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"Age Independent Face Verification"

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Abstract— Human faces undergo a lot of change in appearance as they age. Though facial aging has been studied for decades, it is only recently that attempts have been made to address the problem from a computational point of view. Most of these early efforts follow a simulation approach in which matching is performed by synthesizing face images at the target age. Given the innumerable different ways in which a face can potentially age, the synthesized aged image may not be similar to the actual aged image. In this paper, we present a graph based face representation for efficient age invariant face verification. The graph contains information on the appearance and geometry of facial feature points. A simple deterministic algorithm which exploits the topology of the graphs for matching process.

Keywords— Face Verification, EBGM, Bunch Graph., Face Graph, Jets.

I. INTRODUCTION:

Automatic face verification is an important yet challenging problem. This challenge can be attributed to (i) large intra-subject variations and (ii) large inter-user similarity. Fig. 1 shows some of the main intra-subject variations (pose, illumination, expression, and aging) commonly encountered in face verification. Among these variations, aging variation is now beginning to receive increasing attention in the face verification community. Designing an age-invariant face verification method is necessary in many applications, particularly those that require checking whether the same person has been issued multiple government documents (e.g., passports and driver license) that include facial images [1], [2].

Published approaches to age invariant face verification are limited. Most of the available algorithms dealing with facial aging problem are focused on age estimation [3]-[5] and aging simulation [6]-[7]. One of the successful approaches to age invariant face verification is to build a 2D or 3D generative model for face aging [4], [6], [7]. The aging model can be used to compensate for the aging process in face matching or age estimation. These methods first transform the face images being compared to the same age as the gallery image using a trained aging model to compensate for the age effect (see Fig. 2). While the model based methods have been shown to be effective in age invariant face verification, they have some limitations. First, construction of face models is difficult and sometimes they do not represent the aging process very well, especially when the training sample size is limited.

Further, the facial aging process is very complex and, consequently, in order to construct the aging model, strong parametric assumptions are needed, which are often unrealistic in real-world face verification scenarios. Second, for constructing the aging model, additional information in the form of the true ages of the training faces and the locations of landmark points on each face image are needed. A further constraint on the training set is that the images should be captured under controlled conditions (e.g., frontal pose, normal illumination, neutral expression). Unfortunately, such constraints are not easy to satisfy in practice, especially in scenarios where the face images being compared are subject to significant changes not only in aging, but also in other possible variations such as pose, illumination, and expression. In order to overcome these problems, approaches based on discriminative models have been proposed for the aging problem. Some of the representative works of discriminative models is [8], [10] which used gradient orientation pyramid (GOP) for feature representation, combined with support vector machine for verifying faces across age progression. Guo et al. [11] investigated the relationship between verification accuracy and age gap, and reported the performance of two well known algorithms (PCA and EBGM) on a large data set. They also showed some improvement in matching by indexing the gallery based on demographic information (gender, race, height, and weight). In this paper, we address the age invariant face verification problem by using elastic bunch graph matching approach. We propose a learning algorithm that has the capability to not only address the aging variations, but also handle the other intra-user variations (e.g., pose, illumination, expression).

Figure 1. Example images showing intra-subject variations (e.g., pose, illumination, expression, and aging) for one of the subjects in the FG-NET database [9].

II. ELASTIC BUNCH GRAPH MATCHING :

Face verification using elastic bunch graph matching is based on recognizing novel faces by estimating a set of novel features using a data structure called a bunch graph. Similarly for each query image, the landmarks are estimated and located using bunch graph. Then the features are extracted by convolution with the number of instances of Gabor filters followed by the creation of face graph. The matching score is calculated on the basis of similarity between face graphs of database and query image. Elastic Bunch Graph Matching was suggested by Laurenz Wiskott, Jean-Marc Fellous, Norbert Kruger and Christoph von der Malsburg of University of Southern California in 1999. This approach takes into account the human facial features and is totally different to Eigenface and Fisherface. It uses elastic bunch graph to automatically locate the fiducial points on the face (eyes, nose, mouth etc) and recognize the face according to these face features.

Elastic Bunch Graph Matching (EBGM) uses the structure information of a face which reflects the fact that the images of the same subject tend to translate, scale, rotate, and deform in the image plane. It makes use of the labeled graph, edges are labeled the distance information and nods are labeled with wavelet coefficients in jets. This model graph can then be used to generate image graph. The model graph can be translated, scaled , rotated and deformed during the matching process.

