SIMILARITY MEASURES FUSION USING SVM CLASSIFIER FOR FACE AUTHENTICATION

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Abstract: In this paper, the problems of measuring similarity in LDA face space using different metrics and fusing the associated classifiers are considered. A few similarity measures used in different pattern recognition applications, including the recently proposed Gradient Direction (GD) metric are reviewed. An automatic parameter selection algorithm is then proposed for optimising the GD metric. In extensive experimentation on the BANCA database, we show that the optimised GD metric outperforms the other metrics in various conditions. Moreover, we demonstrate that by combining the GD metric and seven other metrics in the decision level using Support Vector Machines, the performance of the resulting decision making scheme consistently improves.

1 INTRODUCTION

Decision making using similarity measure or scoring function is a usual approach to classification problem especially when the training data is limited. A typical example of such a case is biometric person verification where only a few training data points are available for each individual. A similarity function, measures the degree of similarity of an unknown patterns to the query person template. If the degree exceeds a prespecified threshold, the unknown pattern is accepted to be the same as the query person. Otherwise it is rejected. The similarity concept can also be used in recognition scenarios where the unknown pattern would be associated with that class, the template of which is the most similar to the observed data.

Different similarity measures have been adopted in different machine vision applications. In (Zhang and Lu, 2003), a number of commonly used similarity measures including the City-block, Euclidean, Normalised Correlation (NC), Chi-square (χ^2) and Chebyschev distance have been considered in an image retrieval system. The reported experimental results demonstrate that the City-block and Chi-square metrics are more efficient in term of both retrieval accuracy and retrieval efficiency. In a similar comparative study, it has been shown that the Chi-square statistics measure outperforms the other similarity measures for remote sensing image retrieval (Bao and Guo, 2004). In another study, the effect of 14 scoring functions such as the City-block, Euclidean, NC, Canberra, Chebyschev and Distance based Correlation Coefficients has been studied in the context of the face recognition problem (Perlibakas, 2004) in the PCA space. It has been shown that a simplified form of Mahalanobis distance outperforms the other metrics. In (Yambor et al., 2002) also four classical distance measures, City-block, Euclidean, Normalised correlation and Mahalanobis distance, have been compared in the PCA space. It has been concluded that when the number of eigenvectors is relatively high the Mahalanobis distance outperforms the other measures. Otherwise a similar performance is achieved using different measures. It has been also proposed that no significant improvement is achieved by combining the distance measures.

The similarity score is computed in a suitable feature space. Commonly, similarity would be quantised in terms of a distance function, on the grounds that similar patterns will lie physically close to each other. Thus smaller the distance, the greater the similarity of two entities. The role of the feature space in similarity measurement is multifold. First of all the

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feature space is selected so as to maximise the discriminatory information content of the data projected into the feature space and to remove any redundancy. However, additional benefits sought after from mapping the original pattern data into a feature space is to simplify the similarity measure deployed for decision making. A classical example of this is the use of the Euclidean distance (ED) metric in Linear Discriminant Analysis (LDA) feature spaces as the within class covariance matrix in the LDA space becomes an identity matrix and such metric becomes theoretically optimal (Belhumeur et al., 1997). Despite the theoretical optimality of Euclidean metric in the LDA space, in (Kittler et al., 2000), it has been demonstrated that it is outperformed by the Normalised Correlation (NC). However, in (Kittler et al., 2000) it has been further demonstrated that the Gradient Direction (GD) scoring function is even more effective.

In (Sadeghi and Kittler, 2006), the performance of the NC scoring function was compared with the GD metric. The study was performed on the BANCA database [1] using an internationally agreed experimental protocols by applying a geometric face registration method based on manually or automatically annotated eyes positions. It was concluded that overall the NC function is less sensitive to miss-registration error but in certain conditions GD metric performs better.

In this study we firstly optimised the GD function by adaptively modelling the impostors distribution, result of which is that almost always the optimised GD metric outperforms the NC metric for both manually and automatically registered data. Also, although the previous studies show that the NC and GD functions outperform the other metrics, we wanted to see if we can get any complementary information from the other similarity functions. Therefore, in this work, the effect of combining a few more similarity/dissimilarity measures with the above mentioned metrics has been considered. Our experimental results confirm that, individually, the other considered metrics do not perform as good as the NC and GD metrics in the LDA space for face verification. However, by fusing experts employing the diverse similarity measures using the Support Vector Machine (SVM) classifier the performance of the system improves compare to any metric individually.

