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The Effect of Database Type on Face Recognition Performance for Surveillance Applications

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ABSTRACT

Face recognition is one of the most important biometric approaches due to its potential applications in surveillance monitoring and access control. This paper presents a PCA and SVM based face recognition system for surveillance application. A proposed training database selection criteria suitable for surveillance application which consist of 1 mean image per distance class from all the available database sessions is also used for the face recognition system. In this study, the ChokePoint database, specifically the grayscale (PPG) and colored (MPCI) versions of the ChokePoint database, were selected for this work. The objectives of this work is to investigate the effect of the using different training data as well as using different similarity matching method on face recognition for surveillance application. It was found that regardless of the type of databases used, the recognition output pattern on different training data selection criteria was found to be similar. It was also found that regardless of the similarity matching method used, the face recognition system also shows the same recognition performance pattern. The experiment suggests that the proposed training database selection criteria will give similar recognition performance regardless of databases type or face recognition technique used. Overall, the ChokePoint colour database (MPCI) gives better recognition performance than the ChokePoint grayscale database (PPG). Finally, it can be concluded that using 1 mean image per class from all the available database sessions (Case-6) is better compared to using 1 image per class that are randomly selected from all the database sessions (Case-4). Even though a straight comparison between this work proposed system and several published system is not meaningful as different face recognition approaches and experiment criteria are used, nevertheless, this work proposed method performs with 100% recall and reject recognition rate.

Key words : Face recognition, surveillance, support vector machine, principal component analysis.

1. INTRODUCTION

Face detection and face recognition have a promising potential for many uses, including security monitoring and human computer interaction. Facial recognition technology has reached an incredibly high standard in the last few years. According to [1], an adequate amount of work has also been done to detect facial emotions. However, this requires a good quality of face image in terms of image resolution, non-existent or minimal variation of illumination and occlusion on the face, as well as the cooperation of the subject. As the performance of the face recognition system has achieved a high quality standard, the existing reports, which discussed the challenges of low resolution or degraded face images acquired at a distance, will be reviewed. Generally, face recognition application can be broken into 3 groups: governmental, industrial, and forensic [2]. The cooperation of subjects are usually required for both commercial and government-related applications, such as user verification process in electronic devices (mobile phone, mobile tablet, laptop) and passport verification or border control activities. But for forensic face recognition application, the subjects usually does not cooperate when photo or video of them are taken. This issue poses challenges when image or video files taken from handheld gadgets or CCTV are required for a face recognition system. Face recognition can be applied to both still images and video images. Security surveillance applications usually use video data for the recognition process, and a number of facial recognition techniques have been proposed for surveillance applications [3]-[5], which can be categorized into two groups: software-based and hardware-based approaches.

Vignesh et al.[6] introduced the CNN-based Automated Face Quality Assessment (FQA) algorithm, a face recognition for surveillance. The ChokePoint dataset was used for the experiment and all the face images used are 64 to 64 pixels. A total of 25 subjects with 64,204 face images have been used. Two sets of databases were set up; 13 subjects for training and 12 subjects for testing. There was, however, no indication of the number of images per person for training and testing. PCA has been used to reduce the size of the image. Gorodnichy and Granger [7] presented a target-based multi-level face recognition performance assessment framework that is appropriate for the screening of the real-time watch list. Their method is evaluated using commercially available face recognition software (the product name is not disclosed) and ChokePoint data set as a training and testing database. However, the details of their training and testing database have not been disclosed. The best rate of recognition reported is 65%. An et al.[8] proposed four approaches to face-recognition in surveillance applications; (i) a dynamic Bayesian network-based surveillance system that used multiple cameras to improve recognition accuracy; (ii) a video-based face-recognition framework that uses Warped Average Face (WAF)[9]. (iii) a probabilistic method for face recognition based on Hidden Markov Model (HMM), suitable for a multi-camera video surveillance network [10], and (iv) a multi-camera face recognition framework using an image representation called Unified Face Image (UFI)[11], which is synthesized from multiple camera feeds. The detection of the face in the systems is based on HMM. LBP, Local Phase Quantization (LPQ) and Histogram of Oriented Gradients (HOG) have been used as face descriptors. ChokePoint dataset was used to evaluate and evaluate all four approaches. However, the details of the training and testing database used for the experiment are not clear. The recognition rates reported for the four approaches are 97.2%, 98%, 73.3% and 48% for proposals (i), (ii), (iii) and (iv) respectively. Tathe et al. [12] proposed a system that is able to perform face detection and recognition in videos. The main focus of their proposed system is to minimize the processing time for detection and recognition process. The face detection is based on the Viola-Jones method. The face recognition is based on PCA approach. Ten videos selected from various internet sources are used in the experiments. However, the criteria of the selected videos was not stated. Mokhayeri et al. [13] proposed an approach that generates multiple synthetic face images per person on a camera to address low-quality image problems caused by variations in illumination. The ChokePoint dataset was used to evaluate the performance of the proposed method. However, the database set up for the experiment has not been specified. Face recognition is based on the LBP method and the Euclidean distance was used as a measure of similarity. No recognition rate has been reported. Tayanov et al. [14] proposed a SR pipeline for rapid decision-making in the online watch list screening, taking advantage of the correlation between posing and sharpness quality measurements, and the ChokePoint dataset was used to evaluate the proposed method. Their experiment shows that the proposed method produces super-resolved face images efficiently by ranking the best quality region of interest in the trajectory. However, the facial recognition test has not been carried out. Saad et al. [15] developed a face recognition based on Enhance Particle Swarm Optimization and Support Vector Machine (SVM), using SCface and CASIA surveillance face database to evaluate their experiments which reported a 95% and 100% highest recognition rate for SCface and CASIA database respectively. Chowdhury et al. [16] presents a face detection and recognition system that based on Generalized Two-Dimensional Fisher's Linear Discriminant and uses multi-classifier SVM for face classification. Their system has been tested in the Honda / UCSD database with a face recognition rate of 91.3 percent. A deep learning-based super-resolution model for surveillance application has been presented by Shamsolmoali et al. [17] using SCface and ChokePoint databases as the test database and approximately 95.6% and 95.8% recognition rate reported for SCface and ChokePoint databases respectively. Rani and Prasath [18] proposed an approach to face recognition using a face feature-vector based on the Normalized Local Binary Patterns (NLBP). Using Euclidean-distance, each video frame from the video is matched with the training database face feature-vector and a rank list of the matched results is generated. The list of several re-ranked test videos are then fused together to create a video signature. The composite ranked lists of a two matched videos are then compared by using a Kendall Tau-based distance measurement. The proposed methods NLBP are tested on the ChokePoint and YouTube database and the best performance reported for ChokePoint and Youtube database are 90.2% and 90% respectively. Al-Obaydy and Suandi [19] presented an open-set single-sample face recognition method-based on HOG and Gabor filter for face feature extraction and fuzzy ARTMAP neural network as classifier. The proposed approach is reported to be suitable for surveillance application. The experiment were evaluated using ChokePoint database and the recognition rate reported for correct classification rate (CCR) is 93.33% while the correct rejection rate (CRR) is 93.46%. In [20], Al-Obaydy and Suandi uses a Delaunay triangulation-based automatic facial landmark detection algorithm and thin-plate splines warping process to normalize pose-varied face images to a canonical frontal pose. The best recognition rate reported are 100% for FERET database and 90.48% (CCR) and 89.38% (CRR) for ChokePoint database. Chokkadi et al. [21] presented a survey of the Deep Learning Face Recognition System, and a number of studies have already established time-invariant, multi-expression, illumination-variation, and image-to-image weight-variation. However, it was noted from the survey that not all work-related databases were a form of face database surveillance.

