ANALYSIS OF FOCUSES OF ATTENTION DISTRIBUTION FOR A NOVEL FACE RECOGNITION SYSTEM

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Abstract: In this paper we propose an automated approach to recognize human faces based on the analysis of the distribution of the focuses of attention (FOAs) that reproduces the ability of the humans in the interpretation of visual scenes. The analysis of the FOAs (distribution and position), carried out by an efficient and source light independent visual attention module, allows us to integrate the face features (e.g., eyes, nose, mouth shape) and the holistic features (the relations between the various parts of the face). Moreover, a remarkable approach has been developed for skin recognition based on the shifting of the Hue plane in the HSL color space.

1 INTRODUCTION

Face recognition is a research area of biometrics that for its complexity and importance is becoming one of the most interesting topics of study in the image analysis and understanding field. A general statement of the face recognition problem is as follows: given a video image of a scene, identify one or more persons in the scene using a stored database of faces. The problem of face recognition is open, because an effective model has not been proposed yet, and the shortcomings of these systems are evident when compared to the human capability to recognize the faces.

Several approaches for automating the process of face recognition have been proposed in the last twenty years. Generally, a face recognition involves automating three related tasks: 1) Face Detection, 2) Features Extraction and 3) Face Matching.

The automatic systems have to execute all the three tasks above.

For *face detection* the majority of the approaches are based on the skin pixels segmentation using the color spaces processing (Brand et al., 2001), (Ikeda, 2003).

An interesting algorithm is proposed in (Phung et al., 2002) where a human skin color model in the YCbCr color space is presented, and the k-means algorithm is proposed for clustering the skin pixels in three Gaussian clusters. The pixels are considered belonging to one of three clusters on the basis of the Mahalanobis distance.

For the *face features extraction* various methods have been developed. Methods based on deformable templates seem to be the most effective. Yuille et al. (Yuille et al., 1991) describe the use of deformable templates called "snakes" (Kass et al., 1998), based on simple geometrical shapes to locate eyes and mouths. Several methods use the active shape model (ASMs), (Jiao et al., 1998) and (Wang et al., 2000), with different approaches (e.g. wavelet, Gabor filter, etc.) for the detection of the features. Cootes et al. (Cootes et al., 1995) have proposed an effective model for interpretation and coding of face images with results in the range [70%-97%], but in their approach the landmarks to detect the main facial features are manually located.

One of the most relevant algorithms for *face matching* is the eigenfaces proposed in (Pentland et al., 1994). The eigenfaces, based on the eigenpictures, removes the data redundancy within

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the face images. Other approaches have pointed out the structural coupling of the face features. One of the most effective is the Elastic Bunch Graphic Matching (Wiskott et al., 1997) which uses the wavelet functions.

All the mentioned methods are not effective in all the possible scenarios, and require a high processing time and great amounts of memory for features storaging.

A techniques commonly used for features dimensionality reduction are Principal Components Analysis (PCA) (Yang et al., 2004) and Linear Discriminant Analysis (LDA) (Etemad et al, 1997). The main goal of PCA is to reduce the dimensionality of the data, while retaining as much as possible of the variation present in the original dataset. The reduction is obtained by selecting a set of orthogonal vectors maximizing the variance overall the samples.

Instead LDA seeks to find the direction in the dataset that maximizes between-class scatter and minimizes the within-class scatter.

Although these two methods reduce the space dimensionality, they face the computational difficulty when the dimension of the data is too huge. Moreover a critical issue of the LDA method is the singularity and instability of the within-class scatter matrix. Indeed, especially in face recognition problems, there are a large number of features available, while the total number of training patterns is limited, commonly less than the dimension of the features space. This implies that the within-class scatter matrix might be singular and instable (Jain et al, 1982).

In order to overcome the singularity problem, an alternative method, called Fisherfaces (Belhumeur et al, 1997), was proposed. Such method is a two stage dimensionally reduction technique carried out by: 1) performing PCA to project the n-dimensional image space onto a lower dimensional subspace and 2) applying LDA to the best linear discriminant features on such subspace.

Although Fisherfaces method solves the singularity problem, often the instability remains a huge drawback. Several methods, based on Fisherfaces, were proposed to bypass such limitation (Liu et al, 1993), (Thomaz et al, 2003).

