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Research paper

Image Compression using Discrete Cosine Transform (DCT) and Features Level Fusion in the Recognition for Multimodal Authentication Biometrics System

Fatma Susilawati Mohamad[1]*, Khaled Alhadi Meftah[2]

Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, Terengganu, Malaysia
**Corresponding author E-mail: fatma@unisza.edu.my*

Abstract

Multimodal biometrics have an important role in security systems by detecting security breaches and authentication systems, as well as security and confidentiality of information transmission. Sometimes, some factors affect the system's authentication noise and lightness when using a single biometric. So, in this paper, we will present a proposal for an authentication system through the compression dataset images using Discrete Cosine Transform (DCT). After extracting the features of each biometric separately (such as face - fingerprint - fingervein - iris), features extraction were normalized and all two biometrics were fusion (such as Face & Fingerprint – Face & Fingervein - Face & Iris – Fingerprint & Fingervein – Fingerprint & Iris – Fingervein & Iris) by the application of a method- Canonical Correlation Analysis (CCA). Recognition results were recorded. We obtained the best recognition rate between each merger by combining biometrics and we find the best rate of accuracy 98.1132%.

Keywords: *Multimodal Biometrics; Fusion; CCA; DCT; Features Level Fusion.*

1. Introduction

Biometrics is a technique for measuring and analyzing biological data through, which we can identify people without any knowledge and authority. Uniqueness was one of the advantages of biometrics, where it reproduces a good and ideal biological identifier. One of the components of the security system and one of the most important elements in the field of information technology are authentication. The process of authentication means verifying the identity of persons using the equipment [1].
Multimodal biometrics system that a system combining two or more biometrics is used to identify and verify the identity of persons. A system that combines face and iris features to biometrics recognition is a "Multimodal" [2].

1.1. Previous Approaches to Multimodal Biometrics Recognition

According to [3], two distinct classifiers were applied based on the biometric traits of voice and face for the users' authentication and identification. A separate "score" showcasing a specific degree of confidence was also formed by both of the classifiers in the rendered decision of classification. These two scores can be easily used by a fusion technique, which is based on transformation in order to take decision for authentication. The obtained rates of the true negative and true positive rates of the performance are more than 99%, whereas the false-negative rate is around 0.71%.
In [4] presented a uni-modal technique fused with other techniques in order to develop the multimodal models in four combinations such as: (a) Fisher faces and LBP (b) Eigen faces and local binary pattern (LBP), (c) Fisher faces and A-LBP and (d) Organics and augmented local binary pattern (A LBP). The suggested system uses Bray Curtis dissimilarity metric and evaluates by using face databases, which are publicly available. Specific development has been shown in the results of the efficiency of recognition accuracies through techniques of multimodal face recognition. The recognition result in LFW face database for the fusion of Eigen-faces and LBP techniques is True Acceptance Rate (TAR) value of 77.50%, TAR of 82.92% for the fusion Fisher-faces and LBP techniques, 80% for the fusion Eigen-faces and A-LBP techniques, and 82.50% for the fusion of Fisher-faces and A-LBP. The recognition result in AT & T-ORL face database for the fusion of Eigen-faces and LBP techniques has True Acceptance Rate (TAR) value of 99.81%, TAR of 99.87% for the fusion Fisher-faces and LBP techniques, 99.84% for the fusion Eigen-faces and A-LBP techniques, and 99.84% for the fusion of Fisher-faces and A-LBP.
In [5] for verification or identification process, fingerprint, hand geometry and palm print which are integrated with multimodal biometric system are proposed in this study. The Region of Interest (ROI) was utilized separately for each of the biometrics such as fingerprint, hand geometry and palm print. The three scores will only be generated when each biometrics' features are separately extracted. Scores that are generated are integrated at first, followed by matching with the database samples. This study discussed about a robust suggestion from multiple secure samples to extract gender information for reducing the search time during verification and identification process.
The study by [6] evaluated the process of spoofing recognition and detection and their ways of mutually benefiting each other. A new multi-biometric fusion method was employed to evaluate 1-median filter. It integrates recognition and live scores. Latest experiments on fingerprint spoofing database (Fingerprint Liveness Detection Competition 2013) and face video database was con-

ducted (ldiap Replay-Attack Database and CASIA Face Anti-Spoofing Database) explain the efficacy of suggested techniques.
In [7] suggested system provides effective fusion scheme combined with information. Based on the Rank Level Fusion Integration method, they are presented by the multiple domain experts. It increases the system efficacy which was not possible from unimodal biometric system. It has number of unique qualities such as Fisher's Linear Discriminate methods and Principal Component Analysis (PCA) for authentication of the individual matcher. To consolidate the obtained results from various biometric matchers, the novel rank level fusion method is applied.

