An Investigation of Face and Fingerprint Feature-Fusion Guidelines

Dane Brown[1,2] and Karen Bradshaw[1]

[1]Rhodes University,
Department of Computer Science, Grahamstown, South Africa
[2]Council for Scientific and Industrial Research,
Modelling and Digital Sciences, Pretoria, South Africa
p.dane49@gmail.com
k.bradshaw@ru.ac.za

Abstract. *There are a lack of multi-modal biometric fusion guidelines at the feature-level. This paper investigates face and fingerprint features in the form of their strengths and weaknesses. This serves as a set of guidelines to authors that are planning face and fingerprint feature-fusion applications or aim to extend this into a general framework. The proposed guidelines were applied to the face and fingerprint to achieve a 91.11% recognition accuracy when using only a single training sample. Furthermore, an accuracy of 99.69% was achieved when using five training samples.*

Keywords: framework, face, fingerprint, feature-level, multi-modal biometrics

1 Introduction

Biometrics is defined as the measurement and analysis of unique biological and behavioural traits for human identification purposes [1]. Their widespread use have introduced security risks posed by forgers [2]. Furthermore, real-world conditions often result in degradation of the biometric data being modelled.

In a bid to counteract these real-world problems, multiple sources of biometric information have been used to improve the security, recognition accuracy and versatility of a biometric system. Multi-modal biometrics can also be used to solve non-universality and insufficient population coverage in well-planned applications [3].

Early use of multi-modal biometrics adopted the matching score level fusion approach. Later, the feature-level approach was shown to outperform the matching score level [4]. Feature-level fusion integrates feature sets corresponding to two or more biometric modalities. The widely used matching score level fusion does not utilize the rich discriminatory information available at the feature-level. The matching score level has been thoroughly reviewed and the results used to construct fusion frameworks [5]. These frameworks provide future research and applications a foundation on which to systematically implement multi-modal systems in the real-world. Feature-level fusion literature lack these frameworks, as it is a lesser studied problem. At present, the guideline used during feature-level fusion is limited to feature set compatibility – uncorrelated feature sets are to be used among different modalities and correlated feature sets among multiple samples of the same modality [6]. Biometric modalities, represented by an image, are independent and complementary. Based on the feature set compatibility guideline, the application of the same feature transformation method on different modalities can yield a very efficient multi-modal biometric system [5]. Fusion is often applied after transforming the feature space using linear or non-linear methods. [2].

In this paper, different feature selection and transformation methods are applied to the face and fingerprint. The resulting feature sets are expected to produce an improved recognition performance compared with the two individual modalities. The scope includes the use of different sized datasets and varying the number of training samples from one to five during data modelling. The experimental results are subsequently used to determine feature-fusion guidelines, relevant to the face and fingerprint, based on the type of data acquired. The contribution of this paper are these guidelines, which serve as the foundation of a general feature-fusion framework that can be constructed in future.

The rest of the paper is organized as follows: Sections 2 and 3 discuss quality enhancing and feature selection techniques, respectively. Three classifiers are explained in Section 4. Section 5 presents the related studies found in the literature. Sections 6 and 7 discuss the construction and application of the face and fingerprint feature-fusion guidelines, respectively. The experimental analyses and results are discussed in Section 8. Section 9 concludes the paper and discusses future work.

2 Quality Enhancement

Quality enhancement is used to recover the legibility of bad input data. This is particular to contours and pores in face images, and similarly the case for ridges and valleys in fingerprint images [7].

The biometric recognition process is often initiated by enhancing the quality of the input image [8–11]. This section discusses important image pre-processing techniques used on the biometric modalities in this paper.

2.1 Non-Local Denoising

Buades *et al.* [12] present an image denoising algorithm, called non-local means filtering (NL-means), described as neither local nor global. NL-means differs from typical neighbourhood filters as it compares the geometrical configuration in an entire neighborhood instead of a single greyscale pixel of one neighbourhood corresponding to another. NL-means preserves the edges of an image. This is important in fingerprint applications as ridges and valleys are key features. However, high filter strength and large neighbourhood size removes fine texture.

2.2 Pixel Normalization

Using this technique, pixel values are set to a constant mean and variance to reduce inconsistencies in lighting and contrast. This is essential for both face and fingerprint images as multiple samples are often captured under different conditions.

