International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
Volume No.3 Issue No.2, pp : 159 – 162 1 Feb 2014

Partially Occluded Face Recognition and Components Estimation

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Abstract—This paper presents a face completion and recognition algorithm under partial occlusion. Component-based algorithm utilized in the proposed method. Individual components are detected using Haar-like features and wild card estimation is used for face completion task. The system performs better results under partial occlusion conditions in comparison to existing methods. AR face database is used for experiments.

***Index Terms*—** Face recognition, face completion, occlusion, Haar-features, topology, components.

I. INTRODUCTION

Face recognition techniques are user friendly and useful to identify people without disturbance. Under constrained conditions most of the face recognition systems give better result results as compared to natural conditions. When images are associated with occlusions, varying illumination, pose variation, the result of face recognition systems decrease. Presently partial occlusion is a huge problem for face recognition, which comes due to scarf, sunglasses. This paper explains how to complete face, which is associated with occlusion or some components are missing.

Main steps for the completion of face are: individual components of occluded face are detected by using Viola and Jones extension proposed by Lienhart et al. [1] [2], and faces from database are used to match with these components using AdaBoost ensemble learning. Euclidean distance can be used for this purpose also. Finally occluded face completed by using graph matching techniques.

There are many other techniques for completion of face, e.g. graph-cuts, Poisson equations and inpainting [3] [4], but these techniques are useful only for high-resolution color images and more information needed in case of damaged images. Available face recognition algorithms are useful for gray images and these algorithms will decrease in their performance. Our proposed method overcomes all these problems and gives better results.

This paper has two major contributions:

1) Our proposed method used component detection and graph matching for completion of face and different from existing methods.

2) Reconstruction rate increases by using this proposed method.

II. RELATED WORK

Detection of objects from images and videos are the main purpose of many available techniques. There are two types of systems component-based and holistic approaches. Individual components are used for detection in component-based methods and holistic approaches detect an object as a whole. Diverse and original face completion techniques are reviewed in this section. Only seminal work of component-based and holistic methods is reviewed in this section and ignores extensions. Features extracted from different components, type of target, and recognition approach are the comparison points for these two methods. Topology verification can be performed by different techniques, in case of component-based approach. Table I gives comparison of recent object detection systems in terms of several characteristics.

TABLE I
Comparison of Object Detection Systems

Name	Features	Classifier	Topology
Heisele [5]	Pixel values	SVM	SVM
Mohan [6], [7]	Haar-wavelets	SVM	SVM
Rowley [8], [9]	Pixel values	Neural networks	-
Schneiderman [10], [11]	PCA coefficients, wavelets	Bayes	-
Felzenszwalb [12]	Derivations of Gaussians	Energy function	Energy function
proposed	Haar-like	AdaBoost	Matching of graph

Eigenfaces are used by Turk and Pendland to completion of face [13]. To remove eyeglasses PCA-based algorithm is used by Saito *et al.* [14]. Due to the occluded pixels reconstructed images are distorted. Damaged photos reconstruction uses stochastic gradient-based technique proposed by Jone and Poggio [15]. Due to many steps the process is slow.

Feature points are manually selected in technique proposed by Hwang *et al*. [16]. The other method proposed by them is based on a morphable face model [17]. They use least-square minimization (LSM) to get optimal coefficients from undamaged parts of face and this method is based on PCA also. An efficient error correction algorithm proposed by Wright *et al.* is robust PCA (RPCA) [18]. In this technique, low-rank structure of face presented using nuclear norm. Internet images are used for face completion in a technique presented in recent study [19]. It gives good performance. Graphic area [20] uses Poisson equation [21] for completion of faces. To perform experiments gray and small images are used by face completion techniques. Small images are not affected by Poisson equation. Gabor features used by Zhang *et al.* for face recognition under occlusion conditions. Gabor-based feature [22] gives good experimental results, between test image and reference images. This method used perceptual-distance-based function and kernel LDA classifier. Small training set is used by Lin *et al.* occluded face recognition. In this method the effect of occlusion reduces by focusing on matched local regions, and Gaussian mixture model is used for similarity feature [23].

Under occlusion conditions SR has done good work, e.g., [24], [25], and [26]. According to this paper certain probability distribution has followed by occluded part. For occlusion condition Gabor-filter based technique represented by Yang and Zhang. Computational cost can be reduces by the combination of gabor wavelet and SR [27].

III. SYSTEM DESCRIPTION

Component based approach is used for the development of proposed system. The first step of proposed method is detection of individual components, than face localization step is performed. Proposed system overview is presented in fig. 2. Statistical and structural techniques are used for the development of proposed system. Statistical concept is used for component detection and structural concept is used for topology verification.

