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A NEW PROBLEM IN FACE IMAGE ANALYSIS: FINDING KINSHIP CLUES FOR SIBLINGS PAIRS

A. Bottino[1], M. De Simone[1], A. Laurentini[1] and T. Vieira[1,2]

[1]*Computer Graphics and Vision Group, Politecnico di Torino, C.so Duca degli Abruzzi, 24,Torino,Italy*
[2]*Departamento de Eletrônica e Sistemas, Universidade Federal de Pernambuco,Recife,Brazil*
{andrea.bottino, matteo.desimone, aldo.laurentini,tiago.figueiredo}@polito.it

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Abstract: Human face conveys to other human beings, and potentially to computers, much information such as identity, emotional states, intentions, age and attractiveness. Among this information there are kinship clues. Face kinship signals, as well as the human capabilities of capturing them, are studied by psychologist and sociologists. In this paper we present a new research aimed at analyzing, with image processing/pattern analysis techniques, facial images for detecting objective elements of similarity between siblings. To this end, we have constructed a database of high quality pictures of pairs of siblings, shot in controlled conditions, including frontal, profile, expressionless and smiling face images. A first analysis of the database has been performed using a commercial identity recognition software. Then, for discriminating siblings, we combined eigenfaces, SVM and a feature selection algorithm, obtaining a recognition accuracy close to that of a human rating panel.

1 INTRODUCTION

Analyzing face images is a main research topic in pattern analysis/image processing, since face is the part of the body that supplies more information to other humans and thus potentially to computer systems. A traditional area of research is identity recognition, but several other areas are emerging, such as affective computing (Pantic and Rothkrantz, 2003), age estimation (Fu and Huang, 2010) and analyzing attractiveness (Bottino and Laurentini, 2010).

In this paper we deal with the new problem of analyzing facial kinship clues with objective pattern analysis/ image processing techniques. The problem of kin recognition has been much studied in human sciences areas such as psychology and sociology. According to the theory of inclusive fitness put forward by Hamilton (1964), recognizing kinship and also the degree of relatedness is very relevant to social behavior of animals and humans. According to Bailenson et al. (2009), facial similarity could also affect voting decisions.

Detecting kinship from face images could have applications in other areas, as historic and genealogic research and forensic science.

Several human scientists have investigated the ability of human raters of recognizing kinship from human face images, and have attempted to locate the facial features more significant as kinship clues. For instance, Kaminski et al. (2009), using a data set of face images shot in uncontrolled condition, reported a correct classification of kinship of 66% for siblings. For a comparison, the raters did not exceed 73% of kinship

assessment when shown two images of the same person. Maloney and Dal Martello (2006), on the basis of a high quality data set of children images, found that the upper part of the face carries more kinship clues.

Very little research on recognizing kinship from face images is reported in pattern analysis area. With regard to facial similarity, a related problem, Holub et al. (2007) described the construction of facial similarity maps based on human ratings. The relationship between human perception of similarity and computer based scores has been investigated also by Kalocsai et al. (1998), which found that the Gabor filter model was closer to human judgment than PCA.

The only research explicitly dealing with the computer analysis of facial features for a set of parent/child images has been presented in a paper by Fang et al. (2010). A database containing 150 semi-frontal image pairs, collected from the Internet and shot in uncontrolled lighting conditions, was analyzed. 22 facial features and small windows surrounding feature points were extracted according to the Pictorial Structure Model. KNN and SVM classifications provided accuracy of 70.67% and 68.60%, respectively. These data should be compared with the average classification accuracy of 67.19% of a panel of human raters on the same dataset.

In this paper we present a new investigation on detecting couples of siblings with computer analysis of facial similarity elements. To avoid problems due to the heterogeneity of images collected on the Internet, we have prepared a high quality database of pairs of siblings, shot in exactly frontal and profile positions, with and without expression and in the same lighting conditions. The database, that will be made available to other researchers, has been first analyzed with a commercial face recognition package. Then, for discriminating siblings, we used PCA, SVM and a feature selection algorithm. Finally, the results of the computer analysis have been compared with the classification supplied by human raters.

