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RESEARCH ARTICLE

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VERIFICATION OF SURGICALLY ALTERED FACE IMAGE USING ELASTIC BUNCH GRAPH MATCHING ALGORITHM

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ABSTRACT

Increasing popularity of plastic surgery and its effect on verification of the face image has attracted attention from the research community. The change in facial geometry and texture increases the feature variability between the pre- and post-surgery images of the same face. Therefore, verifying post-surgery images with pre-surgery images becomes an difficult task for automatic face verification algorithms. In this work, EBGM (Elastic Bunch Graph Matching) and Viola Jones algorithm are proposed to verify face images before and after plastic surgery. First the face is recognized using the real time face detection system called viola jones and then individual faces and general knowledge about faces are represented by labeled graphs. EBGM is designed to cover all possible variations in the appearance of faces. This algorithm is based to a maximum on a general data structure graphs labeled with wavelet response and general transformation properties. On the plastic surgery face image, the proposed algorithm yields high identification accuracy as compared to existing algorithms and a commercial face verification system.

Keywords – Plastic surgery; viola jones; face verification; Elastic Bunch Graph Matching.

INTRODUCTION

Plastic surgery is a medical term worried with the correction or rebuilding of structure and function. In spite of the fact that cosmetic or aesthetic surgery is the best-known sort of plastic surgery, plastic surgery is not as a matter of course corrective and incorporates numerous sorts of reconstructive surgery, craniofacial surgery, hand surgery, microsurgery, and the treatment of burns.

An objective of the Evaluation of Face Recognition Algorithms venture is to set up an arrangement of standard calculations to use for calculation correlation. One of these calculations depends on the Elastic Bunch Graph Matching (EBGM) algorithm. This proposal portrays the usage of the EBGM calculation and inspects how the algorithm capacities.

Fig 1 illustrating the changes in texture, facial appearance and structural geometry before and after plastic surgery

The EBGM algorithm is one of the good algorithms for two reasons. To begin with, the algorithm is in a general sense unique in relation to others on the grounds that it perceives faces by contrasting their parts, rather than performing comprehensive picture coordinating. Second, the algorithm perform exceptionally well in the FERET study. Despite the fact that the subsequent EBGM execution does not recreate execution on the FERET database, the outcomes are good in connection to different algorithms assessed in the FERET test.

The framework is a piece of an open source extend that incorporates four benchmark algorithms and an arrangement of devices and scripts that can be utilized to assess the execution of face acknowledgment algorithm.

In this paper EBGM algorithm includes the sequence of processes used to overall verification of surgically altered face image. For the detection purpose the tool created by Paul viola and Micheal jones abbreviated as viola jones method. This is real time face detection system with the prominent result comparing to the other face detection system. The detected face is different in some factors with the original or natural face of human being.

Fig 2 Real time face detection through viola jones.

The viola jones technique for face detection is effective with respect to the working strategy of different phases it contributes the following steps first is Feature extraction then classification using boosting and last multi-scale detection algorithm. For the feature extraction and feature evaluation the combination of rectangular features are used, with a new image representation and their calculation is very fast. Classifier training and feature selection using a slight variation of a method is known as AdaBoost. A combination of simple classifiers is very effective. With the help of rectangular boxes containing of features with black and white areas with the image based and this technique makes it easy to calculate. The white areas are subtracted from the black ones. A special representation of the sample is known as the integral image makes feature extraction efficient and faster.

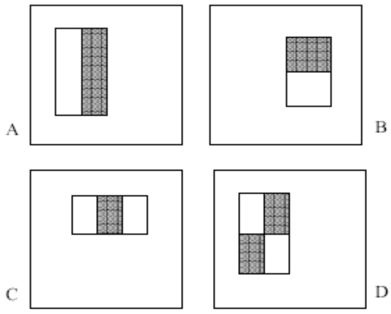

Fig 3 sample of feature extraction from sub window of an image

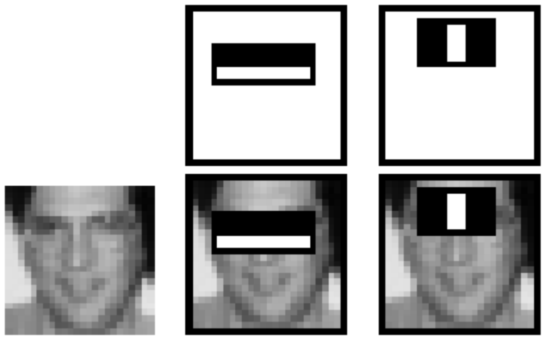

Fig 4 useful feature learn by boosting

EBGM ALGORITHM

As for as method concerned the Elastic Bunch Graph Matching Algorithm consist of following major steps-

1. The location of features is estimated
2. For every point of location

i. create a jet and calculate convolutions with all wavelets.

ii. For the purpose of detection displacement is calculated.

iii. Estimation of Jet for the new location.

