Facial Verification Using Probabilistic Methods

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Facial recognition using PCA based techniques is well established and many techniques have also used PCA for subject verification (Rizvi et al, 1998); including Euclidean distance, support vector machines and normalised correlation (Sadeghi et al, 2003). In recent years probabilistic techniques such as Bayesian classification have become a common research area for identification (Moghaddam et al, 2000, Chellappa et al, 2002), though this interest does not appear yet to have translated to verification. One possible reason for this is that the posterior probabilities tend to cluster whereas the likelihoods can span a wide range. This does not affect performance in recognition tasks since the classifier simply selects the maximum value from across many classes. However, badly-distributed probabilities make difficult the task of setting thresholds for verification. Here, we show how a probabilistic framework can be used to improve performance in a Bayesian approach to face verification, in particular examining the effect of histogram mapping of the posterior probability and its consequences in verification.

We use a six step probabilistic framework based on PCA:

1. Images are transformed using PCA for compression.
2. The 'global' intra-subject variance is estimated by combining intra-subject variance estimates from a number of subjects in a manner similar to that proposed by Lui and Weschler (1998).
3. The estimated covariance matrix is used in a multidimensional Gaussian to calculate the likelihoods of a candidate image arising from the claimed subject.
4. A mapping is found from the histogram of the likelihoods to an equalised histogram of various shapes:
    i. Flat – all likelihoods are equally probable;
    ii. Gaussian – likelihoods about 0.5 are most probable; and
    iii. Twin Gaussian – one Gaussian scales impostor likelihoods around 0.25, another Gaussian scales true subject likelihoods around 0.75.
5. The likelihoods are mapped using the transforms in step 4 to new likelihoods covering the entire range from 0 to 1.
6. Finally we threshold these transformed probabilities to gain a verification decision.

We constructed an experiment to evaluate any performance benefit from steps 4 and 5 of this framework. Our experiment compared the equal error rates (EER) from a verification task in five different conditions: the flat, Gaussian or twin Gaussian mapping was used; the raw likelihoods were used (steps 4 & 5 were omitted); or posterior probabilities were calculated from the likelihoods through Bayes rule (in place of steps 4 & 5).

For this experiment 138 images were used for training, 714 images of 119 subjects were used to estimate the covariance matrix, and 200 images of 200 subjects were used to find the histogram mappings. 800 images of 200 subjects and 800 impostor images were presented to the system for verification. All of these images were taken from the UND HumanID database B (Flynn et al, 2003).

The threshold was varied between 0 and 1 to gain receiver operator characteristic (ROC) curves for the flat, Gaussian and twin Gaussian histogram methods and for the posterior probability methods. Reasonable threshold steps could not be found for the raw likelihood method, so results are given for the four remaining arrangements. The EER for each method can be seen in Table 1 with the ROC curves in Fig. 1. The performances of the histogram mapped techniques are significantly better than the posterior probability method at the 1% significance level using a McNemar test (Beveridge et al, 2001); however the performance difference between the three histogram techniques is not significant.

We have shown that by using a probabilistic framework we can obtain significant improvements in EER for the verification task, by mapping the posterior probability in an appropriate way. These results point to the need to more fully investigate the different mappings used and to expand the size of the database used.

Method	EER %
Posterior Probability	17.3
Flat Histogram	14.8
Gaussian Histogram	14.5
Twin Gaussian Histogram	14.9

Table 1 – Equal Error Rates

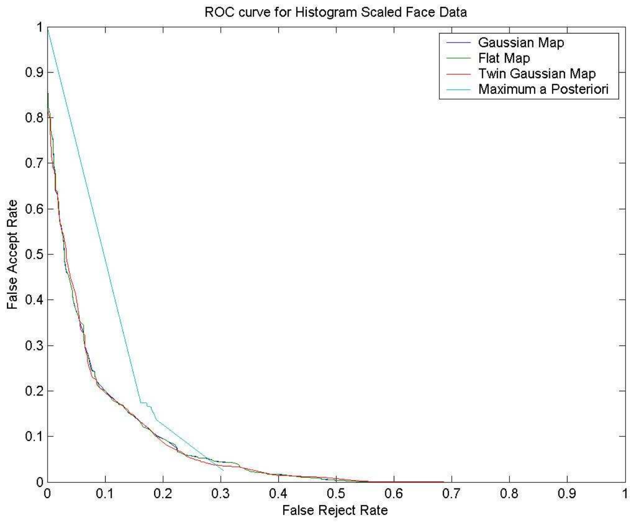

Figure 1 – Receiver Operator Characteristics

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