The content of the paper is as follows. In section 2 we describe the databases used. In section 3, we report the results obtained using a commercial identity recognizer software for discriminating pairs of siblings. In section 4, the proposed method for automatic siblings recognition is discussed. In section 5 we compare the results of our classifier with that obtained by human raters on the same dataset. Finally, conclusions and future works are presented in section 6.

2 DATABASES

Heterogeneous data sets, as those containing images collected over the Internet, have been used several times in face analysis. However, uncontrolled imaging condition can introduce disturbing elements which can seriously affect the result of the research. In order to avoid these problems, we constructed for our analysis a high quality database, called HQfaces, containing images of 97 pairs of siblings. A subset of 79 pairs contains profile images as well, and 56 of them have also smiling frontal and profile pictures. The images, with resolution 4256×2832, were shot by a professional photographer with uniform background and controlled lighting. The subjects are voluntary students and workers of the Politecnico di Torino and their siblings, in the age range between 13 and 50. All subjects are Caucasian and around 57% of them are male. As an example, some cropped frontal expressionless images of siblings in HQfaces are shown in Figure 1 (top row). Currently, the DB is available on request contacting the authors. In order to verify the advantages of using high quality images, we also prepared a second database, LQfaces, containing 98 pairs of siblings found over the Internet, where most of the subjects are celebrities. The low quality photographs have an average size of 378x283, they are almost frontal, but not always expressionless, and with various lighting conditions. Profiles are not available in LQfaces. The individuals are 45.5% male, 87.9% Caucasian, 9.1% Afro-descendants and 3% Asiatic. Examples of siblings in LQfaces are shown in Figure 1 (bottom row).

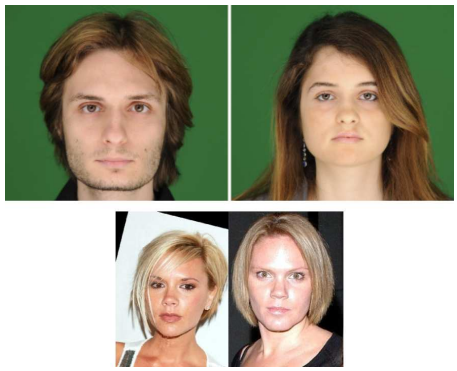

Figure 1: Pairs of siblings from the HQfaces (top row) and from the LQfaces (bottom row).

2.1 Databases normalization

Images in the DBs have been normalized. This process was first aimed at aligning them and delimiting the same section for all frontal and profile faces, including the most significant facial features. Geometric normalization is based on the position of two landmarks in the images. For frontal images, those points are the eye centers. For profiles, the repere points are Nasion (the depressed area directly between the eyes, just superior to the bridge of the nose) and Pogonion (the most anterior point on the chin). Eye centers are detected using the Active Shape Model (ASM) technique (Milborrow and Nicolls, 2008) while the profile landmarks are identified using an algorithm derived from that in Bottino and Cumani (2008). Examples of extracted keypoints are shown in Figure 2.

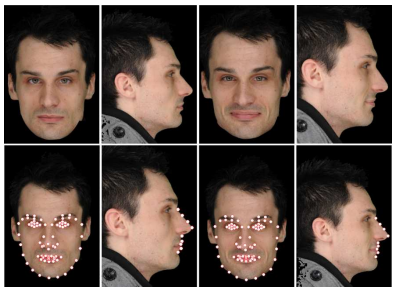

Figure 2: Expressionless/smiling frontal and profile, faces from HQfaces (top row). Keypoints extracted from corresponding photographs (second row).

The result is a *normalized image* enclosed within a fixed area of interest (*standard area*) with the selected landmarks aligned and coincident with two predefined fixed points (*reference positions*). The transformations involved are rotation and translation, to align the line joining the landmarks with the corresponding line in the standard area, isotropic scaling to make the landmarks coincident, and finally cropping. The dimension of the standard area and the reference positions, in pixel units, for frontal and profile HQfaces and frontal LQfaces are shown in Table 1.