From the reviewed articles, although some researchers use the surveillance database for their experiment, the criteria for the selection of their training data, such as the distance between the person and the camera, have not been properly stated and justified. In addition, some of the test procedures were unclear. In addition, no comparisons are made of all face-recognition reports published with respect to the resources used by the published system. It was also found that the ChokePoint database is commonly used for surveillance-based application recognition research. The ChokePoint database is therefore selected for this work. In our previous articles [22], [23], using the ChokePoint Grayscale and Colored Database [24], [25], the effect of the YCBCR color space as well as the selection criteria for training data on the facial recognition system for surveillance applications have been investigated. In addition, a comparison of several merger strategies has been investigated. However, the type of database used in our previous articles is different [22], [23].

This paper presents an extended investigation on the effect of the database type on the different selection criteria of training images from a face recognition database suitable for surveillance purposes. A Principal Component Analysis (PCA)-based face recognition system is used to carry out the investigation. Also, instead of using only Euclidean-distance for similarity matching, SVM will also be considered. SVM was chosen for comparison because it has a different way of making its decision during classification compared to the Euclidean-based Classifier and PCA is used as a feature dimension reduction tool. An investigation will be presented on the effect of similarity-matching approaches on the different selection criteria of the data used for training suitable for face recognition for the surveillance system.

2. THE SURVEILLANCE DATABASE PREPARATION

The ChokePoint database [24] contain video frames of a person walking towards a camera. P2L database includes better frontal images, so the database was chosen for all subsequent studies. The database has four sessions of video databases, but only sessions 1, 2, and 3 were used because the face images in session 4 is not as frontal as images in sessions 1, 2, 3, as seen in Figure 1(a) and Figure 1(b). The ChokePoint Database provided two type of databases; (i) a grayscale and (ii) a coloured images database. From here on, the grayscale database and the coloured images database will be denoted as PPG database and MPCI database, which stand for Pre-processed Grayscale (PPG) and Manually Pre-processed Colour Images (MPCI) databases respectively. For the PPG database, all the face images has been properly normalized (both eyes aligned in a horizontal line) in grayscale format with dimension of 96 by 96 pixels. For the MPCI database, all the images are 800 by 600 pixels, covering the full view of the person walking towards the camera. The eyes coordinates for all subjects are provided. All images in MPCI are cropped according to the coordinates of the given eyes, and a person's eyes are horizontally aligned. As illustrates in the face cropping template shown in Figure 1(c); the length from the left to the right eyes is defined as EL, while M is the center point between the left and right eyes. EL also represents the length from L to the left eye, from R to the right eye, and from T to M. Finally, the length from B to M is equal to 2EL. All of the images in PPG and MPCI are divided into the FAR, MEDIUM, and CLOSE classes with 14 frames and 18 frames per class for PPG and MPCI databases respectively. The FAR class consist of the first 14 frames from the 42 frames and the first 18 frames from the 54 frames per person for PPG and MPCI databases respectively. The following 14 and 18 frames of PPG and MPCI respectively are defined as MEDIUM class, while the CLOSE class is the last 14 and 18 frames for the PPG and MPCI databases respectively. The total number of cropped video frames with a front-face was 3528 for PPG and 4536 for MPCI databases. Six databases covering three separate sessions were drawn up. Three databases for PPG and MPCI were generated from the database of 1176 images from PPG and 1512 images from MPCI. Both PPG and MPCI databases comprise 28 individuals where 14 people are used for training and testing and 14 people are used for testing alone. By default, the PPG from ChokePoint database includes a front-face image of 96 pixels by 96 pixels. Thus, 96 by 96 pixels are set for the cropped face images from the MPCI database. Finally, all the images are converted to grayscale format and histogram equalization was then applied on all the images.