The paper is organised as follows. In the next section the adopted scoring functions are introduced. The adopted Fusion method is then briefly reviewed in Section 3. A description of the experimental design including the face database used in the study, the experimental protocols and the experimental setup is given in Section 4. The experimental results using the adopted scoring functions and the fusion results are presented and discussed in Section 5. Finally a summary of the main findings and conclusions can be found in Section 6.

[1] http://www.ee.surrey.ac.uk/banca/

2 SIMILARITY FUNCTIONS

In a similarity measure based face verification system, a matching scheme measures the similarity or distance of the test sample, x to the template of the claimed identity, μ_i. Note that x and μ_i are the projections of the test sample and class mean into the feature space respectively. The general form of a group of similarity measures which is called *Minkowski Distance* or *power norm metrics* (L_p) is defined as:

$$s_M = \Big[\sum_{j=1}^{m} (\mu_{ij} - \mathrm{x}_j)^p\Big]^{1/p} \tag{1}$$

where m is the dimensionality.

The most commonly used similarity measures, *Manhattan* or *City-block* metric, *Euclidean* Distance (ED) and *Chebyschev* Distance are derived from the above definition considering $p = 1$, $p = 2$ and $p \rightarrow \infty$ respectively , i.e. L_1, L_2 and L_∞ metrics:

$$s_{City} = \sum_{j=1}^{m} \left|\mu_{ij} - \mathrm{x}_j\right| \tag{2}$$

$$s_{ED} = \sqrt{(\mathrm{x} - \mu_i)^T (\mathrm{x} - \mu_i)} \tag{3}$$

$$s_{Cheby} = \max_j \left|\mu_{ij} - \mathrm{x}_j\right| \tag{4}$$

The *Canberra* Distance is also given by

$$s_{Canb} = \sum_{j=1}^{m} \frac{\left|\mu_{ij} - \mathrm{x}_j\right|}{\left|\mu_{ij}\right| + \left|\mathrm{x}_j\right|} \tag{5}$$

This can be considered as the normalised Manhattan Distance. The *Chi-squared* (χ^2) Distance is defined by

$$s_{\chi^2} = \sum_{j=1}^{m} \frac{(\mu_{ij} - \mathrm{x}_j)^2}{\left|\mu_{ij}\right| + \left|\mathrm{x}_j\right|} \tag{6}$$

Which is basically a relative Euclidean squared distance and is usually meant for non negative variables only.

In (Kittler et al., 2000), it has been demonstrated that a matching score based on *Normalised Correlation* (NC) scoring function, defined by Equation 7, is more efficient.

$$s_N = \frac{||\mathrm{x}^T \mu_i||}{\sqrt{\mathrm{x}^T \mathrm{x} \mu_i^T \mu_i}} \tag{7}$$

Another similarity measure which is conceptually same as the NC function is Distance based *Correlation Coefficients*. For more details, the reader is referred to (Perlibakas, 2004).

In (Kittler et al., 2000) and (Sadeghi and Kittler, 2004) an innovate metric called the *Gradient Direction* (GD) metric has been proposed. In this method the distance between a probe image and a model is measured in the gradient direction of the aposteriori probability of the hypothesised client identity. A mixture of Gaussian distributions with Isotropic covariance matrix has been assumed as the density function of the possible classes of identity. The Isotropic covariance matrix assumed to have a variance of the order of the variation of the image data in the feature space. It was demonstrated that applying GD metric is even more efficient than the NC function. The proposed optimal matching score is defined as

$$s_O = \frac{||(\mathrm{x}-\mu_i)^T \nabla_O P(i|\mathrm{x})||}{||\nabla_O P(i|\mathrm{x})||} \tag{8}$$

where $\nabla_O P(i|\mathrm{x})$ refers to the gradient direction. Considering an isotropic structure for the covariance matrix, i.e. $\Sigma = \sigma \mathrm{I}$,the optimal direction would be

$$\nabla_I P(i|\mathrm{x}) = \sum_{\substack{j=1 \\ j \neq i}}^{m} p(\mathrm{x}|j)(\mu_j - \mu_i) \tag{9}$$

Note that the magnitude of the σ will affect the direction through the values of density $p(\mathrm{x}|j)$.