3. Feature vectors comparison:

i. feature points location from sum of correlations,

ii. Support vector machine based comparison

This area will give an abnormal state prologue to the EBGM algorithm by outlining how the calculation functions and characterizing the key terms utilized throughout the work. The algorithm needs examples of what the landmark jets look like to locate the landmarks in a novel picture. The elements are selected by Gabor jets, for this situation referred as model jets. The jets are extracted from images with manually selected landmark locations.

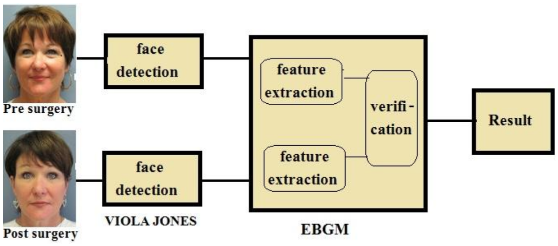

Fig 5 Block diagram illustrating different stage of proposed algorithm

The model jets are then collected in a data structure called a bunch graph. The bunch graph has a node for every landmark on the face. Every node is a collection model jets for the corresponding landmark. The bunch graph serves as a database of landmark descriptions that can be used to locate landmarks in novel imagery.

This algorithm processes the similitude of two pictures. To fulfill this undertaking, the algorithm first discovers landmark locations on the images that correspond to facial features, for example, the eyes, nose, and mouth. It then uses Gabor wavelet convolutions these points to describe the features of the landmark. All of the wavelet convolution values at a single point are referred to as a Gabor jet and are used to represent a location of point called landmark. A face graph is used to represent each image. The face graph nodes are placed at the landmark locations, and each node contains a Gabor jet extracted from that particular location. The similarity of those two images is a function of the relevant face graphs.

It requires major two steps to locating a landmark. First, the position of the landmark is estimated based on the other discovered locations of landmarks in the image, and second, that estimate is refined by extracting a combination of jets called Gabor jet from that image and comparing that jet to one of the models. The algorithm assumes that the eye coordinates are already known. Estimating the location of the other landmarks is easy based on the known eye coordinates. In theory all the landmark locations could be estimated from the eye coordinates because after plastic surgery the location of eyes remains unchanged. Each new landmark location is estimated based on the set of previously positioned points. For example, the eye coordinates are used to estimate the landmark location corresponding to the bridge of the nose, the location of nose is also permanent. Because the bridge of the nose is relatively close to the location of eyes the estimate should be very accurate. That landmark location is then refined by comparing a Gabor jet extracted from the estimated point to a model jet from the bunch graph from an detected image. Now the location of three points is known, the eyes and the bridge of the nose, now estimate the location of the left eyebrow and right eyebrow by all three known location which discovered previously. This process is iterated until all landmark locations are found.

Some face verification system depends on client characterized face-particular elements. For instance, spoken to eyes by a circle inside of an almond-shape and characterized a vitality capacity to upgrade an aggregate of model parameters for coordinating it to a image. The disadvantage of these frameworks is that the components as well as the systems to concentrate them must be recently characterized and customized by the client for every item class, and the framework has no way to adjust to tests for which the component models come up short. For instance, the eye models specified above may come up short for countenances with shades or have issues if the eyes are shut. In these cases the client needs to outline new elements and new calculations to concentrate them. With this sort of methodology, the framework can never be weaned from architect intercession. Our framework, conversely, can be taught uncommon cases, for example, shades or facial hair, or completely new protest classes, by the presentation of illustrations and fuse into bunch graph.

The EBGM System

1. Pre processing with Gabor wavelets

The illustration of native options is predicated on the Dennis Gabor ripple rework. Gabor wavelets are biologically driven convolution kernels within the form of plane waves restricted by a Gaussian envelope function (Daugman, 1988). The set of convolution coefficients for kernels of different orientations and frequencies at one image constituent is named a jet. During this section we tend to define jets, different similarity functions between jets, and our procedure for precise localization of jets in a picture.

2. Jets

A jet describes a small patch of grey values in an image I($\vec{x}$) around a given pixel $\vec{x}$ = (x; y). It is based on a wavelet transform, defined as a convolution

$$J_j(\vec{x}) = \int I(\vec{x})\psi_j(\vec{x}-\vec{x}')d^2\vec{x}'$$

With the family of Gabor kernels

$$\psi_j(\vec{x}) = \frac{k_j^2}{\sigma^2}\exp\left(-\frac{k_j^2 x^2}{2\sigma^2}\right)\left[\exp(i\vec{k}_j\vec{x}) - \exp\left(-\frac{\sigma^2}{2}\right)\right]$$

A jet J is defined as the set $\{J_j\}$ of complex coefficients obtained for one image point. It can be expressed as

$$J_j = a_j \exp(i\theta_j)$$

Having magnitudes, which vary with position, and phases which rotate at a rate approximately determined by the spatial frequency or wave vector of the kernel,

3. Comparing jets

Due to the phase rotation, jets are taken from image points. Only a few pixels have very different coefficients, although they are representing almost the same local feature. This can cause problems for matching the jets.

