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A COMPARISON OF FEATURE NORMALIZATION TECHNIQUES FOR PCA-BASED PALMPRINT RECOGNITION

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Abstract. Computing user templates (or models) for biometric authentication systems is one of the most crucial steps towards efficient and accurate biometric recognition. The constructed templates should encode user specific information extracted from a sample of a given biometric modality, such as, for example, palmprints, and exhibit a sufficient level of dissimilarity with other templates stored in the systems database. Clearly, the characteristics of the user templates depend on the approach employed for the extraction of biometric features, as well as on the procedure used to normalize the extracted feature vectors. While feature-extraction methods are a well studied topic, for which a vast amount of comparative studies can be found in the literature, normalization techniques lack such studies and are only briefly mentioned in most cases. In this paper we, therefore, apply several normalization techniques to feature vectors extracted from palmprint images by means of principal component analysis (PCA) and perform a comparative analysis on the results. We show that the choice of an appropriate normalization technique greatly influences the performance of the palmprint-based authentication system and can result in error rate reductions of more than 30%.

1 Introduction

The term *biometrics* refers to a scientific discipline which involves automatic methods for recognizing (verifying or identifying) people based on their physical and/or behavioral characteristics. Many biometric systems, i.e., systems which exploit these methods to establish identity, have already been presented in the literature; among them, systems which make use of biometric characteristics such as fingerprints, face, voice, iris, retina, hand-geometry, signature or palmprints are the most common [3].

While a considerable research effort is directed towards the development of efficient, fast, robust and user-friendly biometric systems, there are still some major problems that need to be tackled before they can be deployed on a larger scale. One of the main challenges, which has yet to be solved, includes increasing the recognition performance of biometric systems. Towards this end, a trend has emerged in recent years, namely, the employment of multi-modal biometric systems which establish identity either by considering several biometric modalities (e.g., the face, the iris, palmprints, voice etc.) or by combining the recognition results of several algorithms performed on the same biometric sample. While such an approach is a valid solution for the problem of recognition performance, it commonly decreases the user-convenience, as it requires a greater effort from the user to operate the system or it increases the time needed to process a single user. From this point of view, other solutions capable of increasing the recognition rates and not influencing the convenience of using the biometric systems should be sought. One possibility of increasing the recognition performance is to closer examine feature normalization techniques, which hold the potential to greatly decrease the error rates of biometric systems, but have so far been largely neglected in most research papers on the subject of biometrics. Commonly, only a sentence or two is devoted to the employed normalization technique, even though feature normalization represents a crucial step in the design of a biometric system. Feature normalization techniques have a great impact on the procedure of constructing user templates (or models), i.e., mathematical representations of the feature vectors extracted from several measurements of the biometric characteristic (e.g., palmprints) acquired during the enrollment stage, and consequently on the way how user-specific biometric characteristics are modeled. They represent a fast and efficient way of boosting the recognition performance of biometric systems which does not significantly increase the processing time of a user.

In this paper we present an empirical evaluation of several feature normalization techniques, namely, unit-length normalization (UL), zero-mean and unit-variance normalization (MV), linear scaling to unit-range (SC), rank normalization (RN) and gaussianization (GS), which we apply to feature vectors extracted from palmprint images by means of principal component analysis (PCA) [2]. We report comparative results with the recognition performance of raw palmprint features, i.e, features without normalization (WN), and assess their performance in conjunction with the nearest neighbor classifier and three popular similarity measures, namely, the Euclidian distance, the City Block distance and the cosine similarity measure.

2 The Structure of palmprint verification systems

Biometric palmprint verification systems basically represent pattern recognition systems which, according to Jain et al. [1], are comprised of four main modules: *(i) the data acquisition module*, which captures a biometric sample an idividual, e.g., the image of the hands palmar surface, or in other words, the palmprint image; *(ii) the feature extraction module*, which extracts a set of representative and discriminative features from the acquired biometric sample; *(iii) the matching and decision making module* that first compares the computed feature set with a template/model , i.e., the mathematical representation of the feature sets extracted during the enrollment session (Figure 1a), and outputs a similarity (or matching) score which is then used to make a decision regrading the validity of the identity claim made by the individual (Figure 1b); *(iv) the system's database module*, which is used by the palm-print verification system for storing the templates/models of the enrolled users.

Of course, the structure of a palmprint verification system can be broken down even further revealing more specialized system modules. In Figure 1, which shows the block diagram of the system employed in our experiments, two additional modules are presented. The first is the *pre-processing module*, which extracts the region of interest (ROI), i.e., the palm-print region, from the acquired image data and normalizes the extracted ROI in respect to size, rotation and illumination; and the second is the *feature normalization module*, which performs a normalization procedure on the extracted feature set [5].