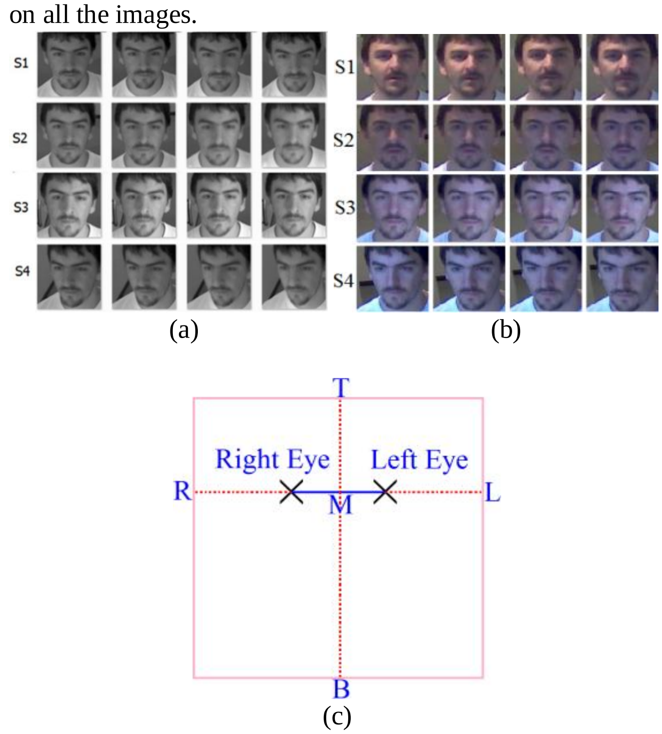


Figure 1: An example of front-face samples in PPG and MPCI P2L database. (a) PPG P2L database, (b) MPCI P2L database, (c) The face cropping template

3. TRAINING AND TESTING DATABASE PREPARATION

Eight cases of training image selection criteria were proposed as described in Table 1. Two test databases have been prepared. For each PPG and MPCI database session, the first testing database, the Client Test Database, contains 588 and 756 images of 14 people, respectively. This database is used to assess the system's recall capabilities. For each session of the PPG and MPCI data databases, the second test database, the Unknown-Person Test Database, there are also 588 and 756 images of 14 persons for PPG and MPCI respectively. This database is used to assess the system's rejection capabilities.

4. PCA AND SVM FOR FACE RECOGNITION

In this work, in addition to Euclidean-distance for similarity matching, SVM will also be used as a classifier. SVM was chosen because it has a different way of making its decision during the classification. The Euclidean-distance algorithm calculates the differences or distance between the person from the test and training database and the calculated distance value is then compared against a defined threshold to either accept or reject the test subject. In the case where the test subject is accepted by the system, the system will straight away assume that the test subject and the person in the training database with the smallest distance to be the same person. On the other hand, for a SVM based face recognition system, a test subject is accepted by the system and then analyzed by SVM algorithm to determine which person in the training database the test subject belongs to.

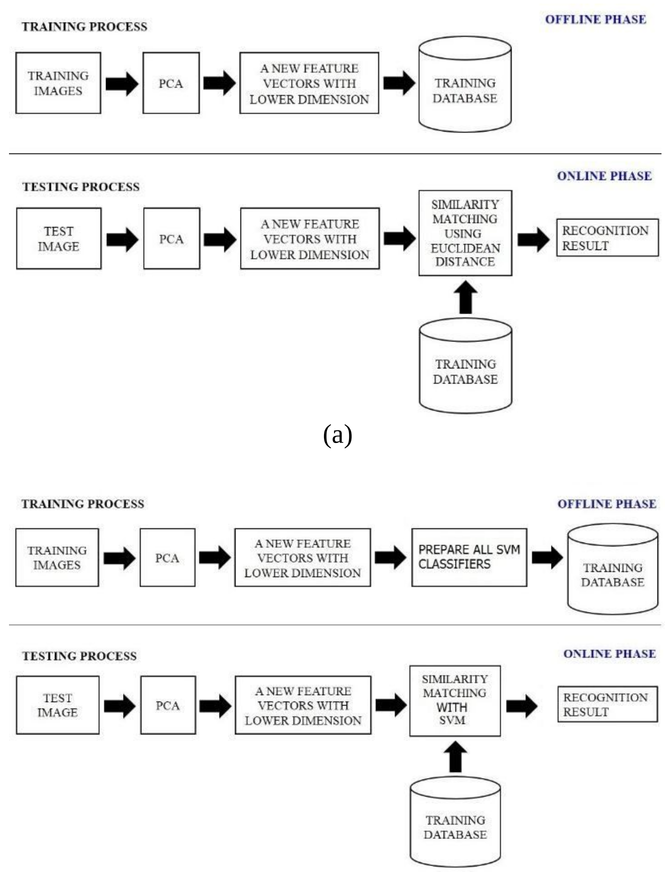
Table 1: A list of training data selection criteria proposed for face recognition system for surveillance application

Case	The details of the training database criteria
Case-1	3 images per person; In the same database session, 3 randomly selected images per person are from the same class.
Case-2	3 images per person; In the same database session, 1 random image are selected from each class
Case-3	9 images per person; In the same database session, 3 images of each class are selected at random.
Case-4	9 images per person; 1 image of each class is selected at random from all the database sessions. There are a total of 3 database sessions.
Case-5	3 images per person; In the same database session, 1 mean image from each class are used.
Case-6	9 images per person; 1 mean image per class from selected from all session
Case 7	6 images per person; In the same database session, 3 randomly chosen images from each class and 3 mean images from each class are used
Case 8	18 images per person; It contain 9 random images from each class and 9 mean images from each class selected from all available database sessions