The aim of our paper is to propose an algorithm that avoids the computational costs inherent to an high features space dimensionality by using a restricted number of features face. Moreover our method shows a reasonable accuracy comparable with the best existing methods as shown in the section results. Sect. 2 outlines the overall face recognition system, Sect. 3, Sect .4 and Sect. 5 illustrate, respectively, the subsystems Face Detection, Face Features extraction, and Face Matching of the algorithm. Results and future work are focused, respectively, in the last two sections.

2 PROPOSED SYSTEM

Many researchers in computer science, neuroscience and psychology have pointed out the importance of either the *face features* (e.g., mouth shape, nose shape, etc.) or the *holistic features* (such as the distance between the nose and the mouth or the distance between the eyes, etc.) for the face recognition. For example, Bruce in (Bruce et al., 1998) has attentioned the holistic features. Other studies support the hypothesis that the face recognition in human relies only on the *face features* (e.g., big ears, crooked nose, etc.). For example, in (Faro et al., 2006) an attentive system, based on the Itti and Koch model of visual attention (Itti et al., 2000), recognizes faces by analyzing and classifying only the face features, located by using the Active Contour Model and Active Shape Model.

The use of only face features has been criticized, based on the evidence provided in the Barlett and Searcy study (Barlett et al., 1993) using the *Thatcher Illusion.* In fact, inverting the main features of a face (i.e. putting the mouth in place of the eyes) the result is an strange object that is not recognized as a face.

This supports the importance of the holistic features in the face recognition process.

The proposed recognition system integrates both theories and is based on the hypothesis that in the recognition process humans memorize the distribution of some particular points, called "focuses of attention" (FOAs) that bind both face and holistic features. It consists of four main parts (shown in fig.1):

- **Face Detection:** by a suitable clustering algorithm based on color processing;
- **Visual Attention for Features Extraction:** where the points of interest are focused by a pure bottom-up attention module;
- **Features Extraction:** by a suitable analysis of the identified FOAs;
- **Face Matching:** where the features (face and holistic ones), extracted by the previous module, are compared with the others stored in the database for face matching.

The FOA extraction module is based on the emulation of the human capability to interpret complex visual scenes. In fact, humans have a remarkable ability to interpret scenes in real time, in spite of the limited speed of the neuronal hardware available for such tasks. Visual processes appear to select a subset of the available sensory information before further processing (Tsotsos et al., 1995), most likely to reduce the complexity of scene analysis. This selection seems to be implemented in the form of a spatially circumscribed region of the visual field, called "focus of attention" (FOA), which scans the scene (by using sequence of eye movements, called *saccades*) both in a rapid, bottom-up, saliency-driven, and task-independent manner as well as in a slower, top-down, volition-controlled, and task-dependent manner. Bottom-up attention directs the gaze to salient regions (image-based saliency cues), while topdown attention enables goal directed visual search (task-dependent cues).

In particular, our algorithm implements the architecture proposed by Koch and Ullman (Koch et al., 1985) where human visual search strategies are explained by the "feature integration theory," based on the *saliency map* that defines the relationships between the components of a scene depending on the importance that the components have for the generic observer.

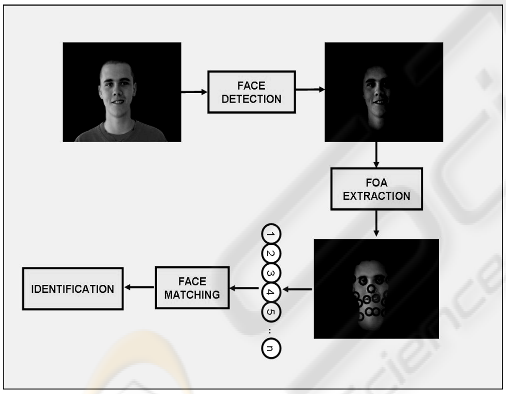
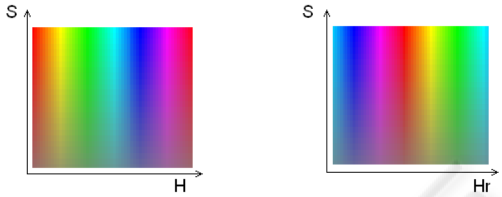


Figure 1: The Overall System.