2.3 Histogram Equalization

Histogram Equalization effectively adjusts contrast intensities to an even amount based on the most frequent intensity values across an image histogram [8]. This uniform distribution is achieved by applying a non-linear transformation resulting in a minor side-effect on the histogram shape. This often produces better results than pixel normalization, but should be avoided in most histogram-based matching methods.

3 Feature Selection

Feature selection optimizes an objective function based on a requirement of specific features. The objective function reduces feature space by removing unwanted features. The remaining features are highly representative of the underlying image class [8]. The following subsections discuss the face and fingerprint features.

3.1 Local and Global Features

The texture pattern of a fingerprint contains richer information than singular points and minutiae [13]. The ridges and valleys that form the texture pattern are known as global features. Global features are effective in biometric fusion at the feature-level, but require registered points for alignment. Local features consist of these registration points known as minutiae and singular points.

Texture patterns, consisting of contours and pores can similarly be used as global features in face images. The local features are the coordinates of the eyes, nose and mouth. These local features are used to align global features in a similar way to fingerprints.

3.2 Core Detection and Region of Interest

The core point in a fingerprint image is often defined as the sharpest concave ridge curvature [14]. It is especially useful as a reference point during image registration. It can be used to define a regions of interest (ROI), which minimizes the discrepancy of stretch and alignment differences within same fingerprint classes.

Poincaré index is an orientation field based core detection algorithm[14]. It works well in good quality fingerprint images, but fails to correctly localize reference points in poor quality fingerprints with cracks, scars or poor ridge and valley contrast. However, since it does not rely on fine grain texture, NL-means can be used to enhance ridge and valley contrast before determining the orientation field.

Haar cascading is a popular method for detecting local facial features [15]. Similarly, local features in face images are used to create a border around the face, centred at the nose. Typical changes to the face such as hair, ears and neck are thus provided for.

3.3 Laplacian of Gaussian Filtering

A Laplacian of Gaussian (LOG) filter increases the dominant spectral components while attenuating the weak components [15, 16]. However, the LOG filter can further degrade the recognition accuracy of badly registered images because the overlap between dominant spectral components of the training and testing images becomes sparse.

3.4 Gabor Filter

A Gabor wavelet is a commonly used method of frequency filtering. This filter is constructed using a special short-time Fourier transform by modulating a two-dimensional sine wave at a particular frequency and orientation with a Gaussian envelope.

The sine waves of the ridges in the fingerprint vary at a slow to medium rate in a local constant orientation. Therefore, it is tuned to specific orientations and frequencies in the bandpass range, isolating undesired noise while preserving the structure of the fingerprint. Similar effects can be achieve when applied to the face, based on the structure of contours. Thus, an effective bandpass filter is constructed when utilizing the frequency and orientation selective properties of a Gabor filter according to the modality [17].

4 Feature Transformation and Classification

Image classification algorithms aim to exploit highly discriminative features. These algorithms often transform a feature vector to another vector space. The following image classification algorithms are considered.

4.1 Eigen

Principal component analysis (PCA) is used in this Eigen classifier to maximize the total variance in data based on linear combination of features. Eigenvectors are the decomposition of features vectors into key components known as principal components, which can then be reconstructed into an approximation of the original image.

The largest variance in data is contained within the first few principal components. These are the key features that are modelled into classes. A training and testing model are compared based on the distances between eigenvalues during matching.

Given N number of sample images x_k the total scatter matrix is defined as [18]:

$$S_t = \sum_{k=1}^{N} (x_k - \mu)(x_k - \mu)^T ,$$

where $m \in \mathbb{R}^n$ is the mean image obtained from the samples.

4.2 Fisher

The total scatter matrix used in Eigen lacks some discriminative information at an inter-class level. On the other hand, linear discriminant analysis (LDA) performs extra class-specific dimensionality reduction by considering the between-class and within-class scatter matrix.

Fisher learns a class-specific transformation matrix, which can lead to inconsistent data in dynamic lighting conditions. Fisher generally requires more training data than Eigen in non-ideal conditions. However, an advantage of Fisher is lower training and testing time and reduced dimensionality compared with Eigen.

Given C number of classes, the between-class scatter matrix is defined as [18]:

$$S_b = \sum_{i=1}^{C} N_k (\mu_k - \mu)(x_k - \mu)^T$$

and the within-class scatter matrix is defined as:

$$S_w = \sum_{i=1}^{C} \sum_{x_k \in \mathbb{X}_i} (x_k - \mu)(x_k - \mu)^T .$$

Where $C - 1$ is the maximum number of non-zero generalized eigenvalues, which leads to extra dimensionality reduction.