1.2. Approach Taken for Multimodal Biometrics Recognition

In this paper presented a recognizing system for Multimodal Biometrics that can be used in application of computer vision. In this portion, a detailed explanation about fusion details from every two biometrics samples of face, fingerprints, finger vein and iris are given separately.

2. Fusion in Multimodal Biometrics System

We proposed fusion between every two biometrics such as Fingerprint and Face – Face & Fingervein – Face & Iris – Fingerprint & Finger vein – Fingerprint & Iris – Fingervein & Iris. In Figure 1, the diagram for our proposed system is showed. In the part (a) as shown in Figure 1 shows how features extraction for dataset, which is selected for biometrics and tested image that used to get recognition after fusion level. We will normalize and after that, it will be fusion employing Canonical Correlation Analysis (CCA) and also the best classification will be identified between every two biometrics. In the part (b) as shown in Figure 1 shows the base step is compression dataset using Discrete Cosine Transform (DCT) to reduce the features set and follow next steps as shown in Figure 1. Finally, compare the recognition rate and the accuracy rate for classification to decide how compression images will effect on biometrics.

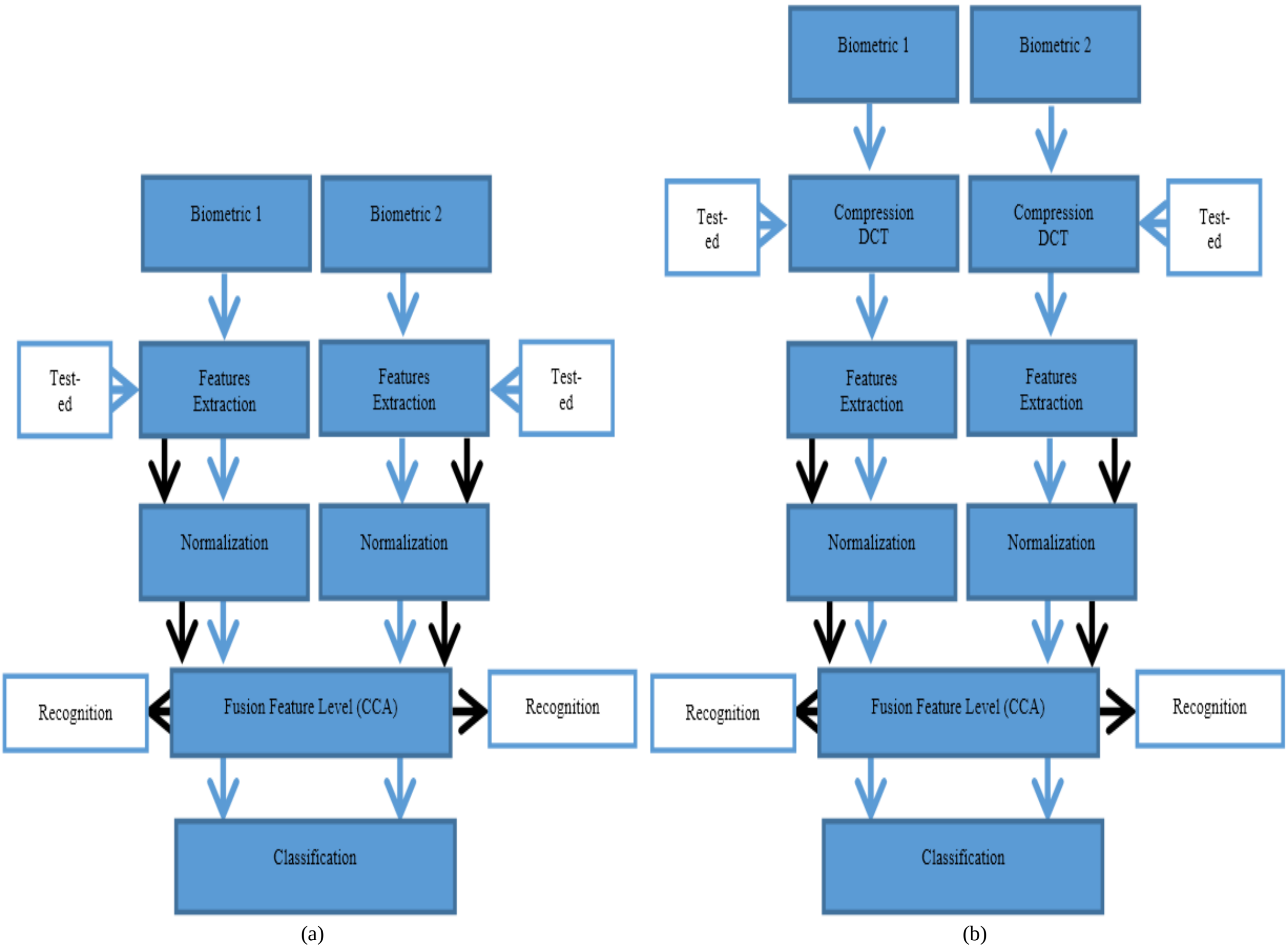

Fig. 1: Propose System (a) Fusion two Biometrics Feature (b) Compression dataset by DCT and Fusion Two Biometrics Feature

2.1. Dataset

In this paper, the biometrics images are taken for feature extraction and compare it with the registered CASIA Face Image Database, CASIA Fingerprint Image Database, CASIA Fingervein Image Database and CASIA Iris Image Database. Database including 106 for every biometrics dataset images.