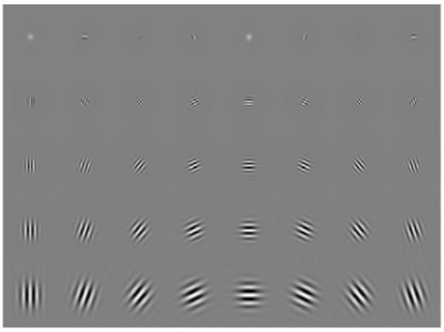


Figure 2 - The real part of the Gabor filter with 5 frequencies and 8 orientations

Gabor wavelet transformation is used to represent the local features of the face images. Gabor wavelets are biologically motivated convolution kernels in the shape of plan waves restricted by a Gaussian envelop function, the set of convolution coefficients for kernels of different orientations and frequencies at one image pixel is called a jet.

Face Bunch Graph-Automatic finding fiducial points in new faces need a general representation rather than models of the individual faces. A wide range of possible variations in the appearance of faces, like different shaped eyes, mouth, variation due to sex, age, etc, should be covered. Combination each feature by a separate graph is not efficient. So we use a stack like structure called a face bunch graph **(FBG) .**

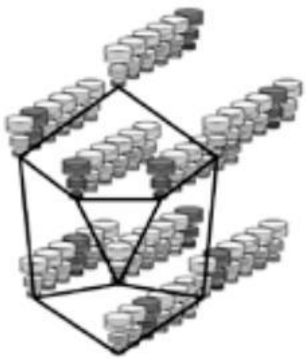


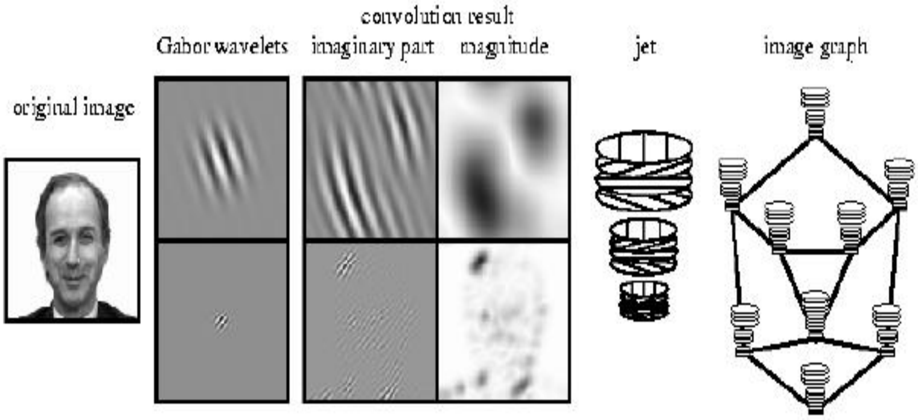
Figure 3– The face Bunch Graph represent the face in general.

The representation of facial feature is based on Gabor wavelet transform. Gabor wavelets are biologically motivated convolution kernels in the shape of plane waves restricted by a Gaussian envelope function. We use the Gabor wavelet because it can extract the human face feature well.

The basic representation used for representing the image is the labeled graph; edges are labeled with distance information and nodes are labeled with wavelet responses locally bundled in jets. Stored model graphs can be matched to new images to generate image graphs, which can then be incorporated into a gallery and become model graphs. Wavelets as we use them are robust to moderate lighting changes and small shifts and deformations. Model graphs can easily be translated, scaled, oriented, or deformed during the matching process, thus compensating for a large part of the variance of the images. Unfortunately, having only one image for each person in the galleries does not provide sufficient information to handle rotation in depth analogously. However, we present results on recognition across different poses. This general structure is useful for handling any kind of coherent object and may be sufficient for discriminating between structurally different object types. However, for in-class discrimination of objects, of which face recognition is an example, it is necessary to have information specific to the structure common to all objects in the class. This is crucial for the extraction of those structural traits from the images which are important for discrimination. In our system, class-specific information has the form of bunch graphs, one for each pose, which are stacks of a moderate number of different faces, jet-sampled in an appropriate set of fiducial points (placed over eyes, mouth, contour, etc.). Bunch graphs are treated as combinatorial entities in which, for each fiducial point, a jet from a different sample face can be selected, thus creating a highly adaptable model. This model is matched to new facial images to reliably find the fiducial points in the image. Jets at these points and their relative positions are extracted and are combined into an image graph, a representation of the face which has no remaining variation due to size, position.

A bunch graph is created in two stages. Its qualitative structure as a graph (a set of nodes plus edges) as well as the assignment of corresponding labels (jets and distances) for one initial image is designer-provided, whereas the bulk of the bunch graph is extracted semi-automatically from sample images by matching the embryonic bunch graph to them, less and less often intervening to correct incorrectly identified fiducial points.Image graphs are rather robust to small in-depth rotations of the head. Larger rotation angles, i.e. different poses, are handled with the help of bunch graphs with a different graph structure and designer-provided correspondences between nodes in different poses.

