Face parts prediction using artificial neural network from fingerprint

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***Abstract*—Biometrics is a deeply studied and highly developed technology. While biometric systems have been used primarily in limited applications requiring high security tasks like criminal identification and police work, more recently they have been receiving increasing demand for person recognition applications. This project presents a novel intelligent approach analyzing the existence of any relationship among fingerprints and face parts. Proposed approach is based on artificial neural networks. Developed system generates the stationary face parts of a person that includes eye and mouth parts from only one fingerprint image of the same person without knowing any information about his or her face. Improving of the proposed system is still sustained for the purpose of analyzing and modeling of this relationship for the future developments in biometrics and security applications.**

***Index Terms*— biometrics, face recognition, fingerprint identification, artificial neural networks**

I. Introduction

BIOMETRICS refers to automatic recognition of an individual based on behavioral and/or stable physiological characteristics such as fingerprint, face, iris, voice, signature or hand geometry which cannot be stolen, lost, or copied. Therefore, differentiating an authorized person from fraudulent impostor supports critical processes in a wide range of applications including criminal applications, execution of the rules, information security, smart cards, access control in building entrances or computer networks, time/place control points, airports etc. [1]-[4]. It should be emphasized that improving the accuracy and processing time of the biometric system, designing the full automatic and more intelligent systems and developing more effective and robust algorithms have called researcher's attention[1], [2].

This study aims to generate face parts of a person from only his or her one fingerprint image without having any prior knowledge about his or her face. In order to achieve the generation process properly, a system based on artificial neural network was developed. The experimental results achieved from the proposed fingerprint to face parts (F2FP) system were also presented. The paper is organized as follows

Section 2 reviews the studies on biometrics, automatic fingerprint identification and verification systems (AFIVSs), face recognition systems (FRSs) and multi-modal biometric systems (MBSs) respectively. Section 3 briefly introduces artificial neural networks (ANNs). Section 4 presents the novelty of the proposed system including basic notation, definitions, performance metrics related to the F2FP and explains the various steps of the new approach. The experiments including numerical and graphical results of the F2FP are given in Section 4. Finally, the proposed work is concluded and discussed in Section 5.

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II. Previous works

In many biometric authentication systems, an enrolment phase and a feature extraction phase are used for acquiring the biometric data from the people and extracting the feature set from the acquired biometric data, sequentially. This feature set is stored in the system database. Later, when the user wants to authenticate himself or herself to the system, a fresh measurement of the same biometrics is taken, the same feature extraction algorithm is applied, and the extracted feature set is compared against the template. If they are sufficiently similar according to some similarity measures, the user is considered as authentic [3], [5]. Generally depending on the application status, a biometric system works in four modes [4]: the enrolment, the verification, the identification and the screening. Scanning, categorization and registration of the biometric characteristics are achieved in *the enrolment* mode. A person desired to be identified by submitting to the system a claim to an identity, usually via a magnetic card, login name, smart card etc. in *the verification* mode. The system either rejects or accepts the submitted claim of the identity at the end [6]. Commercial applications, such as physical access control, computer network logon, electronic data security, ATMs, credit-card purchases, cellular phones, personal digital assistants, medical records management, and distance learning are samples of the verification applications [2], [4]. The system identifies a person's identity without the person having to claim an identity in *the identification* mode. System fails if the person is not enrolled in the system database. The input and the outputs of the system are just a biometric feature and a combination of a list of identities and the scores indicating the similarity among two biometric features, respectively [6]. Welfare-disbursement, national ID cards, border control, voter ID cards, driver's license, criminal investigation, corpse identification, parenthood determination, missing children identification are from typical identification applications [2], [4]. The results of determination whether a person belongs to a watch list of identities or not is displayed in *the screening* mode. Security at airports, public events and other surveillance applications are some of the screening examples [4], [7]. A generic biometric system is given in **Fig.** 1.

