

Feature extraction for face recognition via Active Shape Model (ASM) and Active Appearance Model (AAM)

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Abstract. Biometric is a pattern recognition system which is used for automatic recognition of persons based on characteristics and features of an individual. Face recognition with high recognition rate is still a challenging task and usually accomplished in three phases consisting of face detection, feature extraction, and expression classification. Precise and strong location of trait point is a complicated and difficult issue in face recognition. Cootes proposed a Multi Resolution Active Shape Models (ASM) algorithm, which could extract specified shape accurately and efficiently. Furthermore, as the improvement of ASM, Active Appearance Models algorithm (AAM) is proposed to extract both shape and texture of specified object simultaneously. In this paper we give more details about the two algorithms and give the results of experiments, testing their performance on one dataset of faces. We found that the ASM is faster and gains more accurate trait point location than the AAM, but the AAM gains a better match to the texture.

Keywords: Face Recognition, Active Shape Model (ASM), Active Appearance Model (AAM).

1. Introduction

With the rapid evolution of information technology, pattern recognition, artificial intelligence and other new technologies, face recognition has a lot of potential computer applications such as social media and multimedia communication, human-computer interaction, human detection, security and access control, which has become one of the important topics of research in recent years. Face recognition mainly includes face detection, feature extraction, texture variance, and classification.

In the face recognition system, locating facial features such as the location points of the eyes, nose, and mouth plays a significant role, because if the facial feature points are situated accurately, the following features extraction and classification stages would be more powerful and efficient [1].

A perfect located method can upgrade the performances of linked research areas, such as a face reconstruction, face recognition and expression recognition [2]. Although humans can easily recognize the accurate location of the facial feature points from a face image, for the computer it is not an easy task, because the computer does not have the complication of the brain of a human. The face has a complicated three-dimensional surface structure, thus, for the formation of a two-dimensional image, the change is very large, particularly for different face pose and facial expression, as well as various lighting conditions, the two-dimensional image distinction is very evident, precise and effective method is a very challenging task. Trait location is very important for the analysis of linked face issues; its accuracy is immediately linked to the reliability of the following application. It is not only to supply a significant geometric information for face image processing and analysis but also plays a



significant application for face recognition, facial animation, face synthesis, model-based face image coding, expression analysis of the face pose and so on.

Interpreting images including objects whose appearance can vary is hard, a robust approach has been to employ deformable models, which can perform the variations in shape and/or texture (intensity) of the target objects [3]. Precise and strong location of trait point is a complicated and difficult issue in face recognition. Cootes et al. proposed a Multi-Resolution-Active Shape Models algorithm [4], which could extract specified shape accurately and efficiently. Furthermore, as the improvement of ASM, Active Appearance Models algorithm [5] is proposed to extract both shape and texture of specified object simultaneously.

To summarize our contribution, we find that a lot of Face recognition algorithms have been proposed. So far, all these algorithms are based on ASM or AAM separately or in cascade [5] [6]. However, Previous research has examined the effects of ASM or AAM on recognize the accurate location of the facial feature points from a face image. In contrast, there is a few researches compares the accuracy and efficiency of two algorithms in facial feature detection. In this research we give more details about the two algorithms and give the results of experiments, testing their performance on one dataset of faces. We measure their accuracy by locating landmark points, and their efficiency.

In this paper, we focus on two associated algorithms, Active Shape Model (ASM), which aims to match a collection of model points to an image that was restricted by a statistical model of shape, and the Active Appearance Model (AAM), which looks to match both the position of the model points and a representation of the texture of the object to an image. ASM and AAM use the same underlying statistical model of the shape of purpose objects. This model represents the shape using a group of landmarks, knowing the appropriate ranges of shape variation from a training set of labeled images [7].

1.1. Active Shape Model (ASM)

The shape of an object is represented through landmarks which are one chain of consecutive traits points, each of which is important, point existent in most of the images being considered, for example, the location of the right eye. Enough number of trait points should be provided to cover the comprehensive shape and details. In the proposed model, a total of 68 trait points are defined to explain the shape of a human face, covering the areas of the eyebrows, cheeks, eyes, mouth, and nose. A group of landmarks forms a shape. Meanwhile, the shapes are represented as vectors: all the x-coordinates pursued by the y-coordinates of the points in the form. Align one shape to other with a correspondence transform (allowing rotation, scaling, rotation, and translation) that reduce the Euclidean distance average between shape points. The mean shape is declared the middle of the stratified training shapes [8]. The ASM beginning the search for facial landmarks from the mean shape aligned to the place and size of the face specified by a global face detector.