By default, SVM only applies to a two-class problem. However, there is a method of applying SVM for multiclass problem [26], [27], [28]. In this paper, the face recognition system approach used is PCA-based and PCA with SVM (PCA+SVM) based as shown in Figure 2. Similar to the PCA-based face recognition shown in Figure 2(a), the PCA+SVM based face recognition system shown in Figure 2(b), consist of training and testing process. All the training images are projected into PCA domain, generating a collection of feature vectors which has lower dimensions than the original data image, and finally kept in the training database. The feature vectors are also fed to an SVM classifiers algorithm during the training process. The SVM classifiers of those feature vectors will be used during the testing process. During the testing process, particularly during the matching, the Euclidean-distance is used to decide whether a test subject pass or fail the recognition threshold. If the test subject passed the recognition threshold, then the SVM will decide which person in the training database the test image belongs to.

4.1 Support Vector Machine

SVM is a binary (two-class) classification method that finds the optimal linear decision surface between two classes. For example, assuming that we have a training data consisting of two class, namely class with +1 label and a class with -1 label. SVM can only produce one output from a max of two possible outcomes.



(b)

Figure 2: Block diagram of the proposed system. (a) PCA and (b) PCA+SVM based face recognition system

For example, let X={x_i, y_i} be a test subject where x_i is the feature and y_i is the label, then SVM can be used to identify if X belong to either class label +1 or class label -1. In face recognition, we are dealing with multiple classes (more than two persons) training database. Each person in the training database is defined as a class in the SVM algorithm. There are two popular methods to apply the SVM for a multiple classes training database, namely; (i) One-Versus-All (OVA) method and (ii) One-Versus-One (OVO) method.

According to the reports in [27], if accuracy is the main focus, then OVO seems much more suitable for a face recognition system with large multiclass training database. Thus, the OVO SVM method [29] was selected for this work. In the OVA method, q SVMs are trained where q is the number of classes available in the training database. While in the OVO method, the total number of SVMs trained are based on (1).

$$S_{TC} = \frac{q \times (q-1)}{2} \tag{1}$$

From (1), q is the number of classes in the training database and the value of S_{TC} from (1) is the total number of SVM classifiers required. The SVM will be applied during the matching. The total number of OVO based SVM classifiers is based on (1) and each classifier is a pair of different classes from the training database. The list of the classifiers, with no repeated pair, are shown in (2).

$$C_1vsC_2, C_1vsC_3, C_1vsC4, \cdots, C_1vsC_q, C_2vsC_1, \cdots, C_{q-1}vsC_q \tag{2}$$

where C is a class and q is the total number of classes in the training database.

Assuming $X = \{x_i, y_i\}$ be a test subject where x_i is the feature and y_i is the label, then X will be fed into all the classifiers. If the label, y_i, of X is unknown, then y_i is ignored by the SVM classifier. Each of the two-class classifiers will give a predicted class label, prc, along with its predicted class score, prs, as a result. The equation shown in (3) shows an example of MATLAB SVM C_1vsC_2 classifier function that takes test subject X and returns two values, prc and prs.

$$[prc, prs] = OVO\_SVM\_C_1vsC_2\_Classifier(X) \tag{3}$$

The range of the SVM predicted class score was normalized to be in the range from -1 to +1. The test subject X is then fed to all the available S_{TC} SVM classifiers from (1). Table 2 shows the output from all the classifiers pair. By using the Voting strategy, prc with the highest majority, denoted as $Mprc$, is assumed to be the class of the test subject X. The equation expressed in (4) is used to calculate the majority of prc.

$$Mprc = mode(prc_{1,2}, prc_{1,3}, prc_{1,4}, \ldots, prc_{q-1,q}) \tag{4}$$

The average prs that belong to the majority prc class label is then calculated, denoted as $Aprs$, and is kept for further usage in the matching. In the case where there are more than one prc with the same highest majority, then $Aprs$ of that prc will be compared. The prc with highest $Aprs$ is chosen as the class label of test subject X.

The SVM classifier algorithms that were used for this work are the built-in MATLAB function *svmtrain*, which is used to prepare the SVM classifiers, and *svmclassify* for the SVM classification process.

Table 2: The predicted class label and score for all the SVM classifiers

Classes Pair	Predicted class label	Predicted class score
C_1vsC_2	$prc_{1,2}$	$prs_{1,2}$
C_1vsC_3	$prc_{1,3}$	$prs_{1,3}$
C_1vsC_4	$prc_{1,4}$	$prs_{1,4}$
⋮	⋮	⋮
$C_{q-1}vsC_q$	$prc_{q-1,q}$	$prs_{q-1,q}$

5. THE TRAINING PROCESS

The differences of two vectors during the training and testing are calculated using the Euclidean-distance measurement. A formula that generates a threshold rate using the feature vectors from training database, defined as t, are proposed to accomplish the matching task during testing.

