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FACE DATASET EVALUATION THROUGH PREPROCESSING RESULTS

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Keywords: face dataset, face recognition, image processing

Abstract. Face datasets are considered a basic and important tool for evaluating the performance of face recognition methods. However, databases currently used for research purposes differ in relevant aspects (e.g. number of subjects, number of images per subject, lighting, backgrounds, etc.) which affect recognition performance. As a result, research papers focused on the comparison of face recognition algorithms usually draw contradictory conclusions, depending on the face dataset being used. In addition to this, most face recognition algorithms rely on a previous preprocessing step. Basically, images are modified in order to diminish the influence of subject pose, lighting, backgrounds, etc. and thus to improve recognition performance. In our paper, we carry out an evaluation of the most widely used face datasets, in order to conclude which of them are more reliable for comparing the performance of face recognition algorithms. To this end, we analyze the effect of different preprocessing steps on the results of a basic recognition algorithm (feature extraction by means of principal component analysis followed by nearest neighbor classification). Those databases where image preprocessing does not improve (or even lowers) the recognition rates are not considered reliable. These databases are studied on a per-case basis in order to detect the specific artifacts that alter the recognition results.

Face databases

Five different face databases have been used for the experiments: AT&T database [1], FERET database [2], YALE database [3], LFW database [4] and UMH database [5].

AT&T database: contains 400 gray level images (92x112 pixels) belonging to 40 different subjects (10 images per subject). All images were captured under controlled lighting and fixed distance to the camera. The main variations between images of the same subject are small pose changes and different facial expressions.

FERET database contains 14126 images of 1199 subjects where at least two images are available per subject (some subjects have a higher number of images taken in different days, in some cases more than one year apart). Images are 24-bit color, 512x768 pixels. Over images taken in the same day, the main variation is facial expression; over images taken in different days there are much more variations, including pose, hairstyle and even aging. We use a subset of FERET containing only the first 100 subjects.

YALE database or *extended Yale database B cropped*: contains 16128 gray level images of 28 subjects, with differences in lighting (64 different lightings) and pose (9 different poses), which makes 64x9 = 576 images per subject. Images have been manually aligned, cropped, and then re-sized to 168x192 pixels. It must be stated that the 64 different images per subject and pose are taken almost instantly, so that facial expression can be considered invariant. For our experiments, we use a subset where only 10 images per subject are kept (in our subset, all images show the same pose and only lighting differs; among the 64 possible lighting scenarios we have manually selected 10 clearly different ones).

LFW database: contains 13233 color images of 5749 subjects, obtained from the internet. The number of images per subject varies from 1 (for the less popular subjects) to 530 (for the most popular subject). There is a high level of variability between images, which makes this database realistic in terms of similarity to a real face recognition scenario. Images have been automatically registered using the Viola-Jones algorithm, and resized to 250x250 pixels. For our experiments, we use a subset of 158 subjects (those subjects with 10 or more images). Besides, we use only the first 10 images of each subject (in order to avoid biasing the classifiers towards the most populated classes) so our subset contains a total of 1580 images.

UMH database: our own database contains 510 color images of 17 subjects (30 images per subject). Lighting is uncontrolled, and variations between images of the same subject include distance to the camera, pose, background, facial expression and focus (different cameras were used). Apart from that, dark glasses and caps introduce occlusions in some of the images. Image size is 121x151 pixels.

Image preprocessing techniques

Image preprocessing techniques evaluated fall in three categories:

- Image registration, namely face detection and alignment. We have selected the well-known Viola-Jones algorithm [6] for our experiments, due to its widespread usage and proved performance.
- Lighting correction. We have selected both the basic histogram equalization technique and a more complex filter proposed by Tan and Triggs [7].
- Background suppression (by image cropping). Background suppression is carried out by cropping the images with a mask defined by two elliptical borders, as suggested in [8].

Viola-Jones algorithm was initially designed to detect any kind of objects (cars, faces, etc); where the kind of object detected depends just on the training images used. Nowadays, it is widely used for frontal face detection, which performs reliably and fast with independence of scale and lighting.

Viola-Jones works by evaluating a huge number of extremely simple features (160000 features per sub-window of 24x24 pixels) over the image. Features are computed as additions and subtractions of pixel values corresponding to different areas; and the concept of integral image is used to speed up the process.

A simple classifier (a perceptron with only one neuron) is adjusted for every feature, and Adaboost [9] is used in order to avoid overfitting.

