COMPARING FACES: A COMPUTATIONAL AND PERCEPTUAL STUDY

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Abstract: The problem of extracting distinctive parts from a face is addressed. Rather than examining a priori specified features such as nose, eyes, mouth or others, the aim here is to extract from a face the most distinguishing or dissimilar parts with respect to another given face, i.e. finding differences between faces. A computational approach, based on log polar patch sampling and evaluation, has been compared with results obtained from a newly designed perceptual test involving 45 people. The results of the comparison confirm the potential of the proposed computational method.

1 INTRODUCTION

Automatic face analysis is an active research area in which interest has grown over recent years.One of the most challenging and interesting issues in the automated analysis of images of faces is the detection of "facial features", intended as characteristic parts of the face. Many approaches have been proposed for the extraction of such facial features (see (Campadelli and Lanzarotti, 2004) and references therein). Most of these are devoted to the detection of a priori specified features, such as the nose, eyes, mouth, eyebrows or other, non anatomically referenced, fiducial points. In practice, however, for face recognition and authentication, it is necessary to consider additional features, in particular those that precisely characterize a given face. Rather than simply extracting standard patterns to distinguish the face of subject "A" from that of subject "B", it is important to extract from the face-image of subject "A" as many as possible of the features that differ significantly from, or are not even present in, face "B".

Recently, an area-based approach aimed at "finding differences" between faces was proposed (a preliminary version appeared in (Bicego et al., 2005)). It extracts from one face-image the most distinguishing, or dissimilar, areas with respect to another face-image, or to a population of faces. In particular, the proposed algorithm extracts, from two face-images, a set of sub-images centered at different locations within each image. This process samples most of the face, in a way similar to that adopted in patch-based image classification (Dorko and Schmid, 2003)) and image characterization (Jojic et al., 2003). At each location, data are sampled according to a "multi-scale" regime in which image patches encode grey-scale pattern at different spatial resolutions. A log polar mapping (Grosso and Tistarelli, 2000) has been adopted for this purpose. The image patches thus extracted constitute two data-set features, each characterizing a single face. Next a classifier is trained so as to best distinguish between the two face-classes purely on the basis of the grey-levels values of the pixels within each patch. By identifying the loci of the patches in the resultant classification space the degree of "distinctiveness" can be assessed as the distance from the trained hyperplane. Since the classifier is trained to separate patches of the first face from patches of the second, we hypothesize that the most important differences between the two faces will be encoded by the patches furthest from the separating hyperplane (i.e. those that the classifier weights highest). In (Bicego et al., 2005) examples of the most important patches were extracted and shown for several different images.

In this paper the computational method has been enhanced and improved, particularly when computing the difference between patches and when visualizing the results. However, the main aim here is to investigate the question: are the differences extracted and assigned importance by our algorithm also judged important by human observers? In section 3 we present an initial perceptual study that provides some preliminary evidence that human observers may indeed con-

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sider important the patch locations identified by our algorithm.

2 COMPUTATIONAL EVALUATION

The idea here is to determine those areas of a given face-image that differ most from any other face-image. In brief, we achieve this by projecting into a feature space two sets of image patches, sampled from two face-images, and scoring the patches by their mutual distances. The most distant features found in the feature space are likely to be the more distinctive face areas for the specific faces.

In detail, our algorithm extracts, from the two face-images, a set of patches centered upon specific points—where these points are uniformly distributed across the face-image such that most, or all, of the face area is covered by the sampling process. Each patch maps on to a coordinate in a multi-dimensional feature space by virtue of its sample grey-levels. We adopt simple feature formulation approach by considering the sample grey-levels in each patch as ordered coordinate values as resulting from the log polar sampling—in practice defining a 400-D space. The patches from one face-image will tend to form their own cluster in this space: the other face-image ought to form a different cluster. Our extracted patches thus constitute two data-clusters of location-independent features, each of which characterize one of the two faces. Based on the distribution of those patches within feature space, degrees of distinctiveness of each face patch can be formulated according to its distance from the projection of the other data-cluster. Patches with the highest weights are then interpreted as encoding the most important differences between the two face-images.

Since face recognition involves information apparent at a various spatial resolutions a multi-scale analysis should provide an advantage over any single scale analysis A multi-scale analysis could repeat the classification procedure with patches of various sizes, and then judiciously combine the results to obtain the important differences. We adopt a variant multi-scale approach designed to avoid two notable pitfalls: (a) blind analysis - whereby information revealed at one scale is not usefully available at other scales, and (b) repeated image processing - which adds to the overall computational expense.