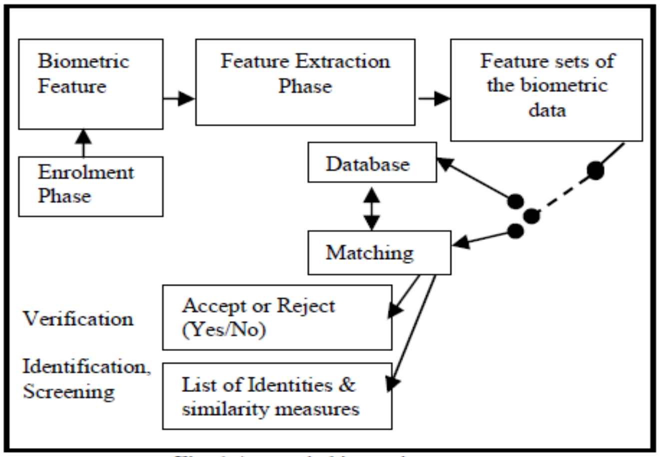


Fig. 1 A generic biometric system

It is expected that a biometric system always takes the correct decisions, when a biometric feature is presented to the system. However, in practice it could not be able to achieve to make perfect match decisions at all times. Generally biometric systems make two basic types of errors: False match rate (FMR) and false non-match rate (FNMR) [1]. These errors generally use to show the accuracy and performance of the system in the literature. Receiver Operating Characteristic (ROC) curve is also used to report the system accuracy and performance at all operating points [7].

When we consider faces, they are probably the most highly accepted and user-friendly biometric characteristics. Face recognition technology is well advanced because of being an active area of research with several applications ranging from static to dynamic [8]. In general, a FRS consists of three main steps including detection of the faces in a complicated background, localization of the faces followed by extraction of the features from the face regions and finally identification or verification tasks [9].Face detection and recognition processes are really complex and difficult tasks due to numerous factors affecting the appearance of an individual's facial features. 3D pose, facial expression, hair style and make-up are frequently encountered factors of them. [10]. In addition to these varying factors, lighting, background, scale, noise and face occlusion and many other possible factors make these tasks even more challenging [9]. The most popular approaches to face detection and recognition are based on each location and shape of the facial attributes, such as the eyes, eyebrows, nose, lips and chin and their spatial relationships or the overall analysis of the face image that represents a face as a weighted combination of a number of canonical faces [4], [11]. Also many effective and robust methods for the face recognition have been proposed [2], [8], [9]-[13]. They are categorized as follows: Knowledge-based methods encode human knowledge of what constitutes a typical face. Feature invariant methods aim to find structural features that exist even when the pose, viewpoint or lighting conditions vary to locate faces. In template matching based methods several standard patterns of a face are used to describe the face as a whole or the facial features separately. Appearance-based methods operate directly on images or appearances of the face objects and process the images as two-dimensional holistic patterns [12].

Fingerprint is one of the most used and reliable biometric characteristic. A fingerprint has a ridge-valleys structure including end points and bifurcations called minutiaes; core and delta points called singular points. Because of being the most commonly used in a variety of the applications, fingerprint identification technology is also well advanced.

Many approaches to AFIVSs have been presented in the literature [1], [2], [6], [8], [14]-[26]. Yet, it is still an actively researched area. The AFIVSs might be broadly classified as being minutiae-based, correlation-based and image-based systems [1], [15]. A good survey about these techniques is given in [1]. In the minutiae-based approaches personal identification is made using the comparisons for similarities and differences of the local ridge attributes and their relationships [8], [16], [17]. It is tried to align two sets of minutiaes from two fingerprints and count the total number of matched minutiaes [4]. If minutiaes and their parameters are computed relative to the singular points, these feature sets will also become rotation, translation and scale invariant [6], [18]-[20]. Core points are the points where the innermost ridge loops are at their steepest. Delta points are the points from which three patterns deviate [19], [21], [22]. The general methods to detect the singular points are Poincare-based methods [23], intersection-based methods [19] and filter-based methods [24].

In the minutiae-based AFIVSs main steps of the operations are given in **Fig. 2**, respectively. All these processes affect the accuracy and performance of the minutiae-based techniques. Especially the feature extraction and the use of sophisticated matching techniques to compare two minutiae sets often more affect the performance. *In the correlation-based AFIVS*, global patterns of the ridges and valleys are compared to determine if the two fingerprints align. The template and query fingerprint images are spatially correlated to estimate the degree of similarity between them. The performance of the correlation based techniques is affected by non-linear distortions and noise present in the image. In general, it has been observed that minutiae-based techniques perform better than correlation-based techniques [26]. *In the image-based approaches*, the decision is made using the features that are extracted directly from the raw image that might be the only viable choice when image quality is too low to allow reliable minutiae extraction [4].