After these preparations the system can extract from single images concise invariant face descriptions in the form of image graphs (called model graphs when in a gallery). They contain all information relevant for the face discrimination task. For the purpose of recognition, image graphs can be compared with model graphs at small computing cost by evaluating the mean jet similarity.



II.1The Graph Similarity Function:

A key role in Elastic Bunch Graph Matching is played by a function evaluating the graph similarity between an image graph and the FBG of identical pose. It depends on the jet similarities and the distortion of the image grid relative to the FBG grid. For an image graph G^I with nodes **n=1, …,N** and edges **e=1, …,E** and an FBG B with model graphs **m=1, …,M** the similarity is defined as:

$$\mathcal{S}_{\mathcal{B}}(\mathcal{G}^{\mathcal{I}},\mathcal{B}) = \frac{1}{N}\sum_{n}\max_{m}\left(\mathcal{S}_{\phi}(\mathcal{J}_n^{\mathcal{I}},\mathcal{J}_n^{\mathcal{B}m})\right) - \frac{\lambda}{E}\sum_{e}\frac{(\Delta\vec{x}_e^{\mathcal{I}} - \Delta\vec{x}_e^{\mathcal{B}})^2}{(\Delta\vec{x}_e^{\mathcal{B}})^2},$$

where **λ** determines the relative importance of jets and metric structure ***Jn.*** are the jets at nodes n, and $\Delta \mathbf{X}_{\mathbf{e}}$ are the distance vectors used as labels at edges e. Since the FBG provides several jets for each fiducial point, the best one is selected and used for comparison. These best fitting jets serve as local experts for the image face.

II.II Matching Procedure:

The goal of Elastic Bunch Graph Matching on a probe image is to find the fiducial points and thus to extract from the image a graph which maximizes the similarity with the FBG. In practice, one has to apply a heuristic algorithm to come close to the optimum within a reasonable time. We use a coarse to fine approach in which we introduce the degrees of freedom of the FBG progressively: translation, scale, aspect ratio, and finally local distortions. We similarly introduce phase information and increase the focus of displacement estimation: no phase, phase with focus 1, and then phase with focus 1 up to 5. The matching schedule described here assumes faces of known pose and approximately standard size, so that only one FBG is required.

Step 1: Find approximate face position.

Condense the FGB into an *average graph* by taking the average magnitudes of the jets in each bunch of the FBG (or, alternatively, select one arbitrary graph as a representative). Use this as a rigid model (A = to) and evaluate its similarity at each location of a square lattice with a spacing of 4 pixels. At this step the similarity function S_a without phase is used instead of *S^*. Repeat the scanning around the best fitting position with a spacing of 1 pixel. The best fitting position finally serves as the starting point for the next step.

Step 2: Refine position and size.

Now the FBG is used without averaging, varying it in position and size. Check the four different positions (±3, ±3) pixels displaced from the position found in Step 1, and at each position check two different sizes which have the same center position, a factor of 1.18 smaller or larger than the FBG average size. This is without effect on the metric similarity, since the vectors x^f are transformed accordingly. We still keep A = to. For each of these eight variations, the best fitting jet for each node is selected and its displacement according to Eq. (8) is computed. This is done with a focus of 1, i.e., the displacements may be of a magnitude up to eight pixels. The grids are then rescaled and repositioned to minimize the square sum over the displacements. Keep the best of the eight variations as the starting point for the next step.

Step 3: Refine size and find aspect ratio.

A similar relaxation process as described for Step 2 is applied, but relaxing the x- and y-dimensions independently. In addition, the focus is increased successively from 1 to 5.

Step 4: Local distortion.

In a pseudo-random sequence the position of each individual image node is varied to further increase the similarity to the FBG. Now the metric similarity is taken into account by setting A = 2 and using the vectors x^f as obtained in Step 3. In this step only those positions are considered for which the estimated displacement vector is small ($d < 1$). For this local distortion the focus again increases from 1 to 5

The resulting graph is called the *image graph* and is stored as a representation of the individual face of the image.

