Active Shape Models to Automatic Morphing of Face Images

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Abstract: - Image metamorphosis, commonly known as morphing, is a powerful tool for visual effects that consists of the fluid transformation of one digital image into another. There are many techniques for image metamorphosis, but in all of them there is a need for a person to supply the correspondence between the features in the source image and target image. In this paper we use the Active Shape Models to find the features in both face images and perform the metamorphosis of face images in frontal view automatically.

Key-Words: - Automatic Image Metamorphosis, Active Shape Models, Facial Features

1 Introduction

Image metamorphosis is a powerful tool for visual effects that consists of the fluid transformation of one digital image into another. This process, commonly known as *morphing* [1], has received much attention in recent years. This technique is used for visual effects in films and television [2,3], and it is also used for recognition of faces and objects [4].

Image metamorphosis is performed by coupling image warping with color interpolation. Image warping applies 2D geometric transformations to images to retain geometric alignment between their features, while color interpolation blends their colors.

The quality of a morphing sequence depends on the solution of three problems: feature specification, warp generation and transition control. Feature specification is performed by a person who chooses the correspondence between pairs of feature primitives. In actual morphing algorithms, meshes [3, 5, 6], line segments [7, 8, 9], or points [10, 11, 12] are used to determine feature positions in the images. Each primitive specifies an image feature, or landmark. Feature correspondence is then used to compute mapping functions that define the spatial relationship between all points in both images. These mapping functions are known as warp functions and are used to interpolate the positions of the features across the morph sequence. Once both images have been warped into alignment for intermediate feature positions, ordinary color interpolation (cross-dissolve) is performed to generate image morphing. Transition control determines the rate of warping and color blending across the morph sequence.

Feature specification is the most tedious aspect of morphing, since it requires a person to determine the landmarks in the images. A way to determine the landmarks automatically, without the participation of a human, would be desirable. In this work, we use the Active Shape Models, together a method for find a face in a image, to find the facial features and the spatial relationship between all points in both images, without the intervention of a human expert. We initially chose work with images of faces in frontal view with uniform illumination and without glasses to simplify the problem.

2 Active Shape Models

The Active Shape Models (ASM) was originally proposed by Cootes [13]. The ASM are statistical models which iteratively move toward structures in images similar to those on which they were trained. The aim is to build a model that describes shapes and typical variations of an object. To make the model able of capturing typical variations we collect different images of that object, and aim that the object is appearing in different ways reflecting its possible variations. This set of images is named the training set. In this work, the trained set comprises 37 different frontal human image faces, all without glasses and with a neutral expression [14]. To collect information about the shape variations needed to build the model, we represent each shape with a set of landmarks points. In this work we use a model of 58 points that represents the eyes, eyebrows, nose, mouth and jaw, see Figure 1.

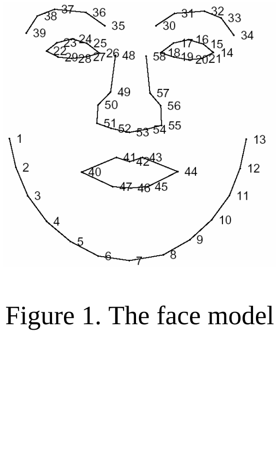


Figure 1. The face model

Each image in the training set is labeled by a set of points; each labeled point represents a particular part of the face or its boundary. Each point will thus have a certain distribution in the image space

3 Point Distribution Models

The Point Distribution Models are generated from examples of shapes, where each shape is represented by a set of labeled points. A given point corresponds to a particular location on each shape or object to be modeled [15]. The examples shapes are all aligned into a standard co-ordinate frame, and a principal component analysis is applied to the co-ordinates of the points. This produces the mean position for each of the points and description of the main ways in which the points tend to move together. The model can be used to generate new shapes using the equation

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{Pb} \tag{1}$$

Where $\mathbf{x} = (x_0, y_0, \ \ldots\ , x_{n-1}, y_{n-1})^T$, (x_k, y_k) is the k^{th} model point.