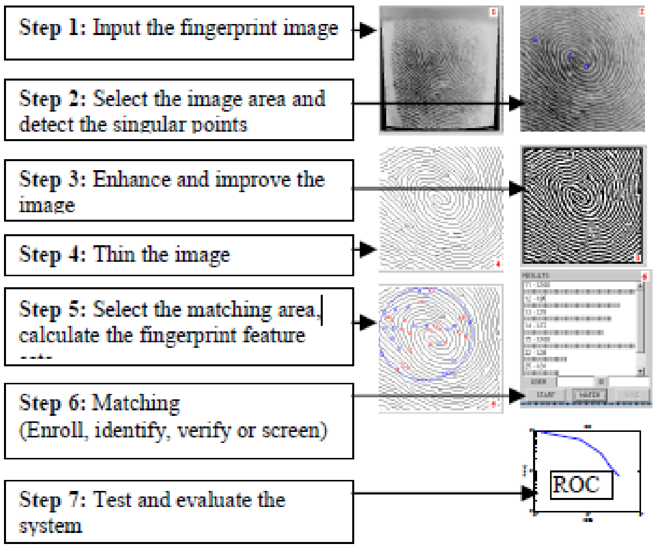


Fig. 2 Main operation steps of a minutiae-based AFIVS [25]

The uni-modal biometric systems have some limitations about accuracy, processing time and vulnerability to spoofing [10]. Multi-modal biometric systems are gaining acceptance among scientist and applicants due to their performance superiority over the uni-modal systems. The MBSs are generally designed as a fusion of the various biometric modality data at different levels. These levels are the feature extraction levels, the score levels, or decision levels [27], [28].Fusion at the feature extraction level can be explained that the data obtained from each biometric feature is used to compute a feature set that has a higher dimensionality and represents a person's identity in a more discriminating feature space. Fusion at the matching score level can be defined that each biometric matcher provides a similarity score indicating the proximity of the input feature vector with the template feature vector. These scores can be combined to assert the veracity of the claimed identity. Fusion at the decision level can be described that each biometric system makes its own recognition decision based on its own feature vector. Finally recognition decision is obtained [3]. Jain et al. have thoroughly explained the basics of the MBSs in different sides of the subject in their paper [3].

III. Artificial Neural Network

In many discipline, researchers have actively used ANNs to solve several problems [29]-[33]. ANN is one of the most highly attractive modeling techniques because of its fascinating features like learning, generalization, less data requirement, fast computation, ease of implementation and software and hardware availability [29], [30]. ANN is also very popular in biometrics [12], [13], [31]-[33]. Multilayered perceptron (MLP) is an ANN architecture that can be trained by many learning algorithms. In the literature, it has been applied to a variety of problems successfully. A general form of the MLP is given in Fig. 3.

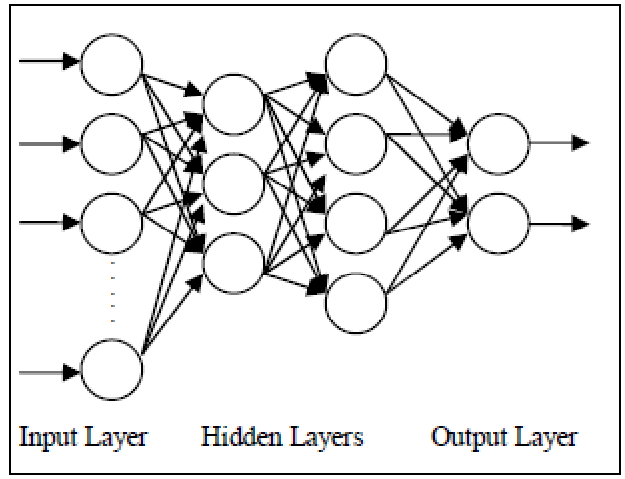


Fig. 3 General form of the MLP

The MLP structure consists of input, output and hidden layers. The neurons in the input layer can be treated as buffers and distribute xi input signal to the neurons in the hidden layer. The output of the each neuron yj in the hidden layer is obtained from sum of the multiplication of all input signals xi and weights wji that follows all these input signals. The sum can be calculated as a function of yj. This function can be a simple threshold function, a hyperbolic tangent or a sigmoid function. The outputs of the neurons in other layers are calculated in the same way. The weights are adapted with the help of a learning algorithm according to the error occurring in the calculation. The error can be calculated by subtracting the ANN output from the desired output value. MLPs might be trained with many different learning algorithms [29]. The ANN based system used in this work is trained with gradient descent with momentum and adaptive learning rate backpropagation algorithm (traingdx) to find out relationship between fingerprints and face parts (Fs&Fs).