4.3 Local Binary Patterns Histogram

The local binary patterns histogram (LBPH) is a robust texture feature descriptor. It uses a local binary pattern (LBP) operator that compares the centre pixel value to a set size of neighbouring pixels.

A special LBP operator called extended LBP (ELBP) is used in this work. The neighbourhood is extended to include interpolated pixels, based on a circular mask, allowing for fine grain texture to be captured. Spatially enhanced histogram matching is used to improve partial matching and automatic pixel normalization at a pixel level, circular neighbourhood level, and image level. This addresses the shortcomings of Eigen and Fisher in terms of illumination, scale and misalignment[19]. ELBP can also be used as a feature selector without the spatially enhanced histogram.

The spatially enhanced histogram trains a significantly smaller model and produces it faster than the former two classifiers. Furthermore, the training time is independent of the resolution of the images. Given m circular neighbourhoods, their corresponding spatially enhanced histograms have size $m \times n$, where n is the length of a single histogram.

5 Related Studies

Karki and Selvi [20] proposed a multi-modal biometric system designed to fuse the face, fingerprint and offline signature in parallel at the feature-level. A feature vector is concatenated and stored in a database by using parallel fusion. The biometric traits of an individual are recorded separately during data acquisition, but required feature selection and transformation techniques are applied to the modalities in parallel. The SVM classifier is used for matching.

Texture features are extracted by a Curvelet transform with a third level low-low subband from each trait. The low level coefficients from the subband of each trait are compatible and each form a feature vector. The three feature vectors are concatenated (F_c). Five feature reduction methods are used to produce the reduced feature vectors, that is, feature averaging (F_a), PCA (F_{PCA}), PCA on individual traits (F_p), statistical moment features without fusion (F_m) and feature concatenation by extracting significant coefficients only (F_s). An SVM with a polynomial kernel of order 2 and parameter C set to 10 is the selected classifier.

Fingerprint, offline signature, and face samples of 100 users were captured to form a database, named ECMSRIT. PCA feature reduction performed on the concatenated feature vector of the ECMSRIT data produced the best equal error rate (EER) of 5.32%. This result was followed by the following feature vectors: F_a, F_p, F_c, F_m and F_s with an EER of 12.00%, 15.33%, 19.31%, 20.54% and 23.54%, respectively. The use of Curvelet transforms produced feature vectors that were robust to rotation of up to $10°$.

Sharma and Kaur [21] designed a multi-modal system by integrating the face, fingerprint and palmprint at the feature-level, similar to Karki and Selvi's work, but without the use of the Curvelet transform. The feature vectors are extracted independently using PCA followed by their concatenation before classification using a multiclass SVM. The performance of the multiclass SVM classifier is compared to an artificial neural network (ANN).

PCA reduction is used to reduce the search space for the SVM. The SVM uses the radial basis function (RBF) kernel. The number of hyperparameters affecting the complexity of the trained model is less in the RBF kernel than the other kernels. This gives the RBF kernel an advantage over the other kernels because the dimensionality of the fused feature vector is often too high.

The fingerprint images were obtained from the DB3_(UPEK) database; face images collected by Markus Weber at California Institute of Technology and palm images were obtained from the CASIA palmprint database. A pseudo dataset was created containing 10 individuals by combining the separate datasets. Five training and testing images were used per individual. The multi-modal system achieved a false acceptance rate (FAR) of 4% and a false rejection rate (FRR) of 6% on the dataset. The SVM significantly outperformed the ANN, but the details were not provided in the study.

Yao *et al.* [22] compared four PCA-based face and palmprint feature fusion algorithms. The proposed method filters EigenFaces and EigenPalms with a Gabor filter followed by weighted concatenation of the resulting feature vectors. The proposed system was designed to produce high accuracy with only a single training sample.

The AR face database and a palmprint database provided by Hong Kong Polytechnic University were used. The datasets consisted of 20 images per 189 individuals with a resolution of 60×60 in both cases. Fused datasets were created using parallel fusion. The highest genuine acceptance rate (GAR) of 95% was achieved with six training samples, while 91% GAR was achieved with only a single training sample.