Let f defined as the training database's feature vector, and f_j and f_k are two different feature vectors, then, t is the maximum Euclidean-distance calculated from whichever two feature vectors defined as $E_{largest}$ as shown in (5), further divide by a tuneable parameter defined as $Tcpara$ as expressed in (6). $Tcpara$ is called as Threshold Tuning Parameter and $Tcpara$ value can be any of the positive real numbers.

$$E_{largest} = \max\{\|f_j - f_k\|\} \tag{5}$$

$$t = \frac{E_{largest}}{Tcpara} \tag{6}$$

From (5), f is a feature-vector (a low dimensional feature of the original image) and (5) yields the largest distance score between any two training feature vectors. The $Tcpara$ in (6) is a parameter used to tune the distance threshold t. The face recognition performance can be changed by tuning the parameter value of $Tcpara$ to have either a high recall rate or a high reject rate or equal recall and reject rates. The Equal Correct Rate (ECR) is defined as the point where the correct recall rate and correct reject rate has the same rate. Thus, in this paper, $Tcpara$ has been set to the ECR for all the experiments. The ECR will also be used when comparing the face recognition systems performance since ECR represents the recall and rejection capability of the system equally.

6. THE TESTING PROCESS

Supposed that $i = 1, 2, \ldots I$ where I for grayscale database is 42 and colour database is 54 and I is the number of frames per person. Also supposed that $m = 1, 2, \ldots W$ where W is the total number of images in the training database. Assuming that we have a test person of $T_R = \{f_{R1}, f_{R2}, \ldots, f_{Ri}, \ldots, f_{RI}\}$ that have I number of test video image frames, where f_{Ri} be the feature-vector that denotes the frame i *of* T_R, and f_m defined as the training database's feature-vector m, the minimum Euclidean-distance calculated between f_{Ri} with all the f_m from the training database, is compiled as a set denoted as $E = \{e_1, e_2, \ldots, e_i, \ldots e_I\}$ where E be the set that encompass all the I 's minimum Euclidean-distance and e_i is the minimum Euclidean-distance calculated between f_{Ri} and f_m.

Supposed that P is a person that exists in the training database, and P has a value of e_i with the test feature-vector f_{Ri}, the label (in this case, the name) of the person P is then denoted as l_i and the collection of l_i is $L = \{l_1, l_2, \ldots, l_3, \ldots l_I\}$. Supposed that P_{mode} is defined as $P_{mode} = mode\{L\}$, where P_{mode} is defined as a value that occurs most often from the set L, then the Euclidean-distance average value, denoted as E_{av}, of all the e_i from E with l_i equal to P_{mode} , is calculated. Figure 3 shows the Euclidean-distance average, E_{av} calculation flowchart.

From Figure 3, at the start of the algorithm, a variables named i, sum, and $P_{mode}counter$ were introduced. The i variable is used to count the frame index, and the value of i started from one (starting from the first frame). The sum variable (starting from zero) is used to accumulate the minimum Euclidean-distance e_i everytime l_i equals to P_{mode} is found. The value of e_i is the minimum Euclidean-distance from set $E = \{e_1, e_2, \ldots, e_i, \ldots e_I\}$ on index i . l_i is the likelihood from set $L = \{l_1, l_2, \ldots, l_3, \ldots l_I\}$ on index i . The $P_{mode}counter$ variable (starting from zero) is used to count the occurrence of l_i equals to P_{mode}.

The maximum number of loops is equal to I frames. On the first decision process, the algorithm will check if l_i equal to P_{mode}. If l_i does not equal to P_{mode}, then the algorithm will increase the index value of i by one and return back to the first decision process. If l_i is equal to P_{mode}, then the algorithm will add up the current value of sum and e_i. $P_{mode}counter$ value is then increased by one and the algorithm proceed to the second decision process.

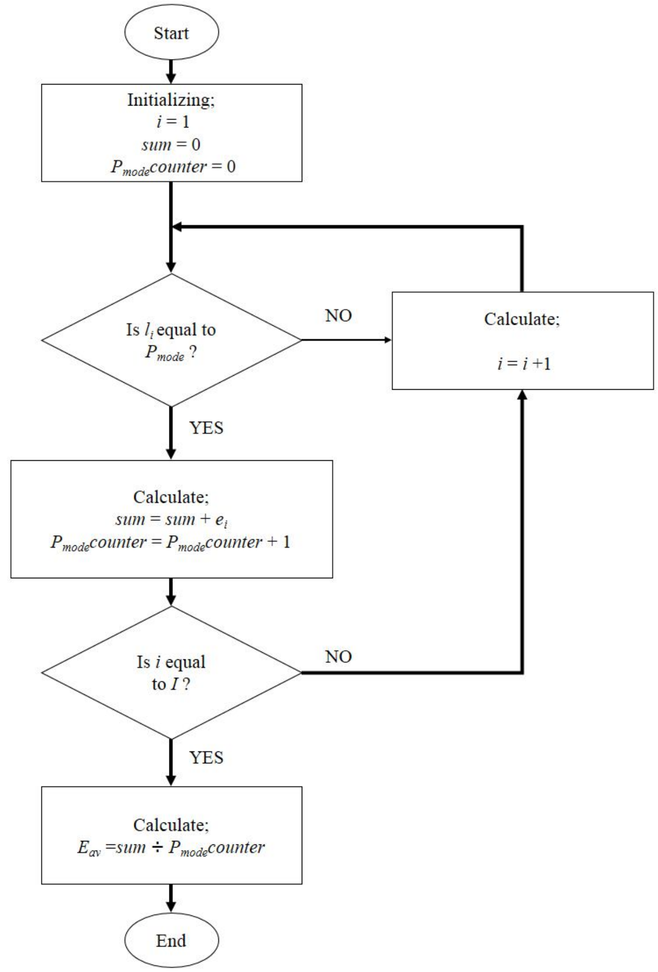


Figure 3: Euclidean-distance average, E_{av} calculation flowchart

On the second decision process, the algorithm will check if i is equal to I. If i is not equal to *I*, then the algorithm increase the index value of *i* by one and go back to the first decision process. If i is equal to I, then the average Euclidean-distance, E_{av}, is calculated by dividing the current value of sum with $P_{mode}counter$.