3 SIMILARITY SCORES FUSION

One of the most exciting research directions in the field of pattern recognition and computer vision is classifier fusion. It has been recognised that the classical approach to designing a pattern recognition system which focuses on finding the best classifier has a serious drawback. Any complementary discriminatory information that other classifiers may capture is not tapped. Multiple expert fusion aims to make use of many different designs to improve the classification performance. In the case considered here, as different metrics span the feature space in different ways, it seems reasonable to expect that a better performance could be obtained by combining the resulting classifiers. In different studies, it has been shown that the SVM classifier is among the best trained fusion rules. A Support Vector Machine is a two-class classifier showing superior performance to other methods in terms of Structural Risk Minimisation (Vapnik, 1995). In this study, decision level fusion strategy using the SVMs has been adopted for combining the similarity measure based classifiers.

For the face verification problem, the size of the training set for clients is usually less than the one for impostors. In such a case, the class of impostors is represented better. Therefore, it is necessary to shift the optimal hyperplane of the SVM classifier towards the better represented class (Seredin et al., 2001). In this work, the size of the shift is determined in the evaluation step considering the Equal Error Rate criterion.

4 EXPERIMENTAL DESIGN

In this section the face verification experiments carried out on images of the BANCA database are described. The BANCA database is briefly introduced first. The main specifications of the experimental setup are then presented.

4.1 BANCA Database

The BANCA database has been designed in order to test multi-modal identity verification systems deploying different cameras in different scenarios (Controlled, Degraded and Adverse). The database has been recorded in several languages in different countries. Our experiments were performed on the English section of the database. Each section contains 52 subjects (26 males and 26 females). Experiments can be performed on each group separately.

Each subject participated to 12 recording sessions in different conditions and with different cameras. Sessions 1-4 contain data under *Controlled* conditions whereas sessions 5-8 and 9-12 contain *Degraded* and *Adverse* scenarios respectively. In order to create more independent experiments, images in each session have been divided into two groups of 26 subjects (13 males and 13 females).

In the BANCA protocol, 7 different distinct experimental configurations have been specified, namely, Matched Controlled (Mc), Matched Degraded (Md), Matched Adverse (Ma), Unmatched Degraded (Ud), Unmatched Adverse (Ua), Pooled test (P) and Grand test (G). Table 1 describes the usage of the different sessions in each configuration. “T” refers to the client training while “C” and “I” depict client and impostor test sessions respectively.

4.2 Experimental Setup

The performance of different decision making methods discussed in section 2is experimentally evaluated

Table 1: The usage of the different sessions in the BANCA experimental protocols.

	MC	MD	MA	UD	UA	P	G
1	TI			T	T	TI	TI
2	CI					CI	CI
3	CI					CI	CI
4	CI					CI	CI
5		TI		I		I	TI
6		CI		CI		CI	CI
7		CI		CI		CI	CI
8		CI		CI		CI	CI
9			TI		I	I	TI
10			CI		CI	CI	CI
11			CI		CI	CI	CI
12			CI		CI	CI	CI

on the BANCA database using the configurations discussed in the previous section. The evaluation is performed in the LDA space. The original resolution of the image data is 720×576. The experiments were performed with a relatively low resolution face images, namely 64×49. The results reported in this article have been obtained by applying a geometric face normalisation based on the eyes positions. The eyes positions were localised either manually or automatically. A fast method of face detection and eyes localisation was used for the automatic localisation of eyes centre (Hamouz et al., 2005). The XM2VTS database [2] was used for calculating the LDA projection matrix.

The thresholds in the decision making system have been determined based on the Equal Error Rate criterion, i.e. by the operating point where the false rejection rate (FRR) is equal to the false acceptance rate (FAR). The thresholds are set either globally (*GT*) or using the client specific thresholding (*CST*) technique (Sadeghi and Kittler, 2004). In the training sessions of the BANCA database 5 client images per person are available. In the case of global thresholding method, all these images are used for training the clients template. The other group data is then used to set the threshold. In the case of the client specific thresholding strategy, only two images are used for the template training and the other three along with the other group data are used to determine the thresholds. Moreover, in order to increase the number of data used for training and to take the errors of the geometric normalisation into account, 24 additional face images per each image were generated by perturbing the location of the eyes position around the annotated positions.

In the previous studies (Sadeghi and Kittler, 2004), it was demonstrated that the Client Specific Thresholding (CST) technique was superior in the matched scenario (Mc, Md, Ma and G) whereas the Global Thresholding (GT) method gives a better performance on the unmatched protocols. The results reported in the next section using thresholding were acquired using this criterion.

Also, the SVM classifier has been used in order to fuse the classifiers employing the diverse similarity measures.