It then reiterates the following two steps until convergence: (i) propose a temporary shape by determining the positions of shape points through template appropriating from the image texture concerning each point. (ii) Confirms the temporary shape to a universal shape model. The special template suitability is uncertain and the form model gathers the outcomes of the weakened form matches to form a powerful classifier. The complete search is reiterated at each level in an image pyramid, from poor to fine resolution.

1.2. Active Appearance Model (AAM)

AAM model suggested by Cootes et al. [8], AAM is one of the most strong model-based object tracking and detecting algorithms. It is generative, nonlinear, parametric model and can be referred to active contour algorithm ("snakes," [9]), and (ASM) algorithm [7]. Especially, the AAM forms the texture, shape of the object to produce a set of immediate and realistic photos. The AAM has been widely applied in different cases [10-12]. The most persistent implementation of AAM model has been facial tracking and modelling [13].

ASMs and AAMs vary in the quantity of texture variation they capture. ASMs capture very few texture variations and basically use models of shape, while AAMs include detailed texture (pattern of intensity or color) alteration information are thus completely generative methods that can make photorealistic images. So ASMs match shape models, while AAMs match full models of appearance to an image. In Cootes' report [8] one can detect that Covell explained that the parameters of an Eigen trait model can be applied to drive shape model points to the right place. Cootes' AAM, Applied here, is an extension of this idea. AAMs, consider what are valid shapes (valid forms) and intensity variations from a training set, to generate synthetically examples similar to those in a training-set. The AAM model has a strong modelling and effective ability for fitting the raised complexity due to the high-dimensional texture representation which restricts its application to numerous concepts, such as real time systems.

To prepare the AAM algorithm which is more suitable to actual applications, more potential should be consumed to optimize the calculation of the AAM. Therefore, several enhancements are suggested to attain this aim. Henceforth, various methods are suggested to decrease the distance of the texture, for example, wedge let-based regression tree [15] and Haar wavelet [14]. Moreover, these processes improve the efficiency of the cost of decreasing accuracy or wasting detail information. A frame process is the inverse compositional image alignment (ICIA) [16] algorithm that averts updating texture parameters for each frame and is a fast fitting algorithm for the AAM model. The determination of this model is that it cannot be used to the active shape model that limit the shape and the appearance variance with a lone group of parameters.

2. Methods

The experiment includes training of ASM and AAM algorithms, the experiment flowchart is shown in Figure 3.

2.1. Active shape model(ASM) algorithm

The algorithm of ASM model consists of five steps [4]: (i) labeling the points as shown in figure 3. (ii) Eliciting gray profile to all landmarks. (iii) Aligning training set for ASM. (iv) Calculating statistics on aligned training set on PCA at every resolution. (v) Repeat steps from step 1 to step 4 for all resolution level.

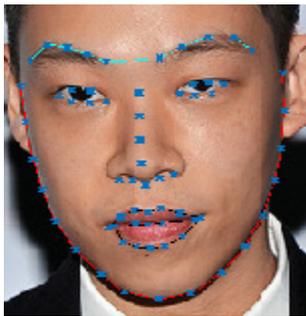


Figure 1. Point's distribution.

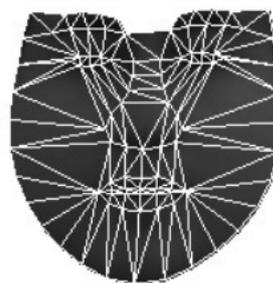


Figure 2. AAM diagram.

After these processes, for each shape X_i can be represented as: $X_i = \bar{X} + P \cdot b$. Where, \bar{X} is the ASM mean of training set, eigenvectors P performs the best significant t methods of variation, b it is a coefficient vector.

2.2. Active Appearance Model(AAM) algorithm

AAM model is originated from ASM model. The full face is splitted into small areas utilizing triangles which vertexes are the ASM landmark points, as shown in Figure 2. The active appearance model connects shape and texture PCA parameters for one group of vectors and a weight vector, then analysis utilizing PCA again.

