face databases.

4. Experimental Results

In this section, we describe a face database we used and then present a face authentication result under variant pose, illumination, scaling, rotation, blur and different expression (smiling, angry, and screaming). Our proposed method was implemented on the AR [34] and XM2VTS [35] facial databases (As shown sample in Fig. 3).

Our proposed method has been compared with other approaches using the same database and test protocol presented in Ref. (36). The success rates corresponding to evaluation and test sets are summarized in table 4.

Table 7 Performance of the propose method (the results with * are from [36]

Condition	Success rate (%)				
	Eigen*	H-ARPMAP*	EBGH*	Trace-Hamming*	Propose Method
Normal case	≈ 92*	≈ 95*	≈ 97*	≈ 99*	≈ 99
Scaling	≈ 67*	≈ 54*	≈ 92*	≈ 97*	≈ 99
Rotation	≈ 53*	≈ 46*	≈ 48*	≈ 98*	≈ 99
Scaling + rotation	≈ 47*	≈ 36*	≈ 38*	≈ 95*	≈ 99
Smiling	≈ 84*	≈ 87*	≈ 92*	≈ 91*	≈ 93
Angry	≈ 71*	≈ 86*	≈ 91*	≈ 91*	≈ 93
Screaming	≈ 34*	≈ 59*	≈ 52*	≈ 67*	≈ 72
Blur	≈ 78*	≈ 87*	≈ 84*	≈ 89*	≈ 99
Illumination	≈ 62*	≈ 85*	≈ 72*	≈ 88*	≈ 92
Pose	≈ 76	≈ 82	≈ 89	≈ 87*	≈ 93

5. Conclusions

This paper proposes a highly robust method for face recognition. Techniques introduced in this work are composed of two parts. The first one is the detection of facial features by using the concepts of Multi-resolution Trace Transform, Fourier Transform and Circle Function. Then, in the second part, the notions of Hamming distance and Image identifier algorithm are employed to measure and to determine the similarity between the models and the tested images. Extensive experimental results demonstrate that the average of accuracy rate of face recognition with variant pose, illumination, scaling, rotation, blur, reflection and difference expression is very high and it was found that our proposed method performed better than the other related works in all cases.

Acknowledgements

This research was supported by Mahanakorn University of Technology. We would like to thank AR and XM2VTS for providing testing image databases. Moreover, we would also like to express special thanks to the CSC-MUT staff for their help in implementing the Hausdorff-ARPMAP and the Enhance-EBGH for face authentication.

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