IV. Proposed Approach

As it has been mentioned earlier goals of this study are establishing a relationship among Fs&Fs, generating the face parts from only fingerprints with requiring no prior knowledge about faces. The majority of these aims are achieved. In this work, biological and physiological evidences were motivated to us to demonstrate the relationships among fingerprints and faces. These evidences are briefly explained below. In dermatoglyphics studies, the maximum generic difference between fingerprints has been found among individuals of different races. Unrelated people of the same race have very little generic similarity in their fingerprints; parent and child have some generic similarity as they share half the genes, siblings have more similarity and the maximum generic similarity is observed in the identical twins, which is the closest genetic relationship [34]. There is a similar relation between faces of people. Identical twins are a consequence of division of a single fertilized egg into two embryos. Thus, they have exactly identical DNA except for the generally undetectable micro mutations that begin as soon as the cell starts dividing. Fingerprints of identical twins start their development from the same DNA, so they show considerable generic similarity [35]. In the case of fingerprints, the genes determine the general characteristics of the pattern [36]. It is also true for face patterns. Consequently, physical appearances of faces and fingerprints are in general a part of an individual's phenotype. These truths indicate that there might be a relationship among biometrics features of fingerprints and faces. In order to support this assumption an intelligent system was developed. The proposed ANN based Intelligent Face Parts Prediction System generates the stationary face parts including eyebrows, eyes and nose of a person from only one fingerprint of the same person without having any information about his or her face. F2FP system has five parts including a data enrolment module, a feature extraction module, an ANN module, an evaluation module and a face parts reconstruction module. These modules are explained below.

A. *Data Enrolment Module*

Biometric data of individuals are properly acquired and stored into the biometric system database via the data enrolment module. During this process, fingerprints and face images (Fs&Fs) of an individual have been captured to produce a digital representation of the characteristics. A real multimodal database that includes Fs&Fs belonging to 50 people was established by using Digital persona Scanner for fingerprints and Canon digital camera for faces. A sample fingerprint & face (F&F) set from used multi-modal database is given in figure 4.

Fig. 4 A sample F&F set from used multimodal database

B. *Feature Extraction Module*

Discriminative feature sets of fingerprints and faces are extracted from the acquired data via the feature extraction module. Extracting local and global feature sets of the fingerprints including singularities, minutiae points and their parameters is achieved. Fingerprint feature sets were computed using Gabor Filter. The incoming signal in form of image pixel will be filter out or convolute by the Gabor filter to define the ridge and valley regions of fingerprint. The Fingerprint enhancement using Gabor filter is one of highly computational complexity in fingerprint verification process. Gabor filter have a complex valued convolution kernel and a data format with complex values is used.

The reason of this preference is to establish an objective assessment for the F2FP prediction. This Gabor filter is known as an effective, robust and reliable AFIVS in the field of biometrics and uses a minutiae-based algorithm. Detailed explanation of algorithms, detailed information of fingerprint feature sets and their storage format are given in [37]. Face feature sets were obtained from the faces 9 reference points were used for representing the stationary face parts in this work. To get the feature sets of the face parts a feature-based face feature extraction algorithm is implemented. Increasing the number of the reference helps to represent the face parts more accurately and sensitively. It was also observed that feature sets contain enough information about faces for getting them again with high sensitivity.