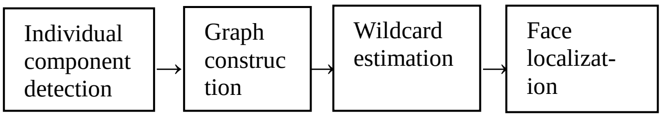

Fig. 2.Overview of the system.

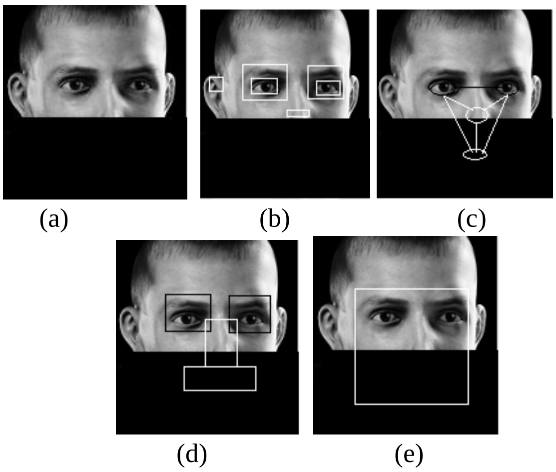

Fig. 3. Example of different parts of the system. (a) Input face. (b) Component detection. (c) Graph matching. (d) Wildcard estimation. (e) Localization of face.

Individual parts of the system are shown in fig. 3. Fig. 3(a) shows occluded input image. Fig. 3(b) shows individual components which are detected by component detection. Mouth and nose are occluded, so can't detect. Graph matching results shown in fig. 3(c). Black box is used to highlight the detected components and white box is used to insert wildcard components. Fig. 3(d) shows the wildcard components. In Fig. 3(e) individual components are used to face localization. Component detector can detect only two components and the proposed approach is used to completion of the face.

A. DETECTION OF INDIVIDUAL PARTS

Individual components such as mouth (M), nose (N), and right eye (R), left eye (E) are localized by the component detection step. Different components are detected by individual detectors. Training data is different for each detector, but machine learning approach is same.

Many classification methods presented in past are used by the face detection systems. Many authors use Viola and Jones [1] method for detection purpose, because it is fast and robust. We use extension of Viola and Jones proposed by Lienhart *et al.* [2].

The detection of objects is performed by different block size which moves row-wise. The classifier takes decision about the object based on the features extracted by the each block.

Actual block is normalized for illumination changes in processing. Block contents explain by extraction of Haar-like features. Extended [2] and standard [1] set of Haar-like features are used. These features extracted from integral image. AdaBoost ensemble learning strategy is used to trained classifier cascade. Many strong classifiers are used to design cascade. Many weak classifiers are used to develop strong classifier. These weak classifiers are combined using a weighted summation. One Haar-like feature with parity and threshold is consisted by each weak classifier. AdaBoost is used to choose suitable weak classifiers. Object of interest represented by actual block is decided by strong classifier at each cascade stage, discarded the irrelevant blocks and passes the relevant blocks to next stage. Block contains the object if it passes the last stage. Classifier cascade improves speed as compared to monolithic classifier. Filter heuristics is used for multiple overlapping detections in case of individual component detection. Multiple detections handle by graph-based topology naturally, so this step is not used in proposed system.

B. GRAPH-BASED TOPOLOGY

Proposed system explains how object detection is performed by using topology of individual components. Statistical approach is used to relate individual components by the component based systems. For example Mohan [7], and Heisele [5], [28] use support vector machine (SVM) approach. Occluded components can't detect by most statistical approaches and these approach required fixed features. By using topological information graph matching and structural pattern recognition can handle these problems. Fischler and Elschlager [29] approaches can be compared with our proposed approach.

International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
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Proposed method uses graph G (V, E), V stands for a finite, non empty set of vertices, and E stands for and a finite set of edges. Facial components define by nodes $v\ \varepsilon\ V$, σ_v is size, and K_v is component type. Euclidian distance $\delta_e = \delta_{ij,}$ is defined by edge $e\ \varepsilon\ E$, between components i and j centers. In matching step ratios are used instead of distance and size. Exact graph matching and inexact (error-tolerant) graph are two types of classical graph matching. Edges and nodes levels should be same in case of exact graph matching and level difference allowed for inexact graph case.

1) ***Face Graph****:* Graph $G^R = (V^R, E^R)$ is used to represent the face. 400 example graphs and geometric mean of node sizes and edge distances are used to design face graph. Size and position of components are used to design each example graph. Fig. 4 shows the resulting face graph.

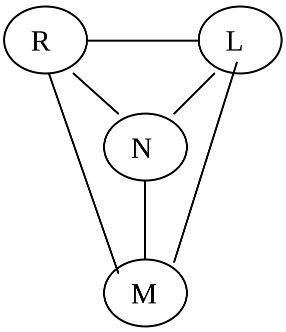

Fig. 4. Face graph (node size and edge distances compute manually).