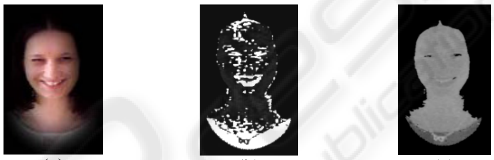
3 FACE DETECTION

Usually, the face detection process depends strongly from the illumination of the scene. For this reason in our algorithm the HSL (Hue, Saturation, Luma) space color has been chosen. In this space H=0 represents red while H = 255 is violet (fig. 2(a)). For the Caucasian, Mongolian and American races, the pixels of the skin are close to the red color, hence for a better analysis we have defined a new space called HrSL (Hue centered on Red-Saturation-Luma) obtained by shifting the HSL space (see Fig. 2). In the new space the red color is represented by the value H=127 and not by 0 as in the HSL space. This shifting allows us to realize an effective thresholding of the skin pixels as is shown in fig.3.



(a) (b)

Figure 2: (a) HSL space, (b) HrSL space.

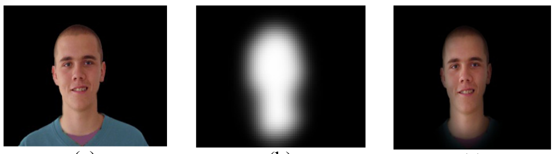


(a) (b) (c)

Figure 3: (a) Original Image. Images obtained by a suitable thresholding in the HSL space (b) and in the HrSL space (c).

The face detection process (shown in fig. 4) uses a clustering algorithm, which consists of three steps:

- Identification of three clusters ;
- Selection of the winner cluster ;
- Filtering the input image with a mask obtained by a smoothing of the winner cluster



(a) (b) (c)

Figure 4: (a) Imput Image, (b) Mask obtained by a smoothing of the winner cluster, (c) Final Image with face detection.

More in details the clustering algorithm used is based on a modified version of the k-means algorithm. The first step aims to divide the Hr plane of the input image in a lot of the clusters using the minimization of the Euclidean Distance between each one points value of the Hr plane and the centroid value, which represents the mean of the values of each one region of the image. A very great number of cluster produces an increasing of the CPU time and the merging problem, whereas few clusters could be non sufficient to separate the main parts of the Hr plane. In according to experimental test, we choose three clusters.

After the clustering algorithm we divide the image in cluster to identify the **winner cluster,** which is the cluster whose the RGB value is nearest at (195,145,155). Applying a suitable filtering we obtain the face mask that allows us to detect the face.

4 VISUAL ATTENTION FOR FEATURES EXTRACTION

The output image of the face detection step is the input image for the algorithm that extracts features based on a visual attention system. The visual attention module proposed in this paper detects salient regions from a color image simulating saccades of human vision using a saliency map similar to the one proposed by Itti & Koch (Itti et al., 2000). The differences in computing the saliency map are: 1) we don't apply Gaussian pyramid, thus reducing the computational complexity and increasing the spatial resolution of the processed images and 2) we don't use the double color opponent mechanism, and therefore the dependence of attention module on the illumination source is reduced, 3) the HSL space is the best representative of how the humans perceive the colors.

The first step to compute the saliency map is to convert the image, obtained by the face detection module, in the HrSL space. Experimentally, we have noticed that the Saturation plane is unnecessary for the computation of the saliency map, while Hr and L planes allow us, respectively, to detect the contours and the shapes of the face (e.g. eyes, nose, mouth, etc…). After having extracted the Hr and L planes, the following filters have been applied to the both planes, obtaining the images partially shown in fig. 5:

- Directional Prewitt filters (oriented at 0°, 45°, 90°, 135°) obtaining $Hr\_Prewitt^{0°}$, $Hr\_Prewitt^{45°}$, $Hr\_Prewitt^{90°}$, $Hr\_Prewitt^{135°}$ and $L\_Prewitt^{0°}$, $L\_Prewitt^{45°}$, $L\_Prewitt^{90°}$, $L\_Prewitt^{135°}$,features;
- Canny Filter to both planes, obtaining the *Hr_Canny_map* and *L_Canny_map*;

The images, processed with the above non-linear filters, are combined with the aim to obtain the *features maps* as follows:

1. All the Hr images processed with Prewitt filters are summed obtaining the *Hr-Prewitt Features Map;*
2. All the L images processed with Prewitt filters are summed giving more weight to the 90° Map, obtaining the so called *L-Prewitt Features Map;*
3. The Hr_Canny map and L_Canny map are processed using a normalization function N(·) that implements the mechanism of *iterative spatial inhibition* by using the DoG (Difference of Gaussian) filter proposed in (Itti et al., 2000). The obtained maps are called respectively *Hr-Edge Map* and *L-Egde Map.*