6 Setting up the Guidelines

This section determines the feature-fusion guidelines that are relevant to the face and fingerprint. The face and fingerprint datasets consist of various scenarios as described in the following subsection.

6.1 Categories of Datasets

Pseudo multi-modal datasets, consisting of 40 individuals, were formed by pairing SDUMLA Fingerprint right index fingers [23] with ORL Face [24] and SDUMLA Fingerprint right middle fingers with Fei Face [25]. Fingerprint images organized into three groups, consisting of partials with absent core points, poorly-defined ridges and well-defined ridges. Face images were organized into two groups, consisting of standard faces and faces that consisted of poses and props. The interactions of image processing modules and classifiers, discussed in Sections 2 to 4, were determined based on preliminary experiments conducted on the organized pseudo multi-modal datasets.

6.2 Preliminary Experiments

General results across all datasets indicated LBPH to be the classifier most robust to misalignment, dynamic lighting and scale. Eigen and Fisher achieved recognition accuracies similar to that of LBPH for face and fingerprint images consisting of standard faces and well-defined ridges, respectively. However, Eigen and Fisher performed poorly in the remaining datasets, which can be attributed to the high variance in data across multiple samples of face and fingerprint images contained within those datasets. Fisher, in particular, requires training and testing images with well-aligned texture and has a significantly lower dimensionality than Eigen.

Typical parameters of ELBP are the one pixel radius and eight neighbouring pixels. Consistent lighting and lower noise were achieved in the Eigen space by multiplying the parameters by four. The results were conclusive across all datasets. This reduced the variation in data across multiple samples of an individual. The ELBP operator outperformed the equalized histogram and pixel normalization under different lighting conditions. However, pixel normalization was applied to LBPH as histogram equalization caused negative effects on the spatially enhanced histogram and the ELBP operator was already part of the LBPH classifier. The best accuracies were achieved when applying the same feature transformation to the different modalities. This is based on the feature set compatibility guideline and confirms the assertion by Raghavendra *et al.* [5].

NL-means filtering improved core detection in fingerprint datasets consisting of poorly-defined ridges. The improved core detection resulted in a well-defined ROI. Partials were catered for by applying LBPH in a sliding window and selecting the ROI that produced the best confidence score. The ROI that best defined the pose and props face dataset made use of multiple Haar cascades to exclude props such as scarfs and hats.

The LOG filter significantly improved the recognition accuracy of all the fused datasets. It was particularly useful at lowering the data variance of multiple samples of face and fingerprint images consisting of poses and poorly-defined ridges, respectively.

The Gabor filter did not improve the accuracies of the fused datasets. Moreover, it reduced the accuracy of the Eigen and Fisher classifiers. It significantly improved the recognition accuracy of non-partial fingerprint datasets and slightly improved the recognition accuracy of all face datasets when using the LBPH classifier. On the other hand, the LOG filter lowered the accuracy of the LBPH classifier. Reducing the data variance by 1% in the Eigen space, followed by reconstructing the image data, produced the best LBPH recognition accuracy across all datasets.

Table 1 provides a summary of the proposed guidelines, based on the results of these preliminary experiments. These guidelines are applied to a multi-modal database in the next section. The rest of the proposed methodology is based on the results of these preliminary tests. The best feature-fusion method, for the given datasets, on average, is illustrated in Fig. 1 and discussed as follows.

Table 1: Feature-Fusion Guidelines

Stage	Name	Advantage	Disadvantage	Suggested Use
Quality Enhancement	Pixel Normalization	Reduces inconsistent lighting.	Not very effective for big changes in lighting.	All biometrics affected by lighting. The first step of quality enhancement.
	Histogram Equalization	Reduces inconsistent lighting.	Minor histogram distortion. Introduces some noise.	Biometrics that are affected by lighting. Histogram-shape invariant classifiers such as Eigen and Fisher.
	NL-means filter	Denoises and preserves edges.	Can remove fine texture.	Use before Poincaré index.
Feature Selection	LOG Filter	Improved feature discrimination, before transforming to the Eigen space.	Requires consistent lighting.	Remove noise in the upper and lower frequencies before fusion.
	Gabor Filter	Improved feature discrimination, especially for fingerprints.	Requires tuning per application.	Adjust frequencies at a specific orientation and scale. Classifiers such as LBPH.
	ELBP Operator	Minimizes inconsistent lighting.	Introduces noise.	Biometrics that are affected by lighting. Classifiers such as Eigen and Fisher.
Feature Transformation and Classification	Eigen Classifier	LOG and ELBP supplement this classifier.	Slow training. High dimensionality.	Small image regions. Useful for fingerprints and fused datasets.
	Fisher Classifier	LOG and ELBP supplement this classifier. Low dimensionality.	Requires good training data.	When Eigen dimensionality is too high.
	LBPH Classifier	Works well on faces. Very robust.	Lowest accuracy after feature selection.	General purpose classifier. Face images. Applications with low storage requirements.