Our solution is to sample the face-image using patches derived from a log-polar mapping (Grosso and Tistarelli, 2000). This mapping can also be motivated by its resemblance to the distribution of the receptive fields in the human retina, where the sampling resolution is higher at the central fovea and decreases toward the periphery. The resultant sampling process ensures that each patch contains both low scale (fine resolution) and contextual (low resolution) information.

Facial features are then selected in two steps:

1. two distinct sets of patches are extracted from the two face-images at specific image locations;
2. for each of the two faces, the patches are ranked according to their distances from the other cluster in feature space.

2.1 Multi-scale Face Sampling

The patches sampled from the original face-image are centered at a pre-specified set of points. To ensure translation-independence the locations of these points ideally ought to be selected randomly (Bicego et al., 2005). Yet since that would require very many sampling points, in order to completely cover the two faces we adopt here a regular sampling regime for which the faces have been manually registered beforehand.

The face-image is re-sampled at each point following a log-polar scheme (Grosso and Tistarelli, 2000) so that the resulting set of patches represents a local space-variant remapping of the original image, centered at that point. Analytically, the log-polar scheme describes the mapping postulated to occur between the retina (retinal plane (r, q)) and the visual cortex log-polar or cortical plane (x, h)). The size of the “receptive fields” follows a linear increment moving from the central region (fovea) outwards into the periphery. Due to lack of space, full details of the log-polar transformation are not given here, interested reader are referred to (Grosso and Tistarelli, 2000).

The set of log-polar image patches, sampled from each face-image, are vectorized, and represent the face in feature space.

2.2 Determining Face Differences

As stated early, the “distinctiveness” of each patch is related to its locus in feature space with respect to the other face. In particular, those patches of the first face, found near loci of the second face in feature space are less distinctive since they may easily be confused with the patches of that second face. On the other hand, patches located near the first face-set should be usefully representative.

More formally, let S_A, S_B the set of patches of face A and B, respectively. The weight of distinctiveness ω of a patch $p_A(x, y)$, centered at the position (x, y) in the face A is computed as:

$$\omega(p_A(x, y)) = d(p_A(x, y), S_B) \quad (1)$$

where

$$d(p_A(x,y), S_B) = \min_{(x',y')} d_E(p_A(x,y), p_B(x',y')) \quad (2)$$

where d_E is some distance metric between feature vectors. Here, for simplicity, we adopt a Euclidean metric. It might be worthwhile investigating other metrics, such as those due to transforming feature space via say a Principal Component Analysis or Linear Discriminant Analysis.

We measure both the difference of face A to face B and vice versa since the two distinctiveness results can and do vary. In each case, the results are projected back on to the spatial image of the face using a parallel flood-filling technique. This renders a "difference" map in which the grey level of each pixel indicates the level of distinctiveness.

3 PERCEPTUAL STUDY

We describe here an informal study of how human observers report seeing difference between faces with the aim of comparing the result obtained with that of our algorithm. This is in anticipation of an objective psychophysical investigation that we intend to present in the future.

A perceptual experiment was implemented in Matlab on a laptop PC. Human subjects, with normal, or corrected vision, were selected for a set of trials. In all 45 university students (7 male, 38 female) were tested. Each trial began (after 2 seconds of mid-gray screen) by presenting a stimulus consisting of two monochromatic face-images side-by-side on a mid-gray background. After a fixed time-interval the stimulus was replaced by a single cartoon-image (of roughly the same size) of a "general face" or mock-up upon which the subject was then asked to navigate and click using the PC's mouse. The task, explained beforehand via a training example, was to indicate any part of the face where they had seen an important difference during the stimulus presentation. After 5 seconds the mock-up was replaced by the mid-gray background ready for the next trial to be initiated. A set of trials consisted of repeating this procedure until each of six chosen face-pairs had been presented to the subject. The results were later reviewed by overlaying the clicked points on the mock-up and displaying it on screen or paper—e.g see Fig. 2.

Viewing parameters were fixed as follows: viewing distance: 50 cm; image height: 9 cm (10 deg, 310 pixels); image width: 6 cm (7 deg, 200 pixels); image-pair separation: 4 cm (5 deg); stimulus width: 14 cm (19 deg); full contrast screen setting under indoor ambient illumination.

In the training example—Fig. 2(Exp. 1)—the two

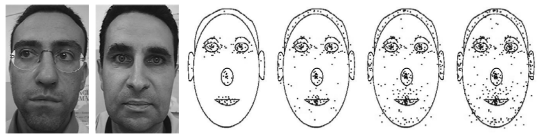


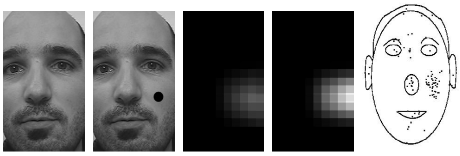
Figure 1: Top line: stimulus faces. Bottom line: results of perceptual study increasing the time interval: 0.5, 1, 2, 4 s. The displayed maps are accumulative, i.e. each is the sum of all the previous map plus the current one.

images were identical except for the artificial superposition of a easily seen dark spot on one cheek. In the trials image pairs presented two different persons, except in one case where the same person with, and without, facial make-up and earrings was employed.

