FACE DETECTION THROUGH FEATURE BASED APPROACHES

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Abstract

There are several methods for face detection and they can be broadly classified into two main classes, which are feature-based, and image-based approaches. Both feature-based and image-based approaches perform effectively while detecting upright frontal faces, whereas feature-based approaches show a better performance for the detection scenarios especially in simple scenes.

Keywords: *Face Detection, Mosaicing, Level Feature Analysis, Template Matching, Generalized Knowledge Rules.*

Introduction

Face identification is one of the tasks which human vision can do effortlessly. However, for computer vision, this task is not that easy. A general definition of the problem can be stated as follows: Identify all of the regions that contain a face, in a still image or image sequence, independent of any three dimensional transformation of the face and lighting condition of the scene. There are several methods issued for this problem and they can be broadly classified in two main classes, which are *feature-based*, and *image-based* approaches. Previous research has shown that both feature-based, and image-based approaches perform effectively while detecting upright frontal faces, whereas feature-based approaches show a better performance for the detection scenarios especially in simple scenes.

Challenges in Face Recognition- Face identification is the problem of determining whether a sub-window of an image contains a face. Looking from the point of view of learning, any variation which increases the complexity of decision boundary between face and non-face classes will also increase the difficulty of the problem. For example, adding tilted faces into the training set increases the variability of the set, and may increase the complexity of the decision boundary. Such complexity may cause the classification to be harder. There are many sources introducing variability when dealing with the face. They can be summarized as follows:

• ***Image Plane Variations***is the first simple variation type one may encounter. Image transformations, such as rotation, translation, scaling and mirroring may introduce such kind of variations. Utilization of image pyramids with a sliding detector window is one common way to deal with such transformations for the input image. Variations in the global brightness, contrast level can also be expressed in the same category.

• ***Pose Variations***can also be listed under image plane variations aspects. However, changes in the orientation of the face itself on the image can have larger impacts on its appearance. Rotation in depth and perspective transformation may also cause distortion. The common way to deal pose variation is to isolate pose types (i.e. frontal, profile, rotated).

• ***Lighting Variations***may dramatically change face appearance in the image. Such variations are the most difficult type to cope with due to fact that pixel intensities are directly affected in a nonlinear way by changing illumination intensity or direction. For example, when using skin color as a feature for face detection, varying color temperature of the light source may cause skin color filtering to fail.

• ***Background Variations***is another challenging factor for face detection in cluttered scenes. Discriminating windows including a face from non-face is more difficult when no constraints exist on background.

Brief Background - Over the last ten years, there has been a great deal of research concerning important aspects of face detection. Using generalized face shape rules, motion, and color information many segmentation schemes have been presented. The use of probabilistic and neural network methods has made face detection possible in cluttered scenes and variable scales. Face detection research can be heuristically classified in two main categories: feature-based approaches and image-based approaches.

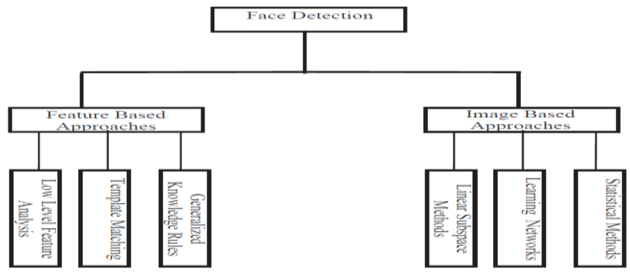

Figure 1: Classifications of Face Detection Techniques

According to the taxonomy in Figure 1, feature-based methods make explicit use of face knowledge and follow the classical detection methodology, in which low level features that are used prior to analysis mostly rely on heuristics or advance templates. The apparent properties of the face, such as skin color and face geometry, are used at different levels of the system. Since features are the main ingredients, these techniques are named as the feature-based approach.

These approaches [9] have embodied the majority of interest in face detection research starting as early as the 1970s. Taking the advantage of the current advances in pattern identification theory, image-based approaches address face detection as a general pattern identification problem. Partly due to well known work by [19], these approaches have attracted much attention in recent years, and have demonstrated remarkable results. According to the image-based methods, face detection is a two class (face, non-face) object identification problem which uses pure image (intensity) representations instead of abstract feature representations.