Table 1: Reference positions used for normalization.

Normalized image	***Standard area***	***Reference position 1***	***Reference position 2***
Frontal HQ	1000x1000	Left eye: (200,200)	Right eye: (800,200)
Profile HQ	800x600	Nasion: (400,100)	Pogonion: (400,700)
Frontal LQ	140x140	Left eye: (20,20)	Right eye: (120,20)

Finally, normalized images are converted to grayscale and their histograms are equalized. For profile images, the background is discarded using simple chroma-keying techniques prior to colour and intensity related processing, since part of it appears in the standard area.

3 PREDICTING KINSHIP WITH A COMMERCIAL FACE RECOGNIZER

The concept of "similarity" of faces is much more encompassing than the concept of "identity". However, we believe to be interesting attempting to recognize pairs of siblings using an effective commercial identity recognition software. For this task, we selected the FaceVACS® Software Development Kit (SDK), supplied by Cognitec Systems (Cognitec, 2011). A previous version of this software was tested in the Face Recognition Vendor Test (FRVT) 2006, obtaining excellent results in identity recognition (Phillips et al., 2010).

When the SDK analyses a pair of images, it provides a score value $s \in [0,1]$. The higher the score, the higher the probability they belong to the same subject. Since siblings are likely to share facial attributes, one can suppose that the score between two siblings should be higher than the score between two unrelated people.

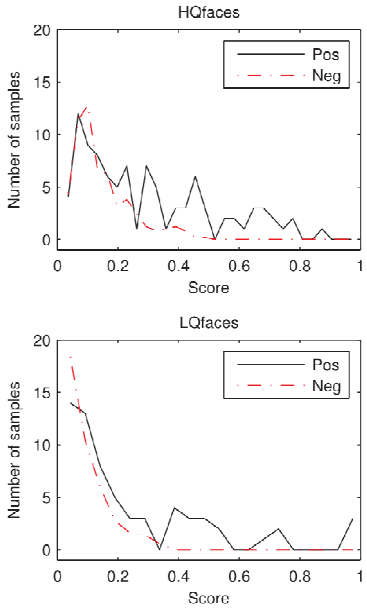

Figure 3: Scores histograms for HQfaces (top) and for LQfaces (bottom).

Indeed, the FaceVACS can provide an initial insight about the possibility of dealing with sibling images. We experimented FaceVACS with all pairs of siblings and with an equal number of randomly selected pairs. The histograms of the scores are shown in Figure 3, where Pos stands for pairs of siblings, and Neg for random pairs of not siblings. The figure shows that no negative pair scored higher than 0.4 for LQfaces and 0.5 for HQfaces. In other words, if the score of a couple of images is above these thresholds, they are likely to belong to siblings, otherwise, another algorithm must be used to make the decision. Using a fixed threshold might guarantee a null False Acceptance Ratio (FAR) but strongly penalizes the False Rejection Ratio (FRR), since there are many positive samples with scores lower than this threshold. For instance, to obtain a null FAR, the FRR is 78.12% for LQfaces, and 82.47% for HQfaces.

4 USING PCA, SVM AND FEATURE SELECTION FOR SIBLINGS VERIFICATION

Eigenfaces, first suggested by Sirovic and Kirby (1987), have been extensively used for face image analysis in reduced dimensionality spaces. The main feature of the eigenfaces is that they capture both facial texture and geometry. Since we do not know yet which are the facial elements more significant for detecting kinship clues for siblings, we decided in this paper to perform a first analysis using this popular catch-all technique for feature extraction.

The main datasets used for our experiments are the following:

i. 196 frontal images of subjects from LQfaces (98 siblings pairs);
ii. frontal expressionless images of 184 subjects from HQfaces (92 siblings pairs);
iii. 158 individuals, represented by a set of a frontal and a profile expressionless images from HQfaces (79 siblings pairs);
iv. 112 individuals, represented by a set of expressionless frontal and profile, smiling frontal and profile images from HQfaces (56 siblings pairs).