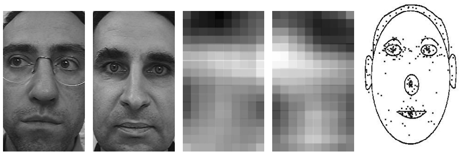
Stimulus presentation time ought to allow the observer to have time at least to scan both faces. Since, it was initially unclear what interval might suffice we repeated each set of trials four times on each occasion doubling presentation time—i.e. 0.5, 1, 2 and 4 s. Note, learning effect might thus contaminate the results of the later set of trials, and so they are avoided in the next section. For short intervals one might expect a concentration on specific location (featural process), while for long intervals the tendency may be to convey the attention to the overall face (see (Collishaw and Hole, 2000)). This is indicated the mock-ups in the lower parts of Fig. 1, which incrementally shows the face areas clicked upon during the four trial sets (the i-th image accumulates the results from the first i trials). It seems that as the interval increases, observers focus their attention upon configurational aspects of the face such as cheeks, the upper lip zone and between the eyes.

4 EXPERIMENTAL COMPARISON

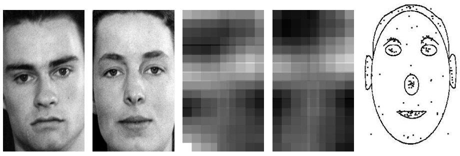
Here we graphically compare difference maps produced by our algorithm with the mock-up results from our perceptual experiment. To this end the algorithm was run on the same face-image pairs presented in the experiment—as follows. Each log-polar patch had a resolution of 23 eccentricity steps and 35 receptive fields at each, with a 10% overlap along the two directions. The images were cropped in order to eliminate the influence of the background, often omitting the ears. Here we employ only the mock-ups that combine the 0.5 and 1 s time intervals in order to reduce any learning effect contamination. Fig. 2 compares three results. In general, these graphical comparisons are indicative of the high, if not perfect, degree of agreement found between the algorithmic-produced



Experiment 1



Experiment 2



Experiment 3

Figure 2: Comparison of computational and perceptual results: For each experiment, the first row contains the original images, the second the results of computational and perceptual experiments.

difference maps and the human-generated mock-ups. Below these comparisons are discussed in turn.

- *Comparison 1*. This is the training example intended to test the system in artificially controlled conditions. The two images are identical, except for the black dot attached to the cheek. The perceptual mock-up result indicates most dots in the correct zone, with a small spatially random component. The algorithm also maps the correct zone as the most important difference—via a light area. Both difference maps are shown: (a) that of the difference between the face-with-dot from the face-without-dot, and (b) vice versa. In the latter case, the maximum difference appears darker—presumably because that spot zone is actually more similar to other parts of the face-with-dot image. Otherwise the two maps have similar structure, as might be expected. In this case, the algorithmic and mock-up results are in good overall agreement.
- *Comparison 2*. This is a more realistic example involving two different faces. The perceptual result, the mock-up, indicates the majority of dots located on the mouth, the eyes and the nose, while a few points are found around the face contour. The algorithm is in agreement, especially highlighting the eye zones where the glasses appear to be fundamental in discriminating between the two faces. Neither the forehead nor the cheeks appear to be important. The two difference maps are structurally similar, except at the upper part of the right eye of the second face. This part, greatly highlighted by the algorithm indicates the right eyebrow, which appears very different from the one on the left (similar to those of the first face). Thus the algorithm is revealing a high level of details here.
- *Comparison 3*. This realistic example, compares a male face to a female face. The mock-up resulting from the perceptual trials distinguishes the eyes, the eyebrows, the mouth, the nose and the hair junction. The eyes and eyebrows are clearly identified by the algorithm, whereas less emphasis has been given to the mouth and to the nose. The hair junction has been detected only in one face, confirming that it is worth while to compute both difference maps. The large erroneous difference in the bottom left corner of the first face, is probably due to the neck that is present in the face-image. It is interesting to note that the algorithm is able to discover the inclination of eye-line of the first face and represents it in the difference map.

5 CONCLUSIONS

Here we addressed the problem of finding differences between faces from two complementary angles: algorithmic analysis and perceptual testing. In several experiments the difference maps computed showed a high degree of similarity to those made apparent by the perceptual testing.

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