1.0 Feature Based Approaches

Most feature-based approaches share similar consecutive steps. Usually, the first step is to make pixel level eliminations by utilizing low level feature(s) e.g. skin color filtering, edge detection. Due to the low level properties, the result that is generated in the first step is ambiguous. In the second step, visual features which are not eliminated in the first step are organized within a global face knowledge or geometry. Using this feature analysis, feature ambiguities are reduced and the locations of face and facial features are determined. The final step may involve the use of templates or active shape models.

1.1 Low Level Feature Analysis

1.1.1 Edges

As a useful primitive feature in computer vision, edge representation was applied to early face detection system by Sakai et al. Later, based on this work, a hierarchical frame work was proposed by Craw et al. [5] to trace the human head line. This approach included a line follower which is implemented with a curvature constraint. Some more recent examples of edge-based techniques can be found in [8, 11].

Edge detection is the important step in edge-based techniques. For detecting edges, various types of edge detector operators are used. The Sobel operator is the most common filter among others for detecting edges [11, 4]. Also, a variety of 1st and 2nd derivatives (Laplacian) of Gaussians have also been used in some approaches [10]. While a large scale Laplacian was used to obtain lines and steerable and multi-scale-orientation filters are preferred in [10].

In a general face detector, which uses edge representation, labeling of the edges are needed. Then the labeled edges are tried to be matched against to a face model. Govindaraju [8] accomplishes this goal by labeling edges as the left side, hairline, or right side of a front view face and then tries to match these edges against a face model by using predetermined ratio of an ideal face.

1.1.2 Skin Color

Human skin color has been used and proven to be effective feature for face detection, and related applications. Although skin color differs among individuals, several studies have shown that the major difference exists in the intensity rather than the chrominance. Several color spaces have been used to label skin pixels including RGB [12], NRGB (normalized RGB) [6, 14], HSV (or HSI) [15], CIE-XYZ [3]. Although, the effectiveness of the different color spaces is arguable, common point of all above works is the removal of intensity component. Terrilon et al. recently presented a comparative study of several widely used color spaces for face detection. In this study, the authors compare normalized TSL (tintsaturation- luminance), NRGB and CIE-xy chrominance spaces, and CIE-DSH, HSV, YIQ, YES, CIE-L* u* v* , and CIE L* a* b* chrominance spaces by modeling skin color distributions with either a single Gaussian or a Gaussian mixture density model in each space. In their face detection test, the normalized TSL space provides the best results, however, their general conclusion is about the most important criterion for skin color filtering, which is the degree of overlap between skin and nonskin distributions in a given space (and this is highly dependent on the number of skin and nonskin samples, available).

Color segmentation can basically be performed using appropriate skin color thresholds where skin color is modeled through histograms or charts [2, 13]. More complex methods make use of statistical measures that model face variation within a wide user spectrum. For instance, Oliver et al. and Yang et. al. employs a Gaussian distribution to represent a skin color cluster, consisting of thousands of skin color samples, taken from the different human races. The Gaussian distribution is simply characterized by its mean and covariance matrix. Any pixel color of an input image is compared with the skin color model by computing the Mahalanobis distance [7]. This distance measure gives an idea of how close the pixel color resembles the skin color of the model. Even though color information seems to be an efficient tool for identifying facial areas, the skin color models may fail when the spectrum (correlated color temperature) of light source varies significantly.

In addition, characteristics of acquisition device (specifically white balance) will also affect color transformation between the environment and the image. To address this problem, Storring et. al. modeled skin color based on the reflectance model of the skin, the camera parameters, and the spectrum of the light source. In particular, these researchers have estimated and verified skin color area in the chromaticity plane for different light sources, while the camera characteristics are given. An important conclusion of their work was the dependency of the skin color model on the spectrum of the light source and camera characteristics. We have also studied the skin color information to utilize a skin color filter in the preprocessing step in face detection. However, in general, the skin color filters are constructed by using fixed boundaries (thresholds) for sample pixel distributions in color space. Illumination and camera parameters are omitted. Hence, the exhaustiveness in the variations for sample pixel set may bottleneck performance of the resulting skin color filter. Response of two skin color filters for same color image can be seen in Figure 1.2. Note that the HSI skin color filter with fixed thresholds is unsuccessful in determining skin color pixels. On the other side, NRGB skin color filter that is using adjustable thresholds is successful in determining skin color pixels by adding false alarms.