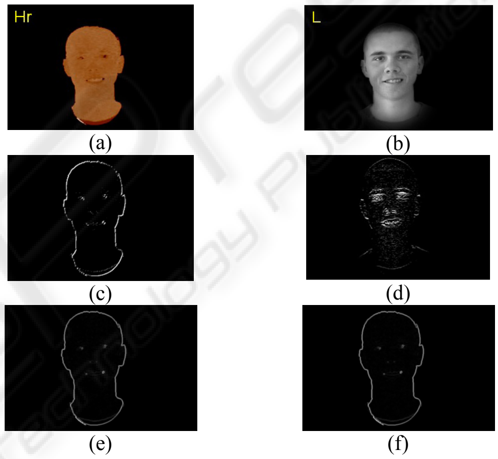


Figure 5: (a) Hr plane of the detected face, (b) L plane of the detected face, (c) $Hr\text{-}Prewitt^{90°}$ Map, (d) $L\text{-}Prewitt^{90°}$ Map, (e) Hr-Canny Map, (f) L-Canny Map.

Applying the normalization factor N(·) to both the *Hr-Prewitt Features Map* and *Hr- Egde-Map* and summing these two maps we obtain the *Hr-Saliency Map* (fig.6(a)).

The same procedure is applied for *L-Saliency Map* (fig.6(b)) which is obtained by summing the L-Prewitt Features Map and L-Egde Map. Finally, the *Saliency Map* (fig.6(c)) is computed by summing the L-Saliency (with a greater weight) with the Hr-Saliency Map.

After having extracted the saliency map, the first Focus of Attention (FOA) is directed to the most salient region (the one with the highest grey level in fig.6(c)).

Afterwards, this region is inhibited according to a mechanism called *inhibition of return (IOR),* allowing the computation of the next FOA.After the FOAs distribution extraction, a FOAs analysis has been carried out in order to identify the eyes, the ellipse surrounding the face and the mouth. For the eyes position detection, we consider the most two salient regions of the obtained FOAs distribution.

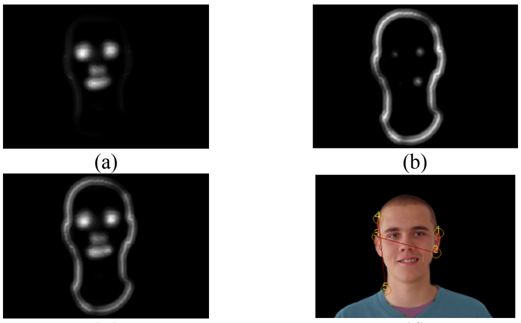


Figure 6: (a) L_Saliency Map, (b) Hr_Saliency Map, (c) Saliency Map, (d) Some identified FOAs.

For the ellipse identification the algorithm computes a set of distances from each extracted FOA. All the FOAs, which distance by the centre is greater than a suitable threshold, are considered as belonging to the face boundaries. By an interpolation of these FOAs we obtain the searched ellipse. By analyzing the remaining FOAs, we are able to extract the mouth. After the feature extraction the holistic face features have been extracted.

5 FEATURES EXTRACTION

The aim of this module is to extract the *face features* and the *holistic features* starting from the most important FOAs previously identified. The identified *holistic features* are:

- The normalized area (**A_N**) and the eccentricity (**E**) of the ellipse that best fits the contour FOAs, as described below:

$$E = 100 \cdot sign(A_y - A_x) \cdot \sqrt{1 - \frac{\min(A_x, A_y)^2}{\max(A_x, A_y)^2}}$$

$$A_N = \frac{A_x \cdot A_y}{\sqrt{A_x^{\ 2} + A_y^{\ 2}}}$$

Where A_x and A_y are, respectively, the horizontal and the vertical axes of the ellipse;

- the distance between the central point of the FOAs eyes (**C_0**) and the center of the such ellipse (**C_{Em}**);
- the focal distance between the eyes (**C_f**);
- the vertical distance (**Yb**) between the central point of the mouth (**C_m**) and the center of the ellipse (**C_{Em}**);
- the distance between the eyes and the mouth: computed as the distance between the central point of the eyes FOAs **C_0** and **C_m**;
- the distribution of the 20 most salient FOAs;

Overall the computed holistic features are shown in fig.7. For the *face features* we consider the position of the most relevant FOAs and starting from these locations we apply the snakes, as in (Faro et al., 2006), that allow us to extract the searched features.