The average Euclidean-distance, E_{av}, will be used by the face recognition system to decide whether a test person T_R is to be accepted or rejected by the system.

For PCA-based face recognition system, if the E_{av} between test person T_R and P_{mode} person in the training database, $E_{av}(T_R, P_{mode})$ is smaller than a given threshold t, then, the person T_R and P_{mode} are presumed to be the same person.

For PCA+SVM-based face recognition system, the OVO-based SVM [14] was used for matching. An OVO based SVM have a total of S_{TC} classifiers. All of the f_{Ri} from $T_R = \{f_{R1}, f_{R2}, \ldots, f_{Ri}, \ldots, f_{RI}\}$ will be fed into all the classifiers. Each of the SVM classifier will give a predicted class, prc, and the predicted class score, prs, as a results. The range of prs were normalized to be in the range from -1 to +1. By using the voting strategy, prc with the highest vote is assumed to be the class of f_{Ri}. The average prs that belong to the prc class were calculated and are kept for further used in the verification in case there is a tie of prc during voting process. After T_R was fed into the SVM classifiers, each f_{Ri} will gives a predicted class prc_i and its average predicted class's score $aprs_i$. So for all the T_R frames, $PRC = \{prc_1, prc_2, prc_3, \dots\ prc_W\}$ and $APRS = \{aprs_1, aprs_2, aprs_3, \dots, aprs_W\}$ where PRC contain the list of predicted class for each frames and $APRS$ contain the average predicted class score for each frames.

In order to determine the T_R belong to which class in the training database, we take the majority predicted class from PRC, denoted as P_{svm}, as the true predicted class for T_R. If there are multiple predicted classes with the same number of vote, then the average of $aprs$ of those predicted classes with the same number of vote will be compared. The majority predicted class from PRC with the highest average $aprs$, denoted as P_{svm}, is assume to be the true predicted class for T_R. In other word, for a PCA+SVM face recognition system, the person T_R and P_{svm} are presumed to be the same person.

Various measurements are used to assess both PCA and PCA+SVM system performance. Supposed that T_a is a test person and P_a is a person from the training database. Also, supposed that a and b are not the same person. For a recall test, a **Correct Classification** is defined if T_a from a Client Test Database matches with P_a in training database correctly. If T_a from the Client Test Database is incorrectly matched with P_b, then it is defined as a **False Acceptance**. A **False Rejection** is defined if T_a from the Client Test database is of a person P_a but T_a is rejected by the system. For a reject test, a **Correct Classification** is defined if T_a from the Unknown-Person Test Database is rejected by the system. A **False Acceptance** defined if T_a from the Unknown-Person Test Database is accepted by the system.

7. GENERAL EXPERIMENTS CRITERIA

All the experiments presented are based on the PPG and MPCI databases and the all the images used has the size of 96 pixels by 96 pixels. A PCA-based and PCA+SVM-based face recognition systems are used. The numbers of PCA eigenvectors used are the same as the number of training database images used throughout the experiments and the number of PCA eigenvectors used was set to the number of training database images. The experiment for all the cases were carried out 10 times with each experiment having a unique set of training database and the mean value of the recognition rates from the 10 runs is used for performance evaluation.

8. RESULTS AND DISCUSSION

Figure 4 shows a comparison of face recognition results of two types of training data (PPG and MPCI) on different cases of training data selection criteria on a PCA-based face recognition. The focus of this experiment is to see the recognition rates pattern when different training database type are used.

From Figure 4, by comparing all the eight cases recognition rates, it can be seen that Case-1 always gives the lowest recognition rate (73.73% and 76.41% on PPG and MPCI database respectively) while Case-6 and Case 8 always gives the highest recognition rate (100% for both Case-6 and Case 8 on both PPG and MPCI database respectively).

Also from Figure 4, comparing Case-1, Case-2, and Case-5 results (each of the cases uses three images per person for training), it can be seen that the recognition rate pattern stays the same where Case-2 (76.27% for PPG, 78.35% for MPCI) always outperform Case-1 (73.73% for PPG, 76.41% for MPCI) performance while Case-5 (77.78% for PPG, 84.92% for MPCI) always outperform both Case-1 and Case-2 performances regardless of the training database type used.

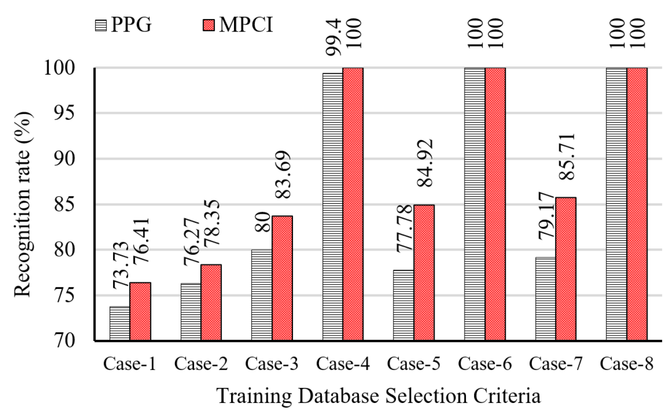


Figure 4: A comparison of recognition rates for different database type on different training data selection.