$\bar{\mathbf{x}}$ represents the mean shape

$\mathbf{P}$ is a $2n$ x t matrix of t unit eigenvectors

$\mathbf{b} = (b_1, \ldots, b_t)^T$ is a set of shape parameters b_i

If the shape parameters b_i are chosen such that the square of the Mahalanobis distance D_m^2 is limited, then the shape generated by (1) will be similar to those given in the training set.

$$D_m^2 = \sum_{k=1}^{t} \left(\frac{b_k^2}{l_k} \right) \le D_{\max}^2 \tag{2}$$

l_k is the variance of parameter b_k in the original training set and $D_{\max}^2 = 3.0$.

By choosing a set of shape parameters $\mathbf{b}$ for a Point Distribution Model, we define the shape of a model object in an object centred co-ordinate frame. We can then create an instance, $\mathbf{X}$, of the model in the image frame by defining the position, orientation and scale:

$$\mathbf{X} = M(s, q)[\mathbf{x}] + \mathbf{X}_c \tag{3}$$

where $\mathbf{X}_c = (X_c, Y_c, \ldots, X_c, Y_c)^T$, $M(s,q)[]$ performs a rotation by q and scaling by s, and (X_c,Y_c) is the position of the centre of the model in the image frame.

4 Modelling Grey Level Appearance

We wish to use our models for locating facial features in new face images. For this purpose, not only shape, but also grey-level appearance is important. We account for this by examining the statistics of the grey levels in regions around each of the labelled model points [16]. Since a given point corresponds to a particular part of the object, the grey-level patterns about that point in images of different examples will often be similar. We need to associate an orientation with each point of our shape model in order to align the region correctly, in this case normal to the boundary. For every point i in each image j, we can extract a profile g_{ij}', of length n_p pixels, centred at the point. We choose to sample the derivative of the grey levels along the profile in the image and normalise.

If the profile runs from p_{start} to p_{end} and is of length n_p pixels, the k^{th} element of the derivative profile is

$$g'_{jk} = I_j(\mathbf{y}_{k+1}) - I_j(\mathbf{y}_{k-1}) \tag{4}$$

where $\mathbf{y_k}$ is the k^{th} point along the profile:

$$\mathbf{y}_k = \mathbf{p}_{start} + \frac{k-1}{n_p - 1}(\mathbf{p}_{end} - \mathbf{p}_{start}) \tag{5}$$

and $I_j(\mathbf{y_k})$ is the grey level in image j at that point.

We then normalise this profile,

$$\mathbf{g}_{ij} = \frac{\mathbf{g}'_{ij}}{\sum_{k=1}^{n_p} \left| g'_{ijk} \right|} \tag{6}$$

The normalised derivative profile tends to be more invariant to changes in the image caused by variations in lighting than a simple grey-level profile,

$$\bar{\mathbf{g}}_i = \frac{1}{N_s} \sum_{j=1}^{N_s} \mathbf{g}_{ij} \tag{7}$$

We can then calculate an n_p x n_p covariance matrix, $\mathbf{Sg}_i$, giving us a statistical description of the expected profiles about the point. Having generated a flexible model and a description of the grey levels about each model point we would like to find new examples of the modelled face in images.

5 Calculating a Suggested Movement for Each Model Point

Given an initial estimate of the positions of a set of model points which we are attempting to fit to a face image we need to estimate a set of adjustments which will move each point toward a better position. At a particular model point we extract a derivative profile **g**, from the current image of some length l ($l > n_p$), centred at the point and aligned normal to the boundary. We then run the profile model along this sampled profile and find the point at which the model best matches (Figure 2). Given a sampled derivative profile the fit of the model at a point *d* pixels along it is calculated as follows [16];

$$f_{prof}(d) = (\mathbf{h}(d) - \overline{\mathbf{g}})^T \mathbf{S}_{\mathbf{g}}^{-1} (\mathbf{h}(d) - \overline{\mathbf{g}}) \qquad (8)$$

where **h**(*d*) is a sub-interval of g of length np pixels centred at d, normalised using (6). This is the Mahalanobis distance of the sample from the mean grey model, the value of f_{prof} decreases as the fit improves. The point of best fit is thus the point at f_{prof} (*d*) is minimum.