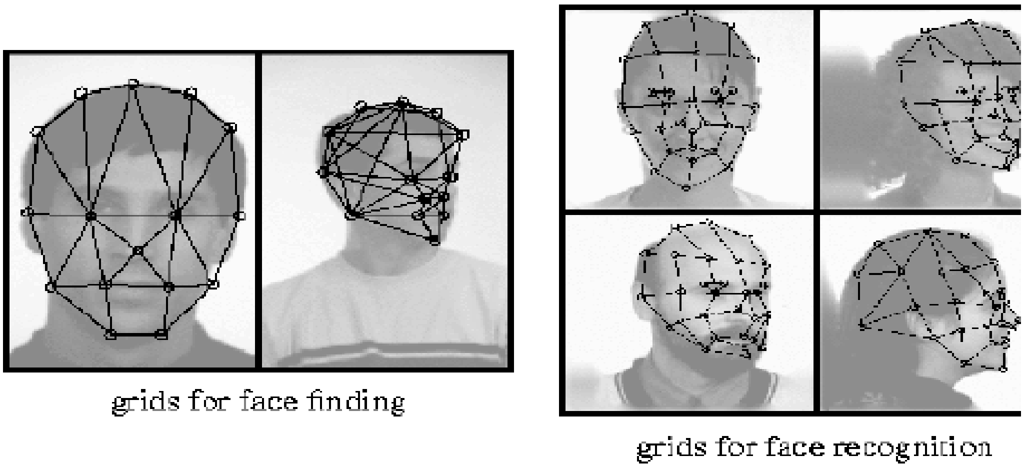


Figure 4:The figure shows the Object-adapted grids for different poses. The nodes are positioned automatically by elastic graph matching against the corresponding face bunch graphs. The two images on the left show originals with widely differing size and grids, as used for the normalization stage with many nodes on the outline for reliable face finding. The images on the right are already rescaled to normal size. Their grids have more nodes on the face, which is more appropriate for recognition. In general, the matching finds the fiducial points quite accurately.

III. ADVANTAGES OF EBGM:

Elastic graph matching is the basic process to compare graphs with images and to generate new graphs. In its simplest version a single labeled graph is matched onto an image. A labeled graph has a set of jets arranged in a particular spatial order. A corresponding set of jets can be selected from the Gabor-wavelet transform of the image. The image jets initially have the same relative spatial arrangement as the graph jets, and each image jet corresponds to one graph jet. The similarity of the graph with the image then is simply the average jet similarity between image and graph jets.In order to increase the similarity one allows the graph to translate, scale and distord to some extent, resulting in a different selection of image jets. The distortion and scaling is limited by a penalty term in the matching cost function.

The image jet selection which leads to the highest similarity with the graph is used to generate a new graph.When a bunch graph is used for matching, the procedure gets only a little bit more complicated. Beside selecting different image locations the graph similarity is also maximized by selecting the best fitting jet in each bunch. This is done independently of the other bunches to take full advantage of the combinations of the bunch graph representation This algorithm takes advantage of the fact that all human faces share a similar topological structure. This makes it possible to represent the face as a labeled graph. The nodes and edges of the graph contain additional information as for example the distance from one node to another.

The Elastic Bunch Graph Matching treats one vector per feature of the face. A feature for the face are the eyes, nose, mouth etc. This has the advantage that changes in one feature (eyes open, closed) do not necessarily mean that the person is not recognized any more. In addition this algorithm makes it possible to recognise faces up to a rotation of 22 degrees. Drawbacks of this algorithm are that it is very sensitive to lightening conditions and that a lot of graphs have to be placed manually on the face. For a reliable system one needs recognition is then done by comparing this graphs, it requires huge storage of convolution images for better performance.

IV. CONCLUSION:

Face recognition is a challenging problem in the field of image analysis and computer vision that has received a great deal of attention over the last few years because of its many applications in various domains. Research has been conducted vigorously in this area for the past four decades or so, and though huge progress has been made, encouraging results have been obtained and current face recognition systems have reached a certain degree of maturity when operating under constrained conditions; however, they are far from achieving the ideal of being able to perform adequately in all the various situations that are commonly encountered by applications utilizing these techniques in practical life. The ultimate goal of researchers in this area is to enable computers to emulate the human vision system.

The aging pattern of an individual depends on a variety of different factors that are difficult to model in a computational framework. But humans are quite good at matching faces across age progression. This may mean that irrespective of the exact manner in which a person ages, there is a coherency in the way facial appearance changes with age. This motivates us to capture and utilize this coherency to recognize age-separated faces. Specifically, we analyze the coherency of the drifts in various facial features to verify whether two age-separated images belong to the same individual or not. We use approach to match the facial features across two images in order to evaluate the displacement. Since facial features are not specific to human faces, it does not always locate all the facial features. Also appearance changes like weight gain/loss will affect the facial features. For different image pairs, different number of features at different locations may be extracted. Moreover, since the displacement of features depend on the underlying facial muscle structure, this information may be used to obtain a better measure of drift coherency. Also, measures to capture textural variations with aging may be useful for matching age-separated images in adults.

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