Also by comparing Case-3, Case-4, and Case-6 results (each of the cases uses nine images per person for training), it can be seen that the recognition rate pattern stays the same where Case-4 (99.4% for PPG, 100% for MPCI) always outperform Case-3 (80% for PPG, 83.69% for MPCI) performance regardless of the training database type used. Both Case-4 and Case-6 achieved 100% recognition rate for MPCI database. Thus, a conclusion on which case better than which case can't be made. However, by observing Case-4 and Case-6 recognition rates for PPG database, it can be seen that Case-6 always outperform Case-4 performance regardless of the training database type used. Thus, it can be concluded that Case-6 always outperform both Case-3 and Case-4 performances regardless of the training database type used. Again from Figure 4, by comparing Case-5 (three images per person), Case 7 (six images per person), and Case-6 (nine images per person), the effect of training database size on face recognition can be observe. It can be seen that the recognition rate pattern stays the same where Case 7 (79.17% for PPG, 85.71% for MPCI) that has six images per person always outperform Case-5 (77.78% for PPG, 84.92% for MPCI) that has three images per person. It can also be seen that Case-6

(100% for both PPG and MPCI) which has nine images per person always outperform both Case-5 and Case 7 performances regardless of the training database type used. Overall, by comparing the recognition rate of each cases of PPG and MPCI shown in Figure 4, it can be seen that the recognition rate pattern stays the same regardless of the training database used. Furthermore, by comparing the recognition rate of each cases of PPG and MPCI, it can be seen that MPCI database gives better recognition performance compared to PPG database regardless of the training database selection criteria used.

Recall that the number of frames per test person (Client Test or Unknown-Person Test) for PPG and MPCI database are 42 and 54 images respectively. The results shown in Figure 4 suggested that as the number of frames per test person increases during the testing (Client Test or Unknown-Person Test), the recognition performance tends to increase. This is because the more images of the test person available for testing, the more data of that test person can be evaluated by the face recognition system during the testing process.

Figure 5 shows a comparison of PCA-based and PCA+SVM-based face recognition system on different cases of training data selection criteria using MPCI database for training and testing. The focus of this experiment is to see the recognition rates pattern when different similarity matching method are used. As discussed in Figure 4 results, Case-1 represents the lowest performance training database criteria, while Case-6 and Case 8 represents the best performance training database criteria. As can be seen from Figure 5, Case-1 always gives the lowest rate (76.41% and 73.1% on PCA and PCA+SVM respectively) while Case-4, Case-6 and Case 8 gives the highest rate (100% on both PCA and PCA+SVM). Thus, it can be concluded that the lowest and the best performance training database criteria pattern stays the same regardless of the similarity matching method used.

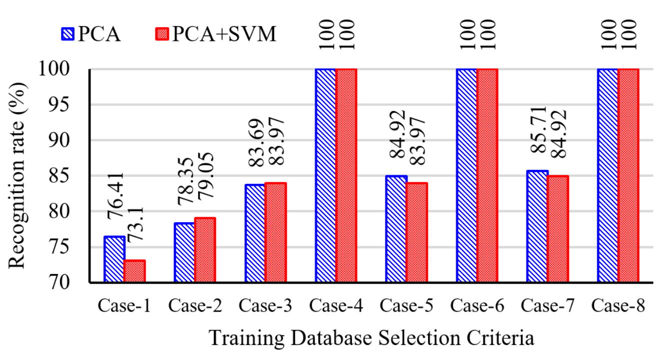


Figure 5: A comparison of recognition rates for different similarity matching method on different training data selection.

From Figure 5, comparing Case-1, Case-2, and Case-5 results shows that when using three images per person, a pattern can be seen where selecting one mean image from each distance class (Case-5) always give better recognition rate compared to using three images from the same distance class (Case-1) or using one randomly selected image from each distance class (Case-2) regardless of the similarity matching method used. Also from Figure 5, comparing Case-3, Case-4, and Case-6 results, which uses nine images per person, a pattern can be seen where selecting 1 mean image per distance class selected from all the available database sessions (Case-6) and using one image per distance class that are randomly selected from all database session (Case-4) always give better recognition performance than using three images per distance class from the same database session (Case-3) regardless of the similarity matching method used. As can be seen from Figure 5, both Case-4 and Case-6 achieved 100% recognition rate for MPCI database. Thus, a conclusion on which case better than which case can't be made.

Assuming that a different database (not MPCI database) was used for training and testing, the recognition results will be different and both Case-4 and Case-6 recognition rate might be lower than 100%. However, as discussed in Figure 4 results, Case-6 is better compared to Case-4, and Case-4 is better compared to Case-3. Lastly, from Figure 5, comparing Case-5 (three images per person), Case 7 (six images per person), and Case-6 (nine images per person) results, a pattern can be seen that there's a positive correlation between the number of images per person used and the recognition performance where the recognition performance increases as the number of images per person increase regardless of the similarity matching method used. As can be seen in Figure 5, Case-6 gives better performance compared to Case 7, and Case 7 gives better performance compared to Case-5. After comparing the recognition rate of each case of both PCA and PCA+SVM matching method, it can be concluded that the recognition rate pattern stays the same regardless of the similarity matching method used.

Overall, both PCA and PCA+SVM gives similar recognition performance with approximately ±1% differences on every cases with the exception of Case-1, where PCA+SVM perform poorer (3.31% lower) than PCA only. This is because Case-1 only represents the image quality (in term of illumination and occlusion variation) from the same distance class. Thus, for SVM algorithm which is a category or class-based, lacks the information from the other distance classes for decision making. This suggest that, compared to PCA+SVM, the PCA-based face recognition system alone is better to be used when using Case-1 selection criteria.

Figure 6 shows a comparison of processing time of a single test person for every case of training database criteria. From Figure 6, the processing time taken for PCA+SVM for matching is longer compared to using PCA only regardless of the cases used. This is because of the complexity of SVM algorithm on the PCA+SVM matching method. Thus, PCA-based face recognition system is much more efficient for surveillance application in term of processing time compared to PCA+SVM. Both the PCA and PCA+SVM uses the same training data, thus, both of them are using the same size of hard disk space to store the training data. The data space used to store the training data is shown in Figure 7.