Figure 1: Response of Color Filters to an Image under Fluorescent Light

Although, it may be more deeply experimented, we may state that a varying threshold skin color filter which includes self adaptation to image illumination properties (e.g. CCT) may result more effective skin color filtering results.

1.1.3 Motion

Motion information is a convenient way of locating moving objects when a video sequence is provided. It is possible to narrow face searching area utilizing this information. The simplest way to achieve motion information is frame difference analysis. Accumulated frame difference is improved frame difference analysis which is used by many reported face detection research. Besides face region, Luthon et.al. [18], also employ frame difference to locate facial features, such as eyes. Another way of measuring visual motion is through the estimation of moving image contours. Compared to frame difference, results generated from moving contours are always more reliable, especially when the motion is insignificant [19].

1.2 Template Matching

Given an input image, the correlation values in predetermined standard regions, such as face contour, eyes, nose and mouth are calculated independently. Although, this approach has the simplicity, it has been insufficient for face detection since it can’t handle variations in scale, rotations pose and shape. Multi- resolution, multi-scale, sub templates and deformable templates have been proposed to achieve scale and shape invariance template matching [20, 16]. In [20], Miao et. al. proposed a hierarchical template matching method for face detection. Initially, the input image is rotated from $-20^o$to 20^o to handle rotation. Then, each rotated image form a mosaic at different scales in which edges are extracted using Laplacian operator. The face template consists of six facial components of two eyebrows, two eyes, nose, and mouth. Face candidates are located by matching templates of face models represented in edges. In the final step, some heuristics are used to determine existence of a face. Experiments show better detection performance for images containing single face, rather than multiple. Kwon et. al. [16] proposed a detection method based on *snakes* and templates. In this approach, an image is first convolved with a blurring filter then with morphological operator to enhance edges. A modified *n-pixel* snake is used to find and eliminate small curve segments. Each candidate is approximated using an ellipse and for each of these candidates, a deformable template method is used to find detailed features. If a sufficient number of facial features are found, and their ratio satisfies the ratio tests based on the template, a face is considered to be detected.

Lanitis et. al. [17] established a detection method utilizing both shape and intensity information. In this approach, training images are formed in which contours are manually labeled with sampled points, and vector sample points are used as shape feature vectors to be detected. They use a point distribution model (PDM) together with the principal components analysis (PCA) to characterize the shape vectors over an ensemble of individuals. A face shape PDM can be used to detect face in test images using active shape model search to estimate face location and shape parameters. The shape patch is then deformed to the average shape, and intensity parameters are extracted. Then the shape and intensity parameters are used together for measuring euclidian distance from the faceness.

1.3 Generalized Knowledge Rules

In generalized knowledge-based approaches, the algorithms are developed based on heuristics about face appearance. Although, it is simple to create heuristics for describing the face, the major difficulty is in translating these heuristics into classification rules in an efficient way. If these rules are over detailed, they may come up with missed detections; on the other hand, if they are more general they may introduce much false detection. In spite of this, some heuristics can be used at an acceptable rate in frontal faces existed on uncluttered backgrounds.

Yang and Huang used a hierarchical knowledge-based method to detect faces. This system consists of three level rules going from general to detail. This method does not report a high detection rate, their ideas for mosaicing (multi-resolution), and multiple level rules have been used with more recent methods.

Conclusion

Therefore, it may be concluded that implementation of Feature Based Approaches is used to identify all of the regions that contains a face in still image or image sequence. The proposed approach consists of three methods, Low Level Feature Analysis, Template Matching and Generalized Knowledge Rules. This approach has embodied the majority of interest in face detection research starting as early as1970s, taking the advantage of the current advances in pattern identification theory.

