# Experiments with LDA and Probabilistic Matching for face verification

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## 1 Introduction

In this report, we present results of various tests involving two state-of-the-art face verification algorithms, namely LDA (Linear Discriminant Analysis [1]) and PM [4] (Probabilistic Matching) . Mainly, we tested the performance degradation when 1) the localization of test images is purposely perturbed 2) the image data are filtered and downsampled. All tests reported in this document were performed on the XM2VTS [3] database using a standard protocol [2](Lausanne protocol configuration I).

## 2 LDA results when image size is reduced

Table 2 shows the results of LDA on several image sizes. When going from a $n \times n$ to a $\frac{n}{2} \times \frac{n}{2}$ image, the image is filtered by a 2x2 uniform filter and downsampled by two. The images are normalized using histogram equalization. Two matching distances are presented: Euclidean and cosine (also called normalized correlation). The two last columns show the number of fisher vectors used, and the dimensionality of the intermediate PCA subspace.

| | | | Eval. | Test | | | | |
|---|---|---|---|---|---|---|---|---|
| size | norm. | dist. | ERR | FAR | FRR | TE | Fish.nb. | PCA dim. |
| 64x64 | HIST | EUCL | 2.67 | 3.53 | 3.50 | 7.03 | 60 | 120 |
| | | COS | 2.93 | 3.89 | 2.75 | 6.64 | 60 | 140 |
| 32x32 | HIST | EUCL | 3.01 | 3.57 | 3.50 | 7.07 | 70 | 100 |
| | | COS | 3.07 | 3.65 | 3.25 | 6.90 | 40 | 110 |
| 16x16 | HIST | EUCL | 3.50 | 4.28 | 3.35 | 7.53 | 40 | 110 |
| | | COS | 3.31 | 3.97 | 2.50 | 6.47 | 40 | 130 |
| 8x8 | HIST | EUCL | 6.33 | 8.06 | 22.00 | 30.06 | 20 | 40 |
| | | COS | 3.83 | 4.59 | 7.25 | 11.84 | 40 | 40 |

Table 1: LDA results for difference image sizes on XM2VTS database with Lausanne protocol configuration I.

The error rates don't seem to be affected by downsampling until 8x8 images. These images however give surprisingly good results as they convey very few information. This suggests that LDA algorithm make use of the low frequency features only, disregarding the high frequencies. These results were obtained on images registred using manually located eye coordinates.

# 3 LDA: image size and misregistration

We perturbed the eye coordinates located manually with 2-dim. vectors drawn from a gaussian distribution $N(0, \sigma)$. We expected that small images, as they contain no high frequencies, will be more robust to misregistration errors, since low frequencies are less localized than high frequencies. However, results in table 3 show that they are at least as sensitive as high resolution images.

| size | no pert. | $\sigma = 2$ | $\sigma = 4$ | $\sigma = 6$ |
|---|---|---|---|---|
| 64x64 | 2.93 | 4.40 | 10.83 | 18.90 |
| 32x32 | 3.07 | 4.31 | 10.26 | 19.89 |
| 16x16 | 3.31 | 4.89 | 11.29 | 21.47 |

Table 2: Sentivity of LDA to misregistration

It should be noted that the $\sigma$ is given in pixel of the original image (which is 586x720). For comparison, the size of the pupil of the eye at this resolution is about 15-20 pixels. Furthermore, the mean radius of the perturbation $\bar{r}$ is related to $\sigma$ by

$$\bar{r} = \sqrt{\frac{\pi}{2}}\sigma$$

# 4 LDA and PM : error correlation vs. misregistration

| Algo. | size | norm. | no pert. | $\sigma = 2$ | $\sigma = 4$ | $\sigma = 6$ |
|---|---|---|---|---|---|---|
| PM | 50x60 | ZMUV | 4.63 | 6.25 | 11.47 | 17.52 |
| LDA | 16x16 | HIST | 3.31 | 4.89 | 11.29 | 21.47 |
| FA error correlation | | | 31.9% | 33.5% | 43.0% | 37.7% |
| FR error correlation | | | 61.7% | 51.7% | 54.1% | 46.1% |

Table 3: Error correlation between LDA and PM versus misregistration

- The 2 algorithms are highly correlated.
- FR errors are much more correlated than FA errors
- Error correlation is +/- constant when misregistration is increased
- Simple combination techniques (logical OR/AND, linear discriminant) fail to improve the performance

We have chosen different normalization techniques (ZMUV stands for zero mean unit variance) different resolutions and image sizes (and also part of the face present in the image: for PM, the image contains actually a close up of the face excluding the face contour. In contrast, for LDA the image contains the face contour.) in order to have the 2 algorithms as less correlated as possible. For completeness, table 4 shows the results for PM with histogram equalization. The PM results are

| size | norm. | EER | FA | FR | TE |
|---|---|---|---|---|---|
| 64x64 | HIST | 3.43 | 4.71 | 3.00 | 7.71 |
| 64x64 | ZMUV | 4.50 | 4.89 | 4.75 | 9.64 |

Table 4: PM results on XM2VTS database configuration I with 2 image normalization

# References


[1] P. Belhumeur, J. Hespanha and D. Kriegman, “Face recognition: Eigenfaces vs. Fisherfaces: Recognition using class specific projection”, IEEE Trans. Pattern Analysis and Machine Intelligence, 19(7) 1997.

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[4] B. Moghaddam, W. Wahid, A. Pentland: ”Beyond eigenfaces: probabilistic matching for face recognition” Int’l conference on Automatic Face and Gesture Recognition, Japan, 1998.