Using phase rotation has two advantages. Firstly, the phase information is required to discriminate between patterns with similar magnitudes, should they occur, and secondly, since phase varies so fast with location, it provides a means for accurate jet localization in a face image. Assuming that two jets *J* and *J'* refer to object locations with small relative displacement, the phase shifts can be approximately estimated for by the notations $\vec{d}\vec{k}_j$, gives a phase-sensitive similarity function

$$S_\phi(J,J') = \frac{\sum_j a_j a_j'\cos(\phi_j - \phi_j' - \vec{d}\vec{k}_j)}{\sqrt{\sum_j a_j^2 \sum_j a_j'^2}}$$

4. Face Representation

4.1 Individual Faces

For face image, we have defined a set of landmarks or Fiducial points, e.g. the corners of eye, the corners of the mouth, the tip of the nose, etc. A labelled graph G representing a face consists of N nodes on these landmarks. This face graph is object-adapted, since the nodes are selected from face-specific points (landmarks points) Graphs for different head pose differ in local features and geometry. Although the fiducially points refer to corresponding object locations at particular point, some may be occluded, and jets as well as distances may vary due to rotation in depth. To be able to compare graphs for different face image in dataset, we have manually defined landmarks on the face image to associate corresponding nodes in the

4.2 Face Bunch Graph

To find landmarks points in face image, it require a general representation rather than basic models of individual faces. This representation should cover a wide range of possible variations in the geometrical look of faces, such as differently shaped eyes, nose, or mouth, different types of beards, variations due to age, sex, and appearance change due to plastic surgery, etc. It is also difficult to locate each feature combination by a separate graph. We instead of that combine a representative set of individual basic model graphs into a stack-like structure, called a face bunch graph (FBG); Each model has the alike grid structure and the nodes refer to identical landmark points. A set of jets referring to one landmark position is called a bunch. The procedure described in the next section selects the best fitting jet at that point, called the local expert which is in gray shade, from the bunch representing to each landmark points. Thus, the full combination of jets in the bunch graph is available, including a larger range of facial variation due to surgery than represented in the constituting model graphs themselves.

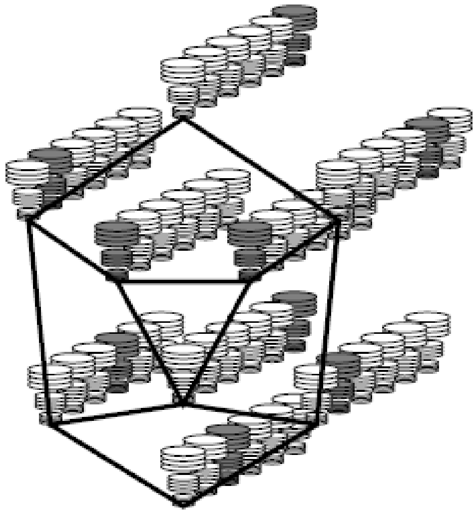

Fig. 6 The Face Bunch Graph (FBG) shows a representation of face image in general. It is developed including all possible variations in the appearance of faces. The FBG combines information from a number of face graphs. Its nodes are labelled with sets of jets known as bunches.

4.3 Matching through EBGM

The various steps are required to match the pre and post surgical face image. Matching is possible with computational technique by comparing an image graph with all model graphs and finding the one with the highest similarity value. The similarity function is based on the average similarity between respective jets from all landmarks. For image and model graphs referring to different face image, we compare jets according to the manually estimated landmarks and feature. Here we use the similarity function without phase. A matching against a gallery of face image in dataset individuals took slightly less than a second.

IV. RESULTS

To evaluate the performance of the proposed algorithm the basic experiments are performed with the dataset of fifty images with pre post plastic surgery face image in frontal pose with proper illumination and neutral expression. The bar graph is represented after evaluating the algorithm on the set of face image having before and after plastic surgery face image. The local plastic surgical procedures effects on amounts of change in the geometric distance between facial features but the overall appearance and texture of the face remains similar to the pre surgical face. This verification experiments are performed on normal face image going through a plastic surgery and altered the face. The bar graph is plotted in between the number of images and accuracy of matching with the pre surgical image. All the experiment is performed starting from the set of ten images then twenty and then so on one by one. Then the accuracy in percentage is along y-axis which gives the first accuracy for ten images then twenty and then so on. Overall by evaluating the result of various experiments the accuracy is about 79% with the dataset of less altered face image through plastic surgery. Evaluating also includes the precision of 79 and sensitivity or recall of value 1.

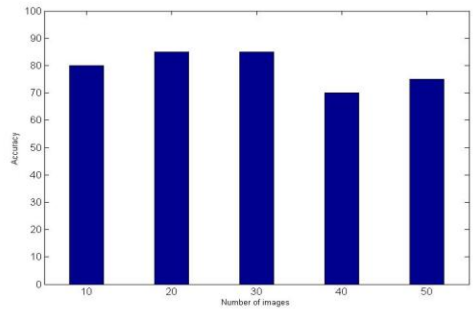

Fig.7 A Bar Graph for Results analysis.

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