The outline of the proposed automatic sibling classification algorithm, irrespective of the dataset it is applied to, is the following:

a) Extract the principal components vectors from all the single images of the dataset and compute the representative vector of each individual;
b) Compute the representative vector for pairs of siblings and not siblings, where the representative vector of a pair is given by the absolute difference of the representative vectors of its composing individuals;
c) Train a SVM classifier with the representative vectors of a training set of pairs, composed by an equal number of siblings and not siblings, and apply the classifier to a test set. In order to improve classification accuracy, a feature selection (FS) algorithm has also been applied, and the output of FaceVACS combined with the SVM classification results.

In the following subsections, we will detail how these steps have been implemented, and we will describe and discuss the experimental results obtained for the classification of image pairs.

4.1 Representative vectors

For each dataset, we first compute its eigenfaces and then the representative vector $\mathbf{v}$ of each face by projecting it on these eigenfaces. For datasets containing different type of images for each person, (e.g. frontal and profile), eigenfaces are computed separately for each type of image and the representative vector of an individual is simply obtained by concatenating the representative vectors of each of its available images. In all datasets (and for each type of image), the dimension n of the representative vector (or of the part of it related to an image type) is the number of principal components that account for 99% of the total variance of the data (150 for frontal and 98 for profiles images in Hqfaces, 119 for images in LQfaces). The representative vector $\mathbf{v}^{(ab)}$ of a pair of images $I^{(a)}$ and $I^{(b)}$ or of a pair of image sets $IS^{(a)}$ and $IS^{(b)}$ in multi-type datasets, is computed from their representative vectors $\mathbf{v}^{(a)}$ and $\mathbf{v}^{(b)}$ as:

$$\mathbf{v}^{(ab)} = \text{abs}\,(\mathbf{v}^{(a)} - \mathbf{v}^{(b)})$$

The representative vector of a pair is such that $\mathbf{v}^{(ab)} = \mathbf{v}^{(ba)}$.

4.2 Building the classifier

For each of the four main datasets (i-iv), 6 different datasets of pairs have been composed, each containing all the positive samples (pairs of siblings) available and an equal number of randomly chosen negative samples (pairs of not siblings). All pairs datasets have been classified using Support Vector Machines. Five-Fold cross-validation technique has been used and a grid search has been done to optimize parameters of the SVM radial basis kernel, as suggested by Chang and Lin (2011). Other classification techniques, as KNN and Classification Trees, have been tested, but they provided worse classification results, that we omit for brevity.

4.3 Improving the classifier

For each pairs dataset, classification has been also performed applying the Minimum Redundancy and Maximum Relevance (mRMR) feature selection (FS) algorithm. This algorithm has been shown to be effective in building robust learning models, increasing the classification accuracy under different datasets and classification techniques (Peng, Long and Ding, 2005).

The mRMR algorithm selects, for each dataset, the more relevant features (eigenfaces) for characterizing the classification variable by assigning a score to each element of the representative vector of an image pair. For each main dataset, mRMR scores have been averaged over its six data sets, and the 20 more effective (on the average) eigenfaces have been used for final classification. The number of chosen feature is the one for which, on average, accuracies have a peak.

We have found that the eigenfaces more significant for discriminating siblings are relatively stable with respect to the pairs dataset used. To support the thesis that the described technique is sufficiently general to also work with other databases of siblings, we performed further tests subdividing each of the 6 pairs datasets into 4 not intersecting subsets, composed by an equal number of siblings and not siblings. For these subsets, we obtained again similar eigenvectors from mRMR. An example of the eigenfaces selected by mRMR is shown in Figure 4 for frontal HQfaces.

Figure 4: Best eigenfaces for dataset ii.

As further improvement, we combined SVM classification, feature selection and the FaceVACS SDK results. In section 2, we observed that FaceVACS SDK was effective in detecting siblings when scores are above a predefined threshold. Then we corrected the SVM classification as follows. For each sample classified as Not Siblings, we check the FaceVACS SDK score, and, if greater than 0.5, we change the classification to Siblings. This heuristic provides slightly better, from 1% to 3.5%, classification accuracies.