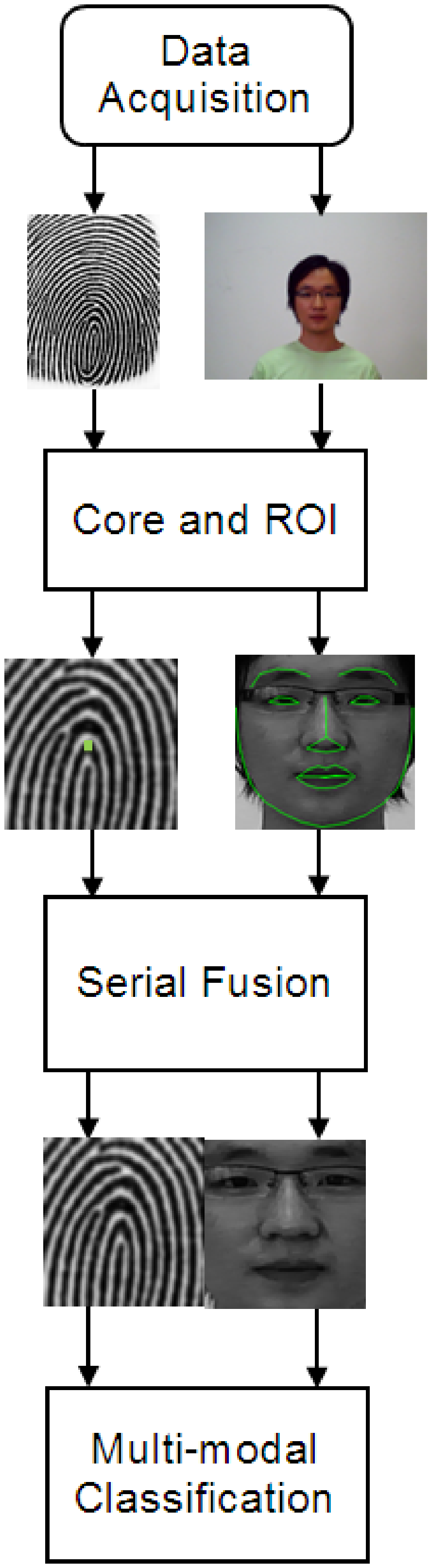

Fig. 1: Overview of Proposed Methodology.

7 Applying the Guidelines

The following list refers to Fig. 1 and details the subsequent evaluation of the results.

1. The SDUMLA multi-modal database [23], consisting of 106 individuals, was used in the final experiments discussed in Section 8. The acquired data assumed the following form: Eight samples of the left thumbprint were selected from the fingerprint images consisting of partials with absent core points, poorly-defined ridges and well-defined ridges. The eight samples of frontal faces selected from the face images consisted of different poses and props – normal, smile, frown, surprise, look down, shut eyes, hat and glasses. The number of training samples were varied from one to five and the rest were used for testing. To the best of my knowledge there are no studies that fuse face and fingerprint data acquired from the SDUMLA multi-modal database.

2. The fingerprint and face datasets were automatically cropped to 75×75 using Poincaré index and multiple Haar cascades, respectively. NL-means was used to remove noise before the Poincaré index algorithm was performed. The fingerprint was cropped around the core point to reduce the amount of stretch caused by inconsistent fingerprint capturing. The Haar cascades detected the face, eyes, nose and mouth as outlined in Fig. 1. The outlining was used to remove or reduce partial occlusions that affect face recognition.

3. The enhanced face and fingerprint feature vectors are combined using serial vector fusion, known as column concatenation.

4. The three classifiers divide the fused dataset into classes to create three baseline systems, as explained in Section 4. The baseline Eigen, Fisher and LBPH classifiers use histogram equalization and pixel normalization. The following feature selection techniques are applied to compare many multi-modal biometric recognition systems: Eigen and Fisher are used to classify combinations of the LOG and ELBP operator and PCA reduction is applied before using the LBPH classifier.