[2] http://www.ee.surrey.ac.uk/Research/VSSP/xm2vtsdb/

5 EXPERIMENTAL RESULTS AND DISCUSSION

As mentioned earlier, in the GD metric, the impostor distributions have been approximated by isotropic Gaussian functions with a standard deviation of σ, i.e. $\Sigma = \sigma I$. The order of σ is related to the order of the standard deviation of the input data (gray level values in the LDA feature space). In the previous work (Sadeghi and Kittler, 2006) a fixed value equal to 10^4 has been used for σ. In this work, in order to optimise the metric for dealing with different imaging conditions, the value of σ is adaptively determined in the evaluation step where the performance of the system considering different values of σ is evaluated. As two examples for matched and un-matched protocols, figure 1 contain plots of the Total Error rate versus the value of σ in the evaluation and test steps considering the Ud protocol.

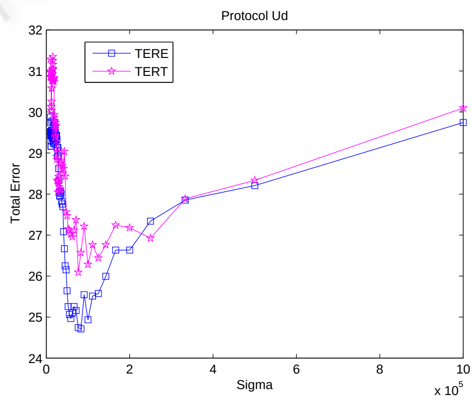

Figure 1: The performance of the GD metric versus the value of σ considering Ud protocol.

The evaluation plots show that by increasing the value of σ, the TE rate first rapidly decreases. Then, for larger values of σ, the TE rate remains relatively constant or increases gradually. From these plots, one can also see that the behaviour of the system in the evaluation and test stages is almost consistent. Therefore, the optimum σ can be found in the evaluation step by looking for the point after which the performance of the system is not significantly improved by increasing the value of σ. The associated value of σ is then used in the test stage.

Tables 2 contains a summary of the results obtained using the individual scoring function on the evaluation and test sets when manually annotated eyes position were used for the face geometric normalisation. The values in the table indicate the Total Error rates in the Evaluation (TEE) and Test (TET) stages respectively. For the sake of simplicity of comparison, the evaluation and test results have been also shown in figures 2(a) and (b) respectively.

These results clearly demonstrate that among the adopted metric, individually, the GD metric is the outright winner. In a few cases, the NC results is comparable to the GD one. The performance of the other metrics is much worse.

Plots (b) and (c) of the figure 2 demonstrate a summary of the results when the face registration step was performed based on automatically localised eyes position. These results also confirm that the GD metric is again the best scoring function for this application. A comparison of the GD results and the results of the similar experiments reported in (Sadeghi and Kittler, 2006)using the basic form of the GD metric shows that by optimising the GD metric as discussed, the problem of sensitivity of this metric to the miss-registration error is reduced so that the optimised GD metric outperforms the NC function for both manually the automatically registered data.

In the next step, the problem of combining classifiers derived from different similarity measures was considered. We adopted the decision level fusion strategy using the SVMs in order to combine the designed classifiers. Table 3 contains the combined verification results using manually and automatically registered data. These results demonstrate that a better performance is achieved using the combined method especially on Mc and G protocols.

6 CONCLUSIONS

The problem of measuring similarity in LDA face space and fusing the resulted classifiers were considered. It was shown that the optimised Gradient Direction metric outperforms the other metrics in different conditions considering both manually and automatically registered data. It was also demonstrated that the performance of the verification system can be further improved by fusing the adopted similarity measures in the decision level using the SVM classifier.

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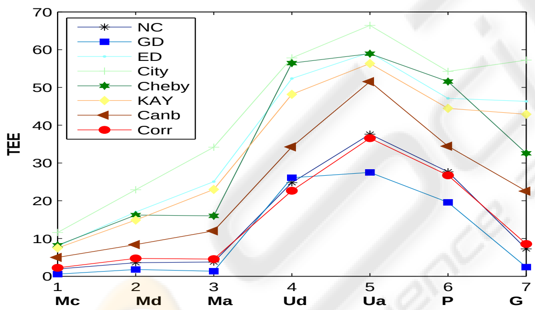
Table 2: ID verification results using different scoring functions with Global and Client Specific Thresholding techniques for unmatched and matched protocols respectively. TEE: Total Error rate Evaluation and TET: Total Error rate Test.