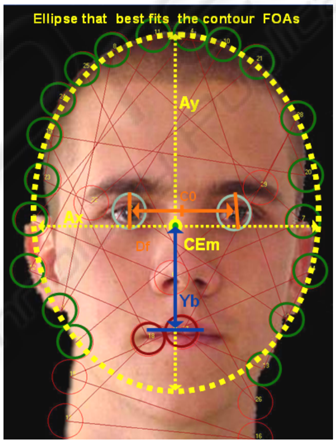


Figure 7: Extracted Holistic Features.

The final step is to match the extracted features with the ones stored in the database. The considered features for the matching are:1) FOAs Distribution, 2) Face Features and 3) Holistic Features.

The face matching must be independent from the rotation, the scaling and the translation. For this reason the first step is to apply a Procrustes analysis (Bin et al., 1999) to the FOAs distribution. After this transformation we extract the holistic (based on the FOAs distribution) and the face features and finally we compute the fitting value that is given by the following formula:

$$Fit = \alpha_1 \cdot T_1 + \alpha_2 \cdot T_2 + \alpha_3 \cdot T_3$$

where T_1 is the fitting value of the distribution, T_2 the fitting value for the features extracted by using the FOAs dist., and T_3 the fitting value for the facial features extracted by deformable models. The recognized person is the one whose *Fit* value is the greatest, and if it is greater than a threshold, otherwise nobody is recognized.

6 EXPERIMENTAL RESULTS

The proposed method has been tested on a database of 114 subjects. Each subject is represented by 5 images in different positions (side view with an angle of 45°, frontal view with serious expression, side view with angle 135°; frontal view showing no teeth and frontal view showing the teeth). Each image is characterized by a spatial resolution of 640*480, with a uniform background and natural light. Subject's age is between 18 and 50 years.

For face matching, the features of the side view with an angle of 45°, frontal view with serious expression, and side view with angle 135° of each person have been used to create the face model; the remaining two images of each person (frontal view showing no teeth and frontal view showing the teeth) have been used for the testing phase.

Concerning face detection, the success rate is 100%. For the features extraction on all the detected images, the percentage of success is about 93%. The 66% of the images whose features have been extracted correctly, has been used for the model face creation. The test for face identification has been carried out on the remaining images (181 images, corresponding to the 34%).

The experimental results are shown in Table 1.

Table 1: Experimental results.

Algorithm	N° Test images	Correct Evaluation	Success rate
Face Detection	570	570	100 %
Features Extraction	570	531	93.1%
Face Matching	181	170	93.9%

The overall recognition rate of our method is 87.42%. The classification performances are more than satisfying, especially if compared with other well-know methods in literature. Indeed Eigenfaces (Pentland et al., 1994) shows an average recognition rate of 88.0%, Fisherfaces(Belhumeur et al, 1997) 86%, Liu Method(Liu et al, 1993) 86.5%.

7 CONCLUSIONS AND FUTURE WORKS

An automated face recognition system based on the emulation of the human capability to interpret complex visual scenes has been proposed. The system proves effective due to the integration of the face and holistic features.

This integration is attained by applying both the FOAs distribution analysis and the algorithm proposed in (Etemad et al, 1997).

An important peculiarity of the system is the independence from both the illumination source and the dimension of the face to be recognized. The independence from the illumination source has been obtained by using the proposed HrSL color space.

Moreover, the HrSL allows us to best detect the skin pixels. The independence from the face dimension has been carried out adopting the Procrustes analysis.

An improvement that generalizes the system regards the face detection module; in fact, the high accuracy of the method is due to the background uniformity of the used images. In other cases for a better clustering it will be necessary to associate at the color processing module a spatial processing system.

In addition, the system is set to work only with Caucasian, Mongolian and American races; for a correct functioning with the other races it is sufficient to shift the Hue color plane. Although the features extraction and the face matching systems have shown good results, they should be tested especially with different face images with different orientation and non-uniform background.

For this reason it will be very interesting to develop a parallel system able to analyze at the same time different locations of the scene, especially for complex scenes with many faces and other objects.

Finally, we plan to apply the proposed approach not only for face recognition but also for gesture recognition.

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