2.2. Compression images using Discrete Cosine Transform (DCT)

Nowadays, as information technology progresses, data transfer is of great importance through the network, Internet and mobile environment, through the volume of data transferred which will be stored on the volumes whether it will occupy a large amount of storage media and whether it will take a lot of time for conversion. Therefore, we have applied DCT technology to compress the image databases used in this paper to reach the best results.

This section presents image compression steps: First, original image is divided into blocks 8×8. Second, the pixel values of a black and white image range from [0:255] but pixel values within each block range from [-128 to 127], so each block is shifted to [-128 to 127] from [0:255]. Then, if applied to each block, it will be observed to be DCT from left to right, top to bottom. After that, quantization is used to compress each block followed by the encoding by entropy of quantized matrix. Compressed image goes through reverse process to reconstruct. Discrete Cosine Transform (IDCT) is applied by this process [8].

2.3. Features Extraction

Features extraction in image processing field involves reducing the number of resources needed to explain a large set of data.

2.3.1. Face

Pre-processing stage can be split into three groups achieving the goal of the processing. In this paper, we will convert RGB images to gray images. Then, we crop face detection and resize all images as 200*180. Extraction of feature in processing image includes reducing the number of resources needed to explain a huge set of data. In the current study, features are extracted via Principle Component Analysis (PCA) for determining the rate of face recognition [9].

2.3.2. Fingervein

In the pre-processing process cuts the image and select the desired part by Region of Interest (ROI) for fingervein [10].

In the current study, features are extracted by applying the Gray Level Co–Occurrence Matrix (GLCM) method. It is a process of extracting features of texture from the dataset of fingervein. The fingervein texture measurements were performed on a gray scale version of the fingervein images [11]. These features were computed from the co-occurrence matrixes for each fingervein image. This includes Contrast, Homogeneity Energy, Correlation and Entropy.

2.3.3. Fingerprint

The first step is binarization which is an algorithm that produces a 1-bit type image, with 0 as ridges with black tint and 1 as valleys with white tint [12]. Before extraction of feature, thinning is considered as the last step of the enhancement of fingerprint image. A unique signature is obtained from the finger print distribution. Finger print will be reconstructed from minutiae and direction.

Minutiae Algorithm:
Input: Grey scale Fingerprint image.
Output: Verified fingerprint image with matching score.

1) Binarization of fingerprint.
2) Binarized image reduction.
3) Extraction of minutiae points.
4) Data matrix is produced to get the direction, minutiae and the position.
5) Test fingerprint matching with template.
6) Calculation of matching score of two images and images are matched if matching score is 1. They are mismatched if it is 0 [13].

2.3.4. Iris

The pre-processing stages include Segmentation - Normalization and Enhancement. For feature sets used Gabor filter. The underlying information in an iris pattern is extracted through encoding of feature and binary iris template is generated that is later on applied in matching. The iris feature set is generated from convolving the normalized iris pattern with 1D Log-Gabor filter.

2.4. Normalization by using Maximum Absolute Column and Row Sum

We perform this process to unify the features extracted from each biometric and therefore because of the use of different algorithms calculation of the 2-norm of a matrix. It is the largest singular value. The maximum absolute column sum of an m-by-n matrix X (with m,n >= 2) is calculated by:

$$\|X\|_i = max_{1\le j\le n}\left(\sum_{i=1}^{m}|a_{ij}|\right)$$

The calculation of maximum absolute row sum of an m-by-n matrix X (with m,n >= 2) is done by:

$$\|X\|_\infty = max_{1\le i\le m}\left(\sum_{i=1}^{m}|a_{ij}|\right)$$

2.5. Features Level Fusion employing Canonical Correlation Analysis (CCA)

One of the valuable multi-data processes are Canonical correlation analysis (CCA). It has been extensively applied to determine the mutual relationships between two sets of variables.
Suppose that $X \in \mathbb{R}^{p\times n}$ and $Y \in \mathbb{R}^{q\times n}$ denote two matrices, each contains *n* training feature vectors from two different modalities. Let $S_{xx} \in \mathbb{R}^{p\times p}$ and $S_{yy} \in \mathbb{R}^{q\times q}$ denote the within sets covariance matrices of *X* and *Y* and $S_{xy} \in \mathbb{R}^{p\times q}$ denote the between set covariance (note that $S_{yx} = S_{xy}^T$, CCA aims to find the linear combinations, $X^* = W_x^T X$ and $Y^* = W_y^T Y$ that maximize the pair-wise correlations across the two feature sets. The transformation matrices, W_x and W_ym we found by solving the eigenvalue equations [15]:

$$\begin{cases} S_{xx}^{-1}S_{xy}S_{yy}^{-1}S_{yx}W_x = R^2 W_x \\ S_{yy}^{-1}S_{yx}S_{xx}^{-1}S_{xy}W_y = R^2 W_y \end{cases}$$

where W_x and $W_y =$ eigenvectors and R^2 = diagonal matrix of eigenvalues or squares of *canonical correlations*. The number of non-zero eigenvalues in each equation is $d = rank(S_{xy}) \le min(n,p,q)$, which will be stored in decreasing order, $r1 \ge r1 \ge \ldots \ge rd$. The transformation matrices W_x and W_y consist of the sorted eigenvectors corresponding to the non-zero eigenvalues. $X^*, Y^* \in \mathbb{R}^{d\times n}$ are known as canonical variates [16].
As defined in [17], Feature-level fusion is performed either by concatenation or summation of the transformed feature vector:

$$Z_1 = \begin{pmatrix} X^* \\ Y^* \end{pmatrix} = \begin{pmatrix} W_x^T X \\ W_y^T Y \end{pmatrix} = \begin{pmatrix} W_x & 0 \\ 0 & W_y \end{pmatrix}^T \begin{pmatrix} X \\ Y \end{pmatrix}$$

or

$$Z_2 = X^* + Y^* = W_x^T X + W_y^T Y = \begin{pmatrix} W_x \\ W_y \end{pmatrix}^T \begin{pmatrix} X \\ Y \end{pmatrix}$$

where Z_1 and Z_2 = *Canonical Correlation Discriminant Features (CCDFs).*

2.6. Recognition

Recognition of score value is carried out after obtaining the Features level Fusion by CCA. Recognition of scores is based on Euclidean distance between two points and will return the Similarity Measure.

$$\text{Euclidean\_Distance} = \sqrt{\sum_{i=1}^{n}(\text{feat\_X}_i - \text{feat\_test}_i)^2}$$

where feat_X_i extracted features for database and feat_test_i extracted features for tested image.

2.7. Classification using Support Vector Machine (SVM)

It is a machine learning method, widely used for pattern recognition and data analyzing. The purpose of classification of support vector is to differentiate two classes by a function. They are induced from available examples. It generates a classifier that differentiates the data. One of the major parts in machine learning have been classifying data. So, SVM is being used to classify for features level fusion.

3. Results and Discussion

The proposed system was implemented under a platform MATLAB 2014. The database used was composed of four parts CASIA Face Image Database, CASIA Fingerprint Image Database, CASIA Fingervein Image Database and CASIA Iris Image Database. In this paper, we use Discrete Cosine Transform (DCT) for compression dataset images and after that we normalize features extraction fusion was done for each two biometrics. This was done by using Canonical Correlation Analysis (CCA). The fusion between every two biometrics was performed and distributed as follows (Face & Fingerprint – Face & Fingervein – Face & Iris – Fingerprint & Finger vein – Fingerprint & Iris – Fingervein & Iris). Table 1 shows that we find the rate of accuracy between 94.396% and 96.2264% when features level fusion without compression dataset images and normalize features extraction. We find the best rate of accuracy 98.1132% when using DCT for compression dataset images, normalize features extraction and use CCA for features level fusion.

Table 1: Results for our proposed system

CCA for Features Level Fusion Between	Accuracy Rate %	When Use DCT for Compression Image + Normalization for Features + CCA for Feature Level Fusion	Accuracy Rate %
Face & Fingerprint	94.3396 %	Face & Fingerprint	98.1132 %
Face & Fingervein	94.3396 %	Face & Fingervein	98.1132 %
Face & Iris	96.2264 %	Face & Iris	98.1132 %
Fingerprint & Fingervein	94.3396 %	Fingerprint & Fingervein	98.1132 %
Fingerprint & Iris	96.2264 %	Fingerprint & Iris	98.1132 %
Fingervein & Iris	96.2264 %	Fingervein & Iris	98.1132 %

4. Conclusion

In this paper, we discussed the fusion of each of the two biometrics features where the base stone used for features extraction from only four biometrics (such as face – fingerprint – fingervein - iris) based on CASIA database. We were using fusion the technique (CCA) and compare each merger between each two and compare the best results. We reached and showed an improvement in the results when uses DCT for compression dataset images and normalization features extraction and CCA for features level fusion with the best recognition rate (100%) and the best accuracy rate (98.1132%).

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