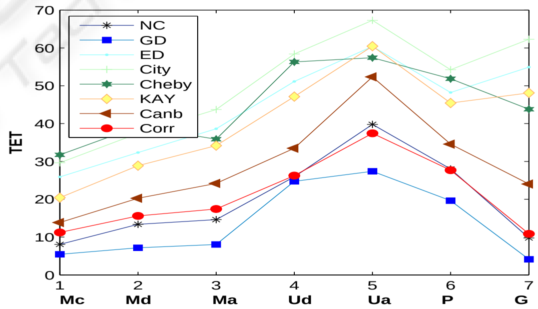
	Mc		Md		Ma		Ud		Ua		P		G	
	TEE	TET	TEE	TET	TEE	TET	TEE	TET	TEE	TET	TEE	TET	TEE	TET
NC	1.93	8.08	3.57	13.36	3.79	14.61	24.81	25.93	37.63	38.81	27.69	28.01	7.26	9.75
GD	0.60	4.87	1.77	7.18	1.55	8.03	26.09	24.74	27.5	27.40	19.56	19.64	2.43	4.12
ED	7.97	25.89	17	32.34	25.06	38.62	52.37	51.15	59.26	60.42	47.12	48.22	46.33	54.93
City	11.6	29.65	22.9	37.4	34.17	43.71	57.82	58.4	66.44	67.3	54.25	54.25	57.24	62.26
Cheb	8.2	31.73	16.22	39.23	16	35.86	56.44	56.3	58.94	57.41	51.56	51.85	32.54	43.79
χ^2	7.49	20.41	14.88	28.88	22.99	34.17	48.17	47.15	56.35	60.48	44.46	45.45	42.91	48.12
Corr	2.25	11.22	4.74	15.6	4.54	17.43	22.66	26.25	36.57	37.44	34.44	34.54	8.02	10.85
Canb	5	13.85	8.69	20.25	12.01	24.2	34.26	33.5	51.54	52.37	26.74	27.69	22.54	24.04

Table 3: ID verification results on BANCA protocols considering SVMs for combining classifiers derived from different metrics, manual registration(left) and automatic registration (right).

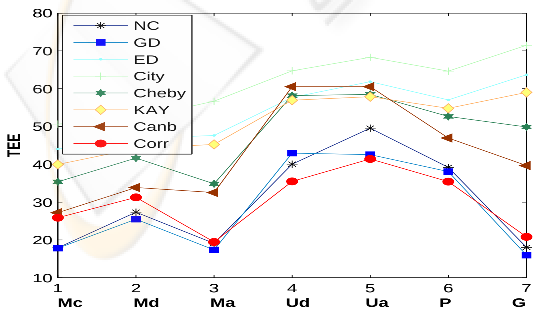
	Manual Registration						Automatic Registration					
	Evaluation			Test			Evaluation			Test		
	FAR	FRR	TER	FAR	FRR	TER	FAR	FRR	TER	FAR	FRR	TER
Mc	0.96	1.03	1.99	0.86	1.54	2.4	8.17	8.2	16.37	5.96	9.36	15.32
Md	3.75	3.85	7.6	2.98	3.97	6.95	8.36	8.46	16.82	12.79	6.28	19.07
Ma	2.4	2.31	4.71	3.65	5.27	8.92	5.57	5.51	11.08	2.02	15.9	17.92
Ud	9.61	9.61	19.22	10.38	13.46	23.84	13.46	13.46	26.92	15.09	15	30.09
Ua	12.88	13.08	25.96	16.63	10.39	27.02	17.88	17.82	35.7	28.17	23.08	51.25
P	8.87	8.85	17.72	9.29	9.06	18.35	15.64	15.6	31.24	14.33	16.62	30.95
G	1.54	1.54	3.08	1.31	1.84	3.15	7.05	7.05	14.1	7.53	8.76	16.29



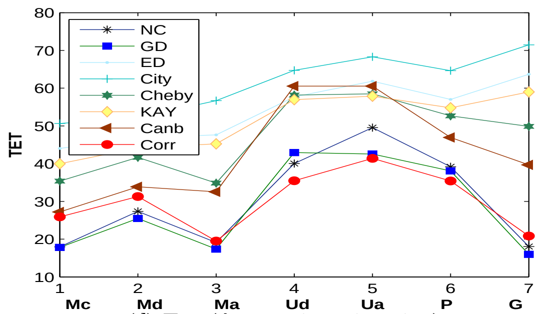
(a) Evaluation (Manual registration)



(b) Test (Manual registration)



(c) Evaluation (Automatic registration)



(d) Test (Automatic registration)

Figure 2: ID verification results using different scoring functions with Global and Client Specific Thresholding techniques for unmatched and matched protocols respectively.