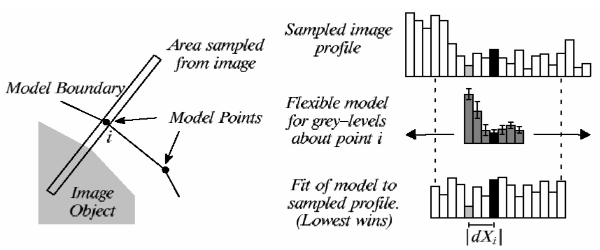


Figure 2. Suggest movement for Each Model Point [17]

6 Estimates the Initial Position of Model Points

The initial position of the model points is estimated using the method for faces detection showed in [18]. This method is based in two stages, each based in one heuristic. The first stage is based in the next heuristic

In a face with uniform lighting, the average intensity of the eyes is lower than the intensity of the part of the nose that is between the eyes.

In this stage we find regions that correspond to the eyes regions of possible faces in the image. The second stage uses the next heuristic

The histograms of the image in grayscale of a face with uniform lighting always have a specific shape

We know that a face has eyes, nose, mouth, eyebrows and it is covered by skin, and some elements of the face are darker than others. The relationship between the elements of the face results in a histogram with a specific shape it is showed in the Figure 3. In this stage we reduced the number of regions of possible faces found in the first stage. Finally we use a mask of seven segments (Figure 4) for finding the face in the remaining regions of the second stage using the horizontal edge image.

(a)

(b)

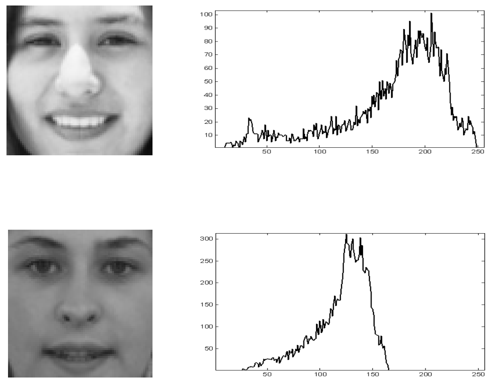
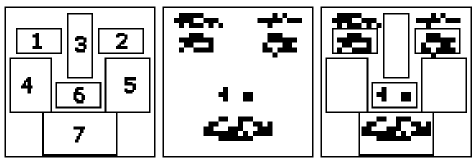


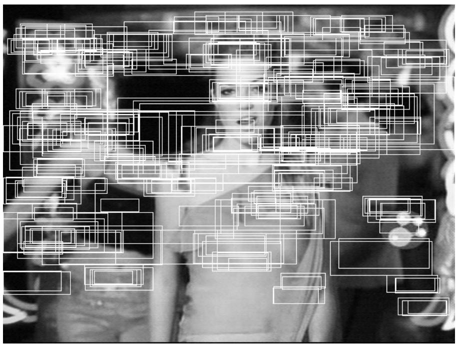
Figure 3. Example of the histograms from two face images. The shapes of histograms (a) and (b) are similar, one is wider than the other one and the values are different, this due to the lighting conditions and the different sizes in the images.