4.4 Classification results

The classification results obtained in our experiments are summarized in Table 2 and organized by main dataset (i-iv) and by whether or not feature selection has been applied (FS / No FS). For each main dataset, results are reported as the mean classification accuracy of its 6 pairs datasets. Results obtained combining SVM and FaceVACS are also reported.

The following remarks can be drawn:

- As expected, accuracies provided for LQfaces are significantly lower than those for HQfaces.
- The more information is available, the higher is the accuracy of the classifier. Profile and expressions significantly improve classification results, as it can be seen in Table 2, where results for set iv outperform those for set iii, which are in turn better than those for set ii.
- FS always significantly increases accuracy, and a further minor improvement is provided by combining the output of our classifier and of FaceVACS.

Table 2: Classification accuracies for sets i, ii and iii.

Set	*Feature Selection*	*SVM*	*SVM+SDK*
i	No FS	52,39	55,75
	FS	59,40	62,05
ii	No FS	61,27	63,19
	FS	70,85	70,94
iii	No FS	62,77	65,78
	FS	73,28	73,48
iv	No FS	69,68	70,94
	FS	75,51	76,33

4 COMPARING AUTOMATIC AND HUMAN CLASSIFICATION

In this section we compare the ability of the automatic system to correctly discriminate between siblings and not siblings with that of human raters. To this purpose, we presented on an Internet site the pairs used for automatic classification, exception made for the LQ data set, since it is composed mainly by well known personages, and then likely to produce biased ratings.

In particular for each main dataset ii-iv, only one of the 6 pairs datasets was used to collect human ratings. The pairs were presented in a random order, and the raters were informed that some of the pairs presented were siblings, but they were not told in which percentage. In total, we collected 213.396 YES (the two individuals are siblings) or NO (they are not) answers from 2.929 students and employees of the Politecnico di Torino; an average of 444 answers for each pair were collected.

In order to perform a meaningful comparison with the classifier, we transformed for each pair the average ratings of the human panel (HP) into the value that obtained the majority of votes. The comparison is presented in Table 3, which shows that the performance of our automatic classifier is very close to that of the HP. Observe that the classification accuracy is lower than that shown in Table 2, which is an average value, while here the classification results refers only to the same pairs datasets rated by human observers.

Table 3: Comparison between automatic and human classifications.

Set	*Feature Selection*	*SVM*	*SVM+SDK*	*HP*
ii	No FS	62.50	65.18	72.55
	FS	65.18	68.75	
iii	No FS	66.96	67.85	71.34
	FS	67.86	70.53	
iv	No FS	68.75	69.64	75.22
	FS	71.43	74.10	

5 SUMMARY AND FUTURE WORK

In this paper, we have presented the first results of a new research aimed at recognizing siblings pairs with pattern analysis/image processing techniques. To this purpose we have constructed a data base of high quality images of pairs of siblings, also containing profile and smiling images, which will be used for further investigation on the subject. The ability of human observers to discriminate pairs of siblings and not siblings from images of this database has been experimentally determined as well. A first automatic analysis of the database has been performed using a commercial identity recognition package, which, although not aimed at this specific problem, has provided some interesting insight about the problem. Then, we experimented a technique based on PCA features and a SVM classifier. Combining them with a feature selection technique, we obtained correct classification percentages close to those of the human raters. Although the PCA features are in principle database dependent, the algorithm experimented appears rather general, since it provides similar results using different training and test sets extracted from our database. The importance of using high quality images for these studies has been proven by the significantly lower percentages of correct classification obtained for a low quality database, collected over the Internet.

Future analysis of the database will experiment other techniques likely to improve the percentage of correct classification. Gabor filters and other feature extraction techniques will be applied. In general, we will focus on approaches able to enhance detailed comparisons of particularly significant areas of human faces which could be relevant to discriminate pairs of siblings.

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