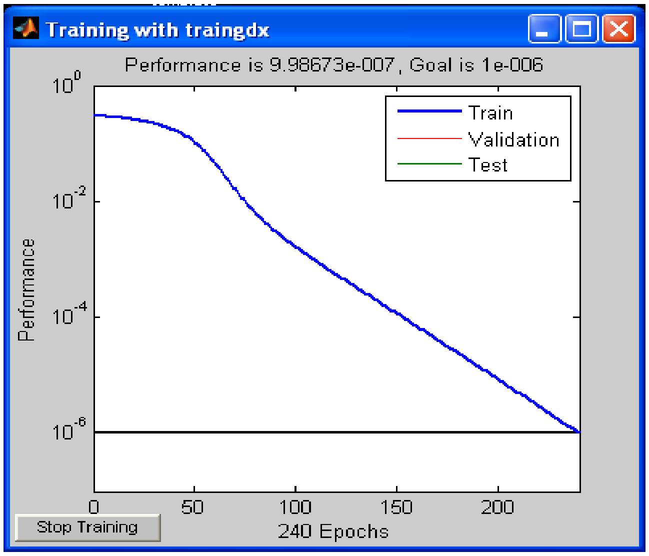
C. *ANN Module*

The ANN module is used to analyze the existence of any relationship among Fs&Fs. Suitable ANN structures and training algorithms were selected and the parameters of them were determined after establishing the training and the test data sets. The training sets included pairs of Fs&Fs while the test sets included only fingerprints. Face feature sets of the test people were used in the evaluation process as the desired outputs. Randomly selected 30 of 60 data sets covering pairs of Fs&Fs were used to train the ANN. Remaining 20 of 60 test sets covering only fingerprints was used to test the system. The sizes of the input and the output vectors were 512 and 9, respectively. This part of the system has been implemented with the help of the MLP structure that is trained with gradient descent with momentum and adaptive learning rate backpropagation algorithm (traingdx) to find out and establish a relationship among Fs&Fs. The ANN module is the most critical and important module of the system. Because, all modules of the system except the ANN module are on duty either in pre-processing or post-processing of the main process that is done by the ANN module. The training process is started with applying a person's fingerprint and face feature sets to the system as the inputs and the outputs, respectively. The system achieves the training process with these feature sets according to the learning algorithm and the ANN parameters. Even if the both Fs&Fs feature sets are required in the training, only fingerprint feature sets are used in the test. In the test, used fingerprints are unknown biometric data for the F2FP system. The outputs of the system for these unknown test data sets indicate the success and reliability of the system. This success and reliability of the system must be shown clearly by evaluating the ANN outputs against to the proper metrics in proper way.

V. Experimental Results

In order to achieve generating the face parts from only one fingerprint image the proposed ANN based face parts generation system was developed. In the experiments, the index finger of the right hand was used because of being the most used finger in AFIVSs. The structure of the ANN module is a 4-layered MLP structure. Training process was finished in 240 epochs because of reaching the minimum gradient that was 9.98673 e-007. MSE (Mean Square error) metric in training was 1e-006.

In this study, all of the processes that were given in the previous section are achieved for producing the face parts as close to the real one as possible. *learngd* is the gradient descent weight and bias learning function and *traingdx* is the network training function that updates weight and bias values according to gradient descent momentum and an adaptive learning rate. In order to evaluate the performance of the developed system effectively, we have benchmarked our system against to the metric MSE.



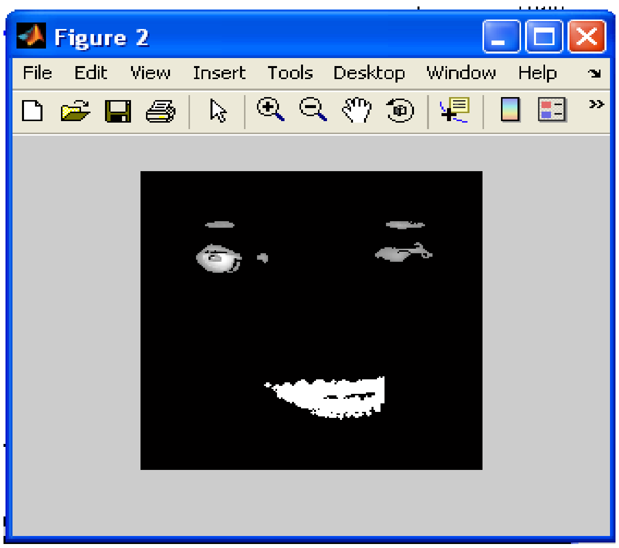


Fig. 5 and **6** Representation of the Training curve and test results achieved from the F2FP system

Fig. 5 indicates that the proposed system performs the tasks with high similarity measures to the desired values. In the **Fig. 6** white color represent the ANN outputs.

As can be seen from **Fig. 5** to **Fig. 6**, the proposed system is very successful in achieving the face parts from only fingerprints. Based on the observations, it is concluded that the fundamental novelty and diversity of the proposed approach over the most other studies in biometrics is that it is the study that generates the face parts including eyebrows, eyes and nose from only one fingerprint image without any information about faces or face parts. This investigation indicates the existence of the relationships among fingerprints and faces.

VI. CONCLUSION AND FUTURE WORK

In this paper, we successfully presented the problem of generating the face parts of a person from only one fingerprint image of the same person without any need of his or her face information. When we applied the proposed approach to fingerprint and face biometrics, we got the encouraging results indicated in this article. It was experimentally demonstrated that there was a close relationship among these biometric features.

Consequently, we have designed, implemented and introduced an intelligent system. This concept might be applied in many features in biometrics including pairs of fingerprint-iris, face-iris, hand geometry-face, etc. It is hoped that this approach would lead to create new concepts, research areas, and especially new applications in the field of biometrics.

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