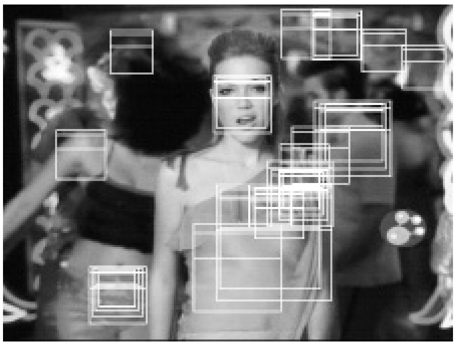
(a) (b) (c)

Figure. 4. (a)The mask of seven segments, (b) The horizontal edge image, (c) The mask used like discriminator

One example of the whole process is presented in the Figure 5, for details see [18].



(a) Number of possible faces: 294



(b) Number of possible faces: 29

(c) Number of faces detected: 1

Figure 5. Process to detect a face. (a) After the first stage. (b) After the second stage. (c) Final result.

7 Results

In the Figure 6 is showed the process to find the face feature in the face image. In (a) is showed the result of the face detection algorithm and in the Figures (b) to (f) is showed the result of the active shape models process.

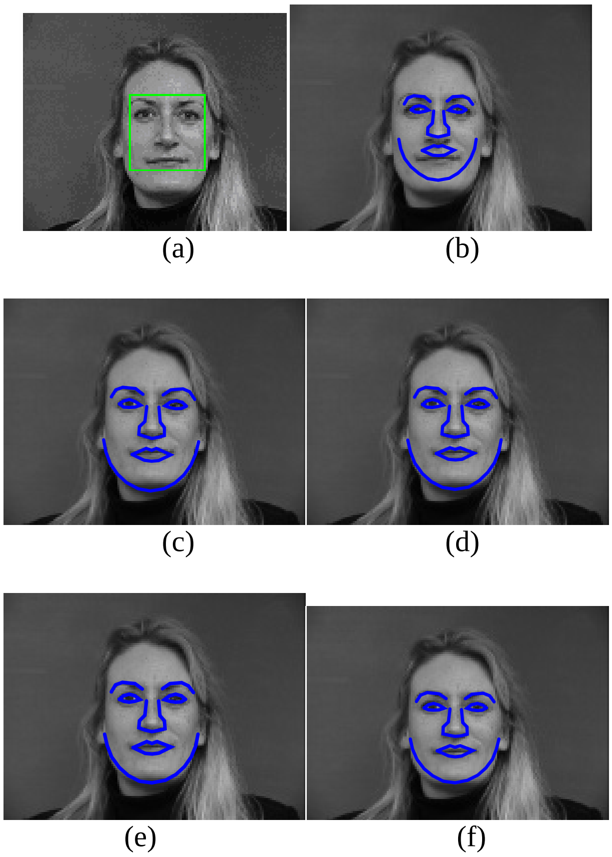


Figure 6. (a) Position of the face in the image, (b) The initial position of the model, (c) After one iteration, (d) After 3 iterations, (e) After 5 iterations and (f) After 10 iterations

In the Figure 7 is showed the model adjusted to four different face images using the method and in Figure 8 is showed the morphing process of the images in Figure 7.

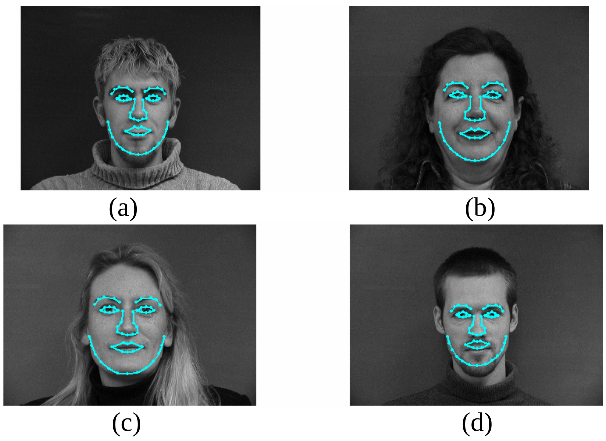


Figure 7.Model adjusted to different face images

(i) (ii)

Figure 8. (i) Morphing between the Figures 7(a) and 7(b), (ii) Morphing between the Figures 7(c) and 7(d).

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