2) ***Designing of Graph****:* Firstly graph G^D is constructed from detected components. A node $v\ \varepsilon\ V^D$ is face components and an edge $e\ \varepsilon\ E^D$ is used to connect nodes. Deviation is represented by the two measures of each node pairs. The representation of size deviation is as

$$\sum (i, j) = \begin{cases} \dfrac{\frac{\sigma i}{\sigma j}}{\frac{\sigma r(i)}{\sigma r(j)}} - 1, \ if \ \dfrac{\frac{\sigma i}{\sigma j}}{\frac{\sigma r(i)}{\sigma r(j)}} \geq 1 \\ \dfrac{\frac{\sigma r(i)}{\sigma r(j)}}{\frac{\sigma i}{\sigma j}} - 1, \ if \ \dfrac{\frac{\sigma i}{\sigma j}}{\frac{\sigma r(i)}{\sigma r(j)}} < 1 \end{cases} \quad (1)$$

Representation of distance deviation is as

$$\sum (i, j) = \begin{cases} \dfrac{\frac{\delta ij}{\sigma i}}{\frac{\delta r(i)r(j)}{\sigma r(i)}} - 1, \ if \ \dfrac{\frac{\delta ij}{\sigma i}}{\frac{\delta r(i)r(j)}{\sigma r(i)}} \geq 1 \\ \dfrac{\frac{\delta r(i)r(j)}{\sigma i}}{\frac{\delta ij}{\sigma i}} - 1, \ if \ \dfrac{\frac{\delta ij}{\sigma i}}{\frac{\delta r(i)r(j)}{\sigma r(i)}} < 1 \end{cases} \quad (2)$$

3) ***Labeling of Connected Components****:* Many connected components of face are consisted by graph $G^{D.}$ The graph G^D extracted in many graphs $G_i^C = (V_i^C, E_i^C)$ and each graph represent single face.

4) ***Matching of Graph****:* There is different size and location of components consisted by each graph $G^{C.}$ Matching process is done and matched subgraph find out in this step. Low similarity combinations should be removed.

A component $v\ \varepsilon\ V^W$, without size and distance information is introduced for completion of face. All subgraphs $G_i^S = (V_i^S, E_i^S)$ with minimum two different detected components are selected from the resulting graph.

5) ***Wildcard Estimation****:* Several wildcard components are included in the resulted matched graph after the graph matching step. Facial components coordinates are required to estimate the face region. Reference graph, orientation information and detected components are used to estimate missing coordinates. The determinant of $P_1 = (x_1\ y_1)^T$, $P_2 = (x_2\ y_2)^T$, $P3 = (x3\ y3)^T$, is used to compute the orientation

$$\det = \left| \begin{pmatrix} x1 - x3 & x2 - x3 \\ y1 - y3 & y2 - y3 \end{pmatrix} \right|$$

Coordinate P_3 is estimated for the wildcard component v_3.

6) ***Face Localization:*** Subgraph components and reference graph are used to estimate the face region. Subgraph components are left eye L, right eye R, nose N, and mouth M. The rectangle $b = (x, y, w, h)$ is used to describe the face region, where w is width, h is height and $(x, y)^T$ is center.

$$w = 2.(x_R - x_L)$$
$$h = 2.(\frac{(yR + yL)}{2 - yM})$$

$$x = x_N$$
$$y = y_N$$

Fig.5. Face completion examples.

IV. EXPERIMENTS

A lot of images are required for the development of face recognition system. These images are used to generate model during training and to obtain general results during testing. There are many databases available but selection of suitable images for specific face recognition system is difficult.

BioID Face Database [30] and AR Face Database [31] are used for training. 1521 images of BioID Face Database and 508 images of AR Face Database are trained for positive samples. For negative samples, 19973 images are taken from Data Becker 222222 image gallery. 143 images from AR Face Database and Corel Gallery Magic 65000 are used for testing.

The first stage of proposed face recognition system is facial component detection. Extended set of haar features are used for the development of component detector. 4000 images of mouth and nose are used for training of positive samples, and 2000 images of each eye are used. 3000 images are used for training of negative samples. Individual component uniqueness is the reason of difference, because number of training images is same.

V. CONCLUSION

In this paper, we have proposed a wild card estimation and topology verification method for completion of occluded face and partial distance measure for recognition task. Viola and Jones approach is used to detect individual components. Specific graph model is used to describe the topology of different components. Size and distance ratios are considered by graph model. The recognition rate improved under partial occlusion of scarf and glass by proposed method. Proposed face recognition algorithm has limitation of resolution, so future work will concentrate to overcome the resolution limitation automatic estimation of components.

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