8 Experimental Analysis and Results

The following suffixes identify a feature-fusion scheme: Histogram equalization is a baseline system, henceforth, referred to as Eh; LOG is, henceforth, referred to as L; Extended LBP is, henceforth, referred to as LBP; Extended LBP followed by LOG is, henceforth, referred to as LBPL; LOG followed by Extended LBP is, henceforth, referred to as LLBP; and PCA reduction is, henceforth, referred to as PCA.

All recognition accuracies discussed in this section are measured at 0% FRR.

The Eigen baseline fusion system always outperforms the face and fingerprint as illustrated in Fig. 2. LBPL performs the best for one training sample with an accuracy of 90.84% and LLBP achieves an accuracy of 99.69% with five training samples.

The Fisher classifier performs similarly to Eigen, but with a significantly reduced accuracy when using two training samples as shown in Fig. 3. This is attributed to a low overlap of the remaining principal components in the two samples caused by the huge reduction in dimensionality.

The LBPH baseline fusion system produces a lower accuracy than the face when using three training samples as illustrated in Fig. 4. Moreover, LBPH is a very good face texture classifier. LBPH has a poor response to the image processing modules described in the bottom half of Section 3. However, PCA reduction improves the recognition accuracy by 3% on average.

The ELBP operator was successfully used together with the LOG filter to significantly improve feature discrimination in the Eigen space. EigenLLBP achieved the lowest EER of all the fusion schemes when using five training samples, at 0.31% as seen in Fig. 5. Furthermore, it should be noted that this fusion scheme shows no increase in FAR after the EER point. EhL and LBP individually improved the accuracies over the baseline, but only the results of their combinations are included in this paper. LBPL achieved the best average recognition accuracy across the varied number of training samples. The results demonstrate the application of the proposed guidelines in this paper. There are no experiments that fuse the face and fingerprint datasets contained in the SDUMLA multi-modal database.

9 Conclusion and Future Work

A comparison was performed on fingerprints, faces and their fused dataset using three baseline classifiers. The comparison was extended by combining a modified ELBP operator and a LOG filter. Additionally, principal components were removed from the LBPH training and testing images. The LBPH classifier achieved the best accuracy in the baseline systems and was robust to misalignment, dynamic lighting and scaling. The Eigen and Fisher classifiers yielded the best accuracies when combining the strengths of ELBP and LOG. Feature-level fusion research often makes use of well-known image processing and classification techniques without reasoning. Analyzing and testing many of these techniques to measure progress in the state-of-the-art is a non-trivial problem. Therefore, the guidelines introduced in this paper is the first step to solving the generalized feature-fusion framework problem.

In future, more combinations of biometric modalities and image processing modules will be investigated with additional experimentation toward a general multi-biometric feature-fusion framework. The framework will provide guidelines and measure progress in multi-modal biometric systems at the feature-level.