Training is carried out with a large dataset of correct images (containing the object of interest) and wrong images (not containing it). The training process is extremely slow (it may take days for a standard computer); but once the system is trained, the on-line computing time is below 50ms for a 300x300 image. In order to achieve such processing speed, a cascade of classifiers is used.

Histogram equalization is one of the most common preprocessing techniques. It is used both for improving the visual appearance of images (by adjusting the contrast) and for making images more homogeneous in terms of lighting.

Basically, the cumulative histogram of the image is linearized, thus making contrast more homogeneous in all the gray level range. The goal when applied as preprocessing in face recognition is to compensate for differences in lighting between images.

The objective of the Tan-Triggs filter is to make images as independent as possible from lighting, even in the presence of shadows. It is a three step process:

- First, a gamma correction is performed by applying a power law to the pixel intensity values (by default, the exponent is set to 0.2). The goal is to make the resulting image independent of the overall illumination intensity.
- Then, a difference of Gaussians (DoG) filter is applied. The goal is to reduce the effect of shadows in the images by band-pass filtering them. By default, the standard deviations of the inner and outer Gaussians are 1.0 and 2.0 pixels.
- Finally, image intensities are rescaled by contrast equalization.

Experiments

Among the most widely used feature extraction techniques for appearance-based face recognition, we have decided to use Principal Component Analysis (PCA) [10] for our experiments. The preprocessing algorithms will be compared in terms of percentage of correct classifications. First, the image database is split in a training subset and a testing subset. Then, PCA is applied to the training subset in order to determine the directions (features) that will be used to compress the data. Then, all images (training and testing) are represented in the basis defined by such directions, and a nearest neighbor algorithm is used to classify the test images. The percentage of correct classifications (test images classified as corresponding to the correct subject) is obtained. The Matlab code used for the experiments, as well as usage information, are available at [11].

The same process is carried out for original images and for images where different preprocessing algorithms have been applied; and all the experiments are run for all image databases considered (AT&T, FERET, YALE, LFW and UMH).

All the possible preprocessing combinations are tested, which results in 12 different scenarios, which are be coded according to the following order:

- 2 options for image registration: no preprocessing (0) or Viola-Jones algorithm (1).
- 3 options for lighting correction: no preprocessing (0), histogram equalization (1) or Tan-Triggs algorithm (2).
- 2 options for image cropping: no preprocessing (0) or cropping by elliptical borders (1).

A complete preprocessing for an image is coded as nmp , where n represents the image registration performed; m represents the lighting correction applied and p represents the image cropping carried out (e.g. code 110 corresponds to first applying the Viola-Jones algorithm, then performing an histogram equalization and, finally, not cropping the image).

Figures 1 and 2 show the results obtained when all possible preprocessing combinations are applied to one of the images belonging to the UMH database. In figure 1 the processing codes (from left to right) are: 000, 001, 010, 011, 020, 021 (note: all possible combinations without image registration); in figure 2 the processing codes are: 100, 101, 110, 111, 120, 121 (all possible combinations with an initial image registration).



Figure 1. Example of preprocessing combinations without image registration.



Figure 2. Example of preprocessing combinations with an initial image registration.

In the set of experiments has been carried out, one image per subject is used for training, and all remaining images of the same subject are used for testing. Figures 3 to 7 show the results obtained.

In the figures, experiments are numbered from 1 (preprocessing code 000) to 12 (preprocessing code 121), except for the YALE database, where images are already cropped and we have decided not to perform experiments with image registration. The results show both the average recognition rate and the standard deviation of the results.

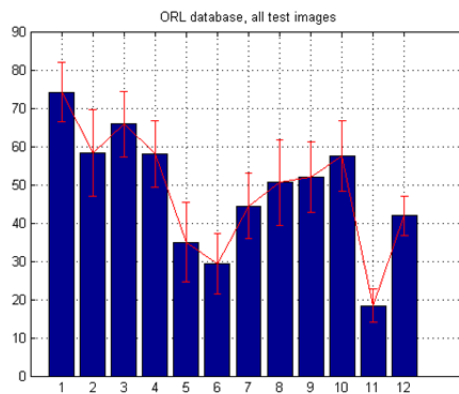


Figure 3. Recognition rates for AT&T database, 1 training image and 9 test images.

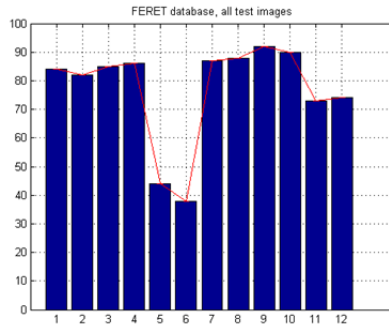


Figure 4. Recognition rates for FERET database, 1 training image and 1 test image.