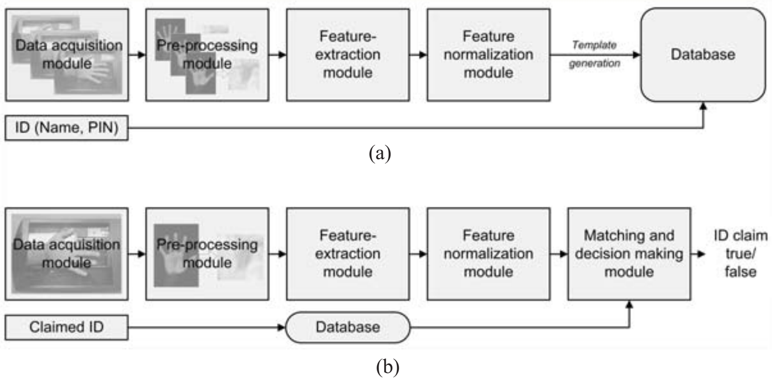

Figure 1: The block diagram of a palm-print verification system: (a) the enrollment stage, (b) the verification stage

3 Feature normalization techniques

Feature normalization techniques represent a vital part of each biometric recognition system. They aim at normalizing the individual components of the extracted feature vectors in such a way that the resulting (normalized) vectors are better suited for classification. Some of these techniques are presented in the remainder of this section.

3.1 Unit length normalization - UL

Consider a $d-$dimensional feature vector $\mathbf{x}$ extracted from the given palmprint image by means of PCA. Unit length normalization (UL) scales all of the components x_i $(i = 1,2,...,d)$ of $\mathbf{x}$ in accordance with the following expression to produce the normalized feature vector $\mathbf{x}^*$:

$$x_i^* = \frac{x_i}{\|\mathbf{x}\|}, \ \ i = 1,2,...,d, \tag{1}$$

where $\|.\|$ denotes the norm operator and x_i^* stands for the $i-$th component of the normalized vector $\mathbf{x}^*$.

3.2 Zero-mean and unit-variance normalization - MV

Using the same notation for the original and normalized feature vector as in the previous subsection, we can define the zero-mean and unit-variance normalization (MV) technique as follows:

$$x_i^* = \frac{x_i - \mu}{\sigma}, \ \ i = 1,2,...,d, \tag{2}$$

where μ denotes the mean value of the feature vector $\mathbf{x}$ and σ represents its standard deviation. the MV technique transforms the feature vector $\mathbf{x}$ to a random variable with a mean value of zero and variance of one. Of course, it is assumed the the individual components of the feature vector are normally distributed.

3.3 Linear scaling to unit range - SC

Linear scaling to unit range (SC) transforms each of the components x_i $(i = 1,2,...,d)$ in the $d-$dimensional feature vector $\mathbf{x}$ using the following expression:

$$x_i^* = \frac{x_i - x_{min}}{x_{max} - x_{min}}, \ \ i = 1,2,...,d, \tag{3}$$

where x_{min} represents the value of the smallest component in the vector $\mathbf{x}$ and x_{max} stands for the feature component with the highest value in $\mathbf{x}$. The resulting normalized feature components x_i^* comprising the feature vector $\mathbf{x}^*$ are in the range of [0,1].

3.4 Rank normalization - RN

Rank normalization (RN) is a nonparametric normalization technique where each of the feature components x_i $(i = 1, 2, ..., d)$ in the $d-$dimensional feature vector $\mathbf{x}$ is replaced with the index (or rank) R the component would correspond to if the feature components would be ordered in an ascending manner. As result of rank normalization the distribution of the feature components in the normalized feature vector $\mathbf{x}$ approximates the uniform distribution.

3.5 Gaussianization - GS

Gaussianization (GS) of the $d-$dimensional feature vector $\mathbf{x}$ transforms the feature components in such a way that their distribution approximates the normal distribution with a predefined mean μ and standard deviation σ. The first step of the procedure is based on the rank normalization. Once the rank R_i of each component is determined, the general mapping function to match the target distribution $f(z)$ may be calculated from [4]:

$$\frac{d - R_i + 0.5}{d} = \int_{z=-\infty}^{x_i^*} f(z)dz, \tag{4}$$

where the goal is to find x_i^* via the inverse of the cumulative distribution function. Here the target distribution f(z) is defined as $f(z) = \frac{1}{\sigma\sqrt{2\pi}}\exp(\frac{-(z-\mu)^2}{2\sigma^2})$. For our experiments we have selected $\mu = 0$ and $\sigma = 1$.

4 Experiments and results

4.1 The PolyU database

To assess the efficiency of the normalization techniques the publicly available PolyU database was employed in our experiments. The database was recorded at the Hong Kong Polytechnic University (China) [6] and contains 7752 (8-bit) grey-scale images that correspond to 386 subjects. Each subject in the database is accounted for with approximately 20 palmprint images, the exact number, however, varies from subject to subject. The images were captured with a CCD camera, thus, all images are of good quality, i.e., uniformly illuminated. For our experiments we have followed the same experimental protocol as described in [5]. The database was partitioned into two parts, one corresponding to client- and the other to impostor-images. The two parts were then further divided into image sets used for training, evaluation and testing[1].