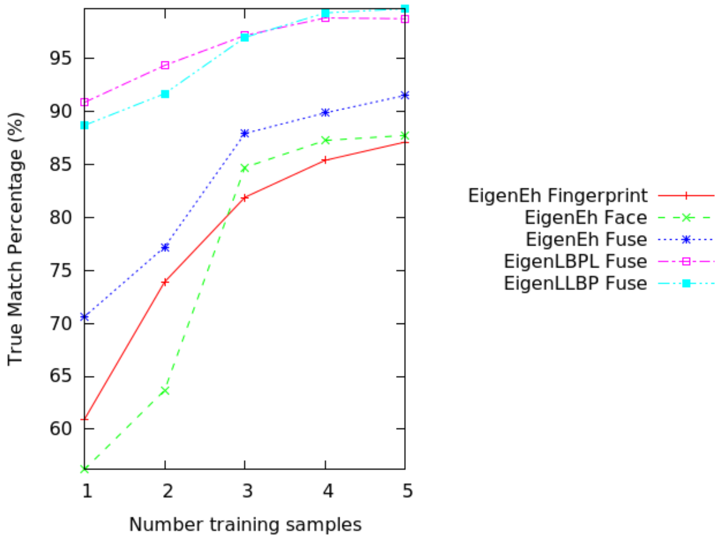

Fig. 2: Comparison of Eigen Methods

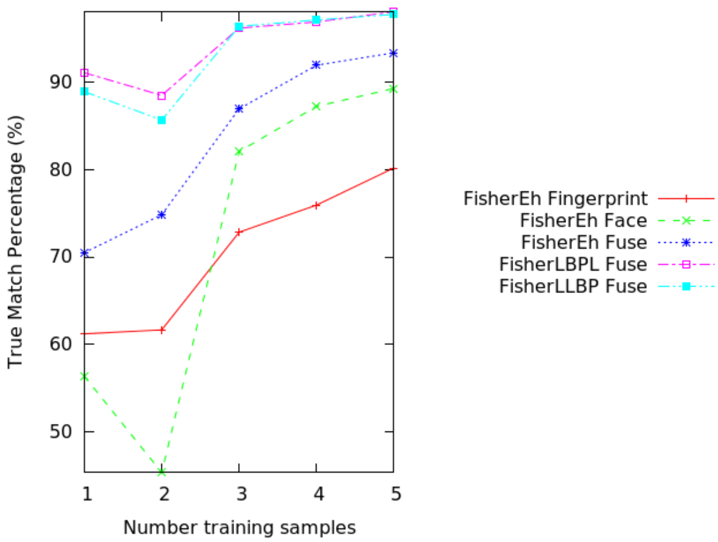

Fig. 3: Comparison of Fisher Methods

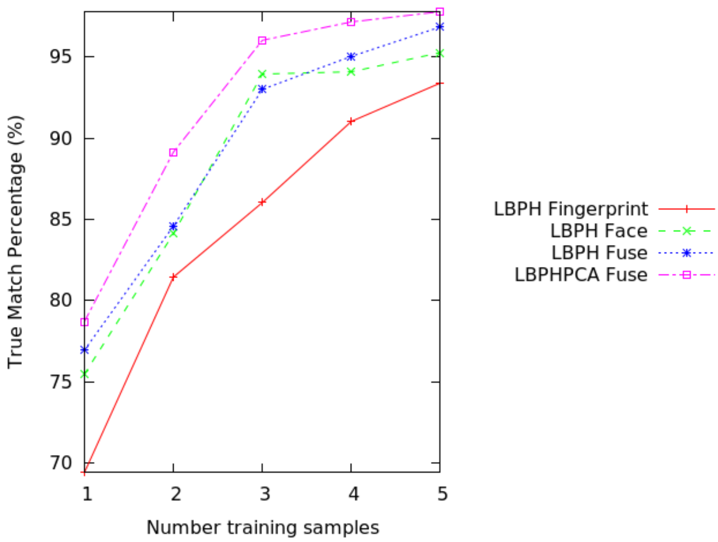

Fig. 4: Comparison of LBPH Methods.

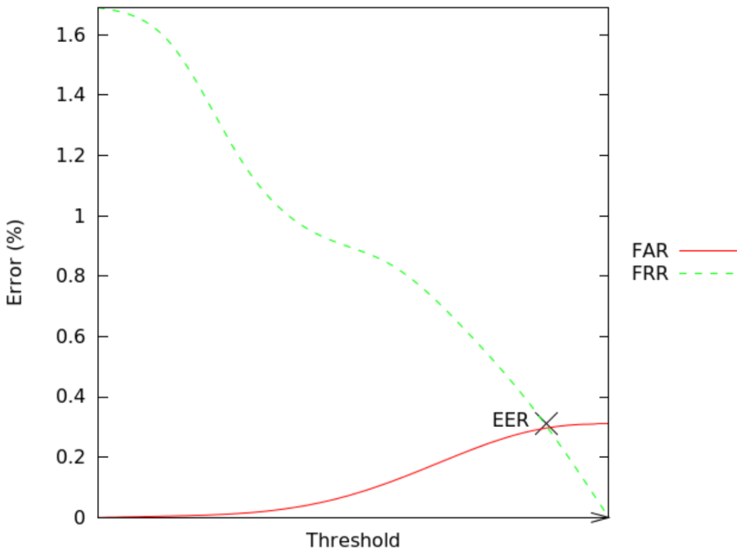

Fig. 5: Equal Error Rate.