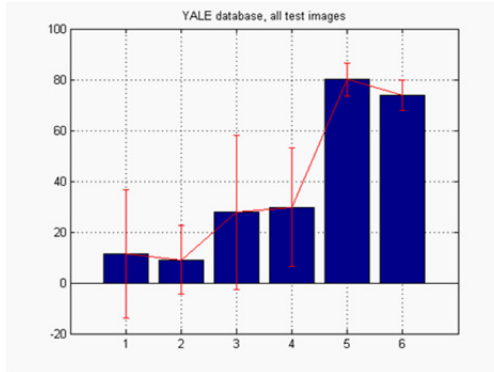


Figure 5. Recognition rates for YALE database, 1 training image and 9 test images (no registration is performed because the images are already cropped).

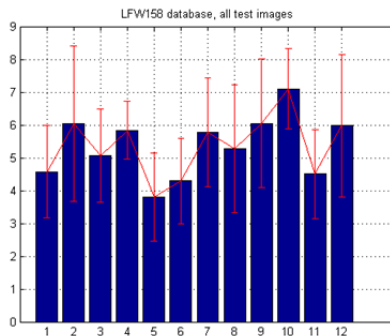


Figure 6. Recognition rates for LFW database, 1 training image and 9 test images.

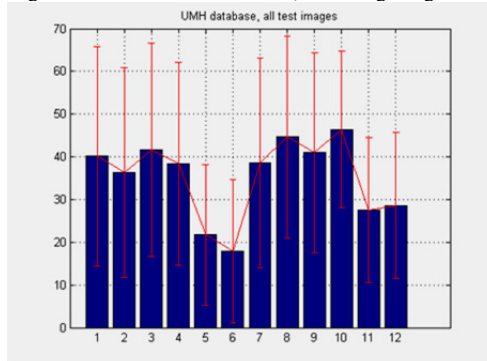


Figure 7. Recognition rates for UMH database, 1 training image and 29 test images.

Conclusions

According to the results: AT&T database is not a good test-bench for preprocessing algorithms, as images were captured under extremely controlled conditions. YALE cannot be considered valid either, as results on this database are always biased towards algorithms performing a high level of lighting correction, even if this supposes a considerable loss of image information. LFW, UMH and FERET (in this second set of experiments) seem to be more valid test-benches.

On the above mentioned three databases, the best preprocessing combination includes image registration through the Viola-Jones algorithm followed by lighting correction through histogram equalization and, finally, image cropping using elliptical borders.

References

- [1] AT&T, The Database of Faces (formerly known as "The ORL Database of Faces"). <http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html>.
- [2] Phillips, P.J., Moon, H., Rauss, P.J., Rizvi, S.: The FERET evaluation methodology for face recognition algorithms. *IEEE Trans. Pattern Analysis and Machine Intelligence*. 22, 10, 1090--1104 (2000)
- [3] Lee, K.C., Ho, J., Kriegman, D.: Acquiring Linear Subspaces for Face Recognition under Variable Lighting. *IEEE Trans. Pattern Anal. Mach. Intelligence*. 27, 5, 68--698 (2005)
- [4] Huang, G.B., Ramesh, M., Berg, T., Learned-Miller, E.: Labeled Faces in the Wild: A Database for Studying Face Recognition in Unconstrained Environments. University of Massachusetts, Amherst, Technical Report 07-49 (2007)
- [5] UMH face database. <http://lcsi.umh.es/investigacion/facerecognition/face-database-umh>.
- [6] Viola, P., Jones, M.J.: Robust Real-Time Face Detection. *International Journal of Computer Vision*, 57, 2, 137--154 (2004)
- [7]. Tan, X., Triggs, B.: Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions. *IEEE Trans. Image Processing*. 19, 6, 1635--1650 (2010)
- [8] Chen, L.F., Liao, H.Y., Lin, J.C., Han, C.C.: Why recognition in a statistic-based face recognition system should be based on the pure face portion: a probabilistic decision-based proof. *Pattern Recognition*. 34, 1393--1403 (2001)
- [9]. Freund, Y., Schapire, R.E.: A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of Computer and System Sciences*, 55, 1, 119--139 (1997)
- [10] Turk, M., Pentland, A.: Eigenfaces for recognition. *J.Cognitive Neuroscience*. 3, 1, 71--86 (1991)
- [11] Matlab code for PCA experiments. http://coolab.umh.es/ica_pca/index_en.html