The performance of the system was assessed by means of the standard error rates: the false rejection error rate (FRR), which accounts for the percentage of falsely rejected clients; the false acceptance error rate (FAR), which corresponds to the percentage of falsely accepted impostors; and the total error rate (TER) defined as the sum of the FAR and FRR. The results in Section 4 are reported at the equal error operating point, which is the most commonly used operating point for assessing the performance of biometric verification systems. Note that there exists a tradeoff between the FAR and FRR, reducing the FAR results in an increase of the FRR and vice versa. Hence, for a fair comparison an operating point has to be chosen. In practice this is achieved with an appropriate selection of the decision threshold.

4.2 Comparative evaluation of the feature normalization techniques

For the experiments described in this section we have used the pre-processing technique proposed by Zhang et al. in [7]. The technique was developed for the extraction of the region of the interest from the PolyU palmprint images and considers the image characteristics induced by the acquisition setup employed when recording the database. In the feature extraction stage a basic PCA procedure was used [2]. Hence, for client template/model construction each of the enrollment palmprint ROIs was projected into the PCA subspace and normalized with the given feature normalization technique. Finally, the client template/model was computed by averaging all of the feature vectors extracted from the enrollment images.

Two kinds of experiments were performed in our comparative assessment: experiments for determining the decision threshold (performed on the evaluation image set) and experiments for assessing the final verification performance with a fixed, predefined decision threshold (performed on the test image set). The results of these experiments are presented in Table 1 and 2, respectively. Here, the best results for each similarity measure are presented in bold.

On the evaluation image set the best results (the lowest TER) were achieved when gaussianization of the feature distribution was used as the normalization technique regardless of the similarity measure employed for matching score calculation. Similar results were also observed on the test image set. Gaussianization again resulted in the

[1] For a detailed description of the employed setup the reader is referred to [5]

Normalization technique		WN	UL	MV	SC	RN	GS
Euclidian	FAR(%)	3.42	2.34	2.30	2.64	3.23	2.26
	FRR(%)	3.48	2.46	2.46	2.75	3.48	2.32
	TER(%)	6.90	4.80	4.76	5.39	6.71	**4.58**
City Block	FAR(%)	4.15	3.80	6.73	3.17	3.35	2.82
	FRR(%)	4.35	4.35	6.96	3.17	3.77	3.04
	TER(%)	8.50	8.15	13.69	6.34	7.12	**5.86**
Cosine	FAR(%)	2.30	2.29	2.28	12.60	3.26	1.53
	FRR(%)	2.32	2.32	3.32	12.75	3.33	1.59
	TER(%)	4.62	4.61	4.60	25.35	6.59	**3.12**

Table 1: Comparison of the normalization techniques for three similarity measures on the evaluation image set.

best performance with all similarity measures except for the Euclidian distance, where scaling the feature vector to unit length performed slightly better. The best overall results on the evaluation as well as the test image set were obtained with the combination of gaussianization as the normalization technique and the cosine similarity measure as the scoring function. This combination resulted in a reduction of the TER of 32.5% on the evaluation set and 21.0% on the test set when compared to the verification performance of the system without any feature normalization. While almost all of the tested normalization techniques (except for RN) reduced the TER for most

Normalization technique		WN	UL	MV	SC	RN	GS
Euclidian	FAR(%)	3.29	2.41	2.56	2.75	3.26	2.32
	FRR(%)	2.82	2.11	3.22	2.65	4.12	2.41
	TER(%)	6.11	**4.52**	5.78	5.40	7.38	4.73
City Block	FAR(%)	3.74	3.84	7.14	3.35	3.45	2.98
	FRR(%)	3.31	3.60	7.28	2.98	4.21	3.22
	TER(%)	7.05	7.44	14.42	6.33	7.66	**6.20**
Cosine	FAR(%)	2.31	2.30	2.30	10.90	3.30	1.62
	FRR(%)	2.17	2.20	2.14	11.73	3.81	1.92
	TER(%)	4.48	4.50	4.44	22.63	7.11	**3.54**

Table 2: Comparison of the normalization techniques for three similarity measures on the test image set.

of the tested similarity measures, gaussianization resulted in the most consistent improvements. Due to the limited space available in this paper we will not discuss the statistical significance of these results, but rather point out the systematic improvements in the observed TER.

5 Conclusion

In this paper we have presented and empirical evaluation of several feature normalization techniques applied on feature vectors extracted from palmprint images by means of principal component analysis. We have shown that gaussianization of the feature components is the most effective normalization procedure among the tested ones and ensures error rate reductions of more than 30% when compared to the feature vectors without normalization.

6 Acknowledgement

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7 References

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