References

1. *Storring, M.H., Andersen,J. and Granurn,E. (1999),"Skin Color Detection under Changing Lighting Conditions", 7th Symposium on Intelligent Robotic Systems, pp. 20–23.*
2. *Yang, G. and Huang, T.S. (1994),"Human Face Detection in Complex Background",Pattern Recogntion, 27:53–63.*
3. *Reinders,M.J.T.,Van Beek,P.J.L.(1995), Sankur, B. and Vander Lubbe, J.C.A.,"Facial Feature Localization and Adaptation of a Generic Face Model for Model-based Coding", Signal Processing: Image Communication, pp. 57–74.*
4. *Schneiderman, H. and Kanade, T. (2000), "A Statistical Model for 3-d Object Detection Applied to Faces and Cars", IEEE Conference on Computer Vision and Pattern Recognition.*
5. *Helomas, E. and Low, B.K. (2001),"Face Detection: A Survey", Computer Vision and Image Understanding, 83:236–274.*
6. *Sakai, T., Nagao, M. and Kanade, T. (1972),"Computer Analysis and Classification of Photographs of Human Faces", Proc. First USA-Japan Computer Conference, 1:2–7.*
7. *Craw, I., Ellis, H. and Lishman, J.R. (1987), "Automatic Extraction of Face-feature", Pattern Recognition Lett., pp. 183–187, Feb.*

8. *Govindaraju, V. (1996),"Locating Human Faces in Photographs", Int Jour. Computer Vision, 19.*

9. *Jacquin, A. and Eleftheriadis, A. (1995), "Automatic Location Tracking of Faces and Facial Features in Video Sequences", IEEE Proc. of Int. Workshop on Automatic Face- and Gesture-Recognition, Jun.*

10. *Wang, J. and Tan, T. (2000), "A New Face Detection Method based on Shape Information", Pattern Recog. Lett, 21:463–471.*

11. *Yuille, A.L., Hallinan, P.W. and Cohen, D.S. (1992),"Feature Extraction from Faces Using Deformable Templates, Int. J. Computer Vision, 8:99–111.*

12. *Choi, J., Kim, S. and Rhee, P. (1999), "Facial Components Segmentation for Extracting Facial Feature, Proc. 2nd IC on Audio and Video-based Biometric Person Authentication.*

13. *Jebara, T. S. and Pentland, A. (1997),"Parameterized Structure form Motion for 3-d Adaptive Feedback Tracking of Faces", Proc. of IEEE Conf. on Computer Vision and Pattern Recognition, pp. 144–150.*

14. *Satoh, S., Nakamura, Y. and Kanade, T. (1999), "Name it:Naming and Detecting Faces in News Videos", IEEE Multimedia, 6:22–35.*

15. *Crowley, J.L. and Berard, F. (1997), "Multi-model Tracking of Faces for Video Communications", IEEE Proc. of IC on Computer Vision and Pattern Recognition, Jun.*

16. *Kim, S., Kim, N., Ahn, S.C. and Kim, H. (1998), "Object Oriented Face Detection using Range and Color Information", Proc. of the 3rd IC on Automatic Face and Gesture Recognition, pp. 76–81.*

17. *Kjedsen, R. and Kender,j. (1996),"Finding Skin in Color Images", Proc. of the 2nd IC on Automatic Face and Gesture Recognition, pp. 312–317.*

18. *Yang, M.H. and Ahuja, N. (1998), "Detecting Human Faces in Color Images", Proc. of the 11th IEEE Conf. on Image Processing, pp. 127–130.*

19. *Terrillon, J.C., Shirazi, M., Fukamachi, H. and Akamatsu, S. (2000), "Comparative Performance of Different Skin Chrominance Models and Chrominance Spaces for the*

Automatic Detection of Human Faces in Color Images", in Proceedings 4th IEEE IC on Automatic Face and Gesture Recognition.

20. *Cai,J. and Goshtasby A. (1999),"Detecting Human Faces in Color Images", Image and Vision Comput, 18:63–75.*