As shown in Figure 5, the Case-4, Case-6, and Case 8 of both the PCA and PCA+SVM achieved 100% recognition rate. However, as can be seen from Figure 7, both Case-4 and Case-6 uses lesser hard disk space compared to Case 8. Thus, Case-4 and Case-6 are much more efficient than Case 8 in term of processing time and data storage space used. However, as discussed in Figure 4 results, using 1 mean image (Case-6) is better compared to using 1 image per class that are randomly selected from all the database sessions (Case-4).

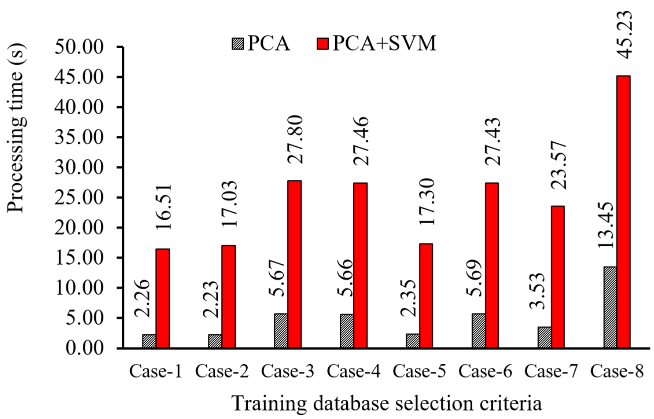


Figure 6: A comparison of processing time of a single test person

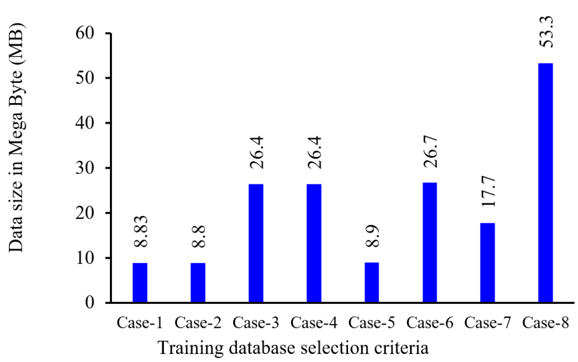


Figure 7: Hard disk space used to store the training data

Thus, the best performance is the PCA-based face recognition with Case-6 training database selection criteria and uses a grayscale image converted from the MPCI database.

9. CONCLUSION

This paper presents an investigation on the effect of the training database type using different training database selection criteria as well as investigation of the effect of similarity matching method using different training database selection criteria on face recognition system was carried out. A PCA+SVM-based face recognition system is used to carry out the investigation. The experiment suggests that the proposed training data selection criteria will give similar recognition performance pattern regardless of databases type used. By comparing the PPG and MPCI database, the results also shows that increasing the number of frames per person increases during testing tend to boost the recognition performance as well. The recognition performance of PCA-based and PCA+SVM-based face recognition system has been compared. It was found that regardless of the similarity matching method used, the face recognition system shows the same recognition performance pattern when compared cases to cases. It was also found that the PCA-based method is much more efficient in term of processing time compared to PCA+SVM. Overall, the experiments suggested that the proposed training database selection will give similar recognition performance regardless of databases or face recognition technique used. Both PCA and PCA+SVM based face recognition systems gives similar recognition performance except for Case-1 training database criteria where SVM gives poorer result. The performance of the proposed face recognition system is also compared with several methods that uses the same Chokepoint surveillance database as shown in Table 3. Table 3 shows a list of published works that applies face recognition systems for surveillance application and uses ChokePoint database as their test bed. If the proposed PCA-based method is used on different databases (aside from Chokepoint database), a 100% recognition rate may not be achieved. However, as discussed from the results shown in Figure 4 and Figure 5, the recognition rate pattern of each case described in Table 1 stays the same regardless of the database used. Even though a straight comparison between this work proposed system and systems in Table 3 is not meaningful as different face recognition approaches and experiment criteria are used, nevertheless, this work proposed method with 100% recall and reject recognition rate performs better than all the systems reported in Table 3. Thus, it has been concluded that the best face recognition performance in this work is PCA-based face recognition that uses 1 mean image (in grayscale format) per distance class selected from all database sessions (Case-6). Therefore, the best training database selection criteria is to use the mean image of the available distance classes from all available database sessions.

Table 3 Comparison of several face recognition methods for surveillance application on ChokePoint database

Authors	**Methods**	**Recognition Rate**
Proposed method	**Case-6 training database selection criteria for PCA-based system**	**100% (recall)** **100% (reject)**
Vignesh et al. [6]	Automated Face Quality Assessment (FQA), Convolutional Neural Network	79% recall rate
Gorodnichy and Granger [7]	Commercial face recognition system (Name not available)	65% recall rate

An et al. [8]	Dynamic Bayesian network, LPQ, LBP, HOG	97.2% recall rate
An et al. [9]	Warped average face (WAF) based image representation, Local Phase Quantization (LPQ)	98% recall rate
Shamsolmoali et al. [17]	Deep learning	95.8% (recall and reject)
Rani and Prasath [18]	Normalized Local Binary Patterns obtained (NLBP)	90.2% recall rate
Al-Obayd and Suandi [19]	HOG, Gabor filter, fuzzy ARTMAP neural network classifier	93.33% (recall) 93.46% (reject)
Al-Obaydy and Suandi [20]	Delaunay triangulation, thin-plate splines warping	90.48% (recall) 89.38% (reject)
An et al. [19]	Unified Face Image (UFI) image representation, SIFT	48% recall rate

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