References

1. Bharadwaj, S., Vatsa, M., Singh, R.: Biometric quality: from assessment to multibiometrics. (2015)
2. Kaur, D., Kaur, G.: Level of fusion in multimodal biometrics: A review. International Journal of Advanced Research in Computer Science and Software Engineering **3**(2) (2013) 242–246
3. Iloanusi, O.N.: Fusion of finger types for fingerprint indexing using minutiae quadruplets. Pattern Recognition Letters **38**(0) (2014) 8 – 14
4. Rattani, A., Kisku, D.R., Bicego, M., Tistarelli, M.: Feature level fusion of face and fingerprint biometrics. In: Biometrics: Theory, Applications, and Systems. (2011) 1–5
5. Raghavendra, R., Dorizzi, B., Rao, A., Kumar, G.H.: Designing efficient fusion schemes for multimodal biometric systems using face and palmprint. Pattern Recognition **44**(5) (2011) 1076–1088
6. Wang, Z., Liu, C., Shi, T., Ding, Q.: Face-palm identification system on feature level fusion based on CCA. Journal of Information Hiding and Multimedia Signal Processing **4**(4) (2013) 272–279
7. Porwik, P., Wrobel, K.: The new algorithm of fingerprint reference point location based on identification masks. In: Computer Recognition Systems. Springer (2005) 807–814
8. Bovik, A.C.: Handbook of image and video processing. Academic Press (2010)
9. Feng, J., Jain, A.: Fingerprint reconstruction: From minutiae to phase. Pattern Analysis and Machine Intelligence, IEEE Transactions on **33**(2) (Feb 2011) 209–223
10. Peralta, D., Triguero, I., Sanchez-Reillo, R., Herrera, F., Benitez, J.: Fast fingerprint identification for large databases. Pattern Recognition **47**(2) (Feb 2014) 588602

11. Zou, J., Feng, J., Zhang, X., Ding, M.: Local orientation field based nonlocal means method for fingerprint image de-noising. Journal of Signal and Information Processing **4** (2013) 150
12. Buades, A., Coll, B., Morel, J.M.: A non-local algorithm for image denoising. In: Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on. Volume 2., IEEE (2005) 60–65
13. Maltoni, D., Maio, D., Jain, A.K., Prabhakar, S.: Handbook of fingerprint recognition. Springer Science & Business Media (2009)
14. Jain, A.K., Prabhakar, S., Hong, L., Pankanti, S.: Filterbank-based fingerprint matching. Image Processing, IEEE Transactions on **9**(5) (2000) 846–859
15. Ahmadian, K., Gavrilova, M.: A multi-modal approach for high-dimensional feature recognition. The Visual Computer **29**(2) (2013) 123–130
16. Chikkerur, S., Cartwright, A.N., Govindaraju, V.: Fingerprint enhancement using stft analysis. Pattern Recognition **40**(1) (2007) 198–211
17. Budhi, G.S., Adipranata, R., Hartono, F.J.: The use of gabor filter and back-propagation neural network for the automobile types recognition. In: 2nd International Conference SIIT 2010. (2010)
18. Belhumeur, P.N., Hespanha, J.P., Kriegman, D.: Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. Pattern Analysis and Machine Intelligence, IEEE Transactions on **19**(7) (1997) 711–720
19. Ahonen, T., Hadid, A., Pietikainen, M.: Face description with local binary patterns: Application to face recognition. Pattern Analysis and Machine Intelligence, IEEE Transactions on **28**(12) (2006) 2037–2041
20. Karki, M.V., Selvi, S.S.: Multimodal biometrics at feature level fusion using texture features. International Journal of Biometrics and Bioinformatics **7**(1) (2013) 58–73
21. Sharma, P., Kaur, M.: Multimodal classification using feature level fusion and SVM. International Journal of Computer Applications **76**(4) (2013) 26–32
22. Yao, Y.F., Jing, X.Y., Wong, H.S.: Face and palmprint feature level fusion for single sample biometrics recognition. Neurocomputing **70**(7) (2007) 1582–1586
23. Yin, Y., Liu, L., Sun, X.: Sdumla-hmt: a multimodal biometric database. In: Biometric Recognition. Springer (2011) 260–268
24. Samaria, F.S., Harter, A.C.: Parameterisation of a stochastic model for human face identification. In: Applications of Computer Vision, 1994., Proceedings of the Second IEEE Workshop on, IEEE (1994) 138–142
25. Thomaz, C.E., Giraldi, G.A.: A new ranking method for principal components analysis and its application to face image analysis. Image and Vision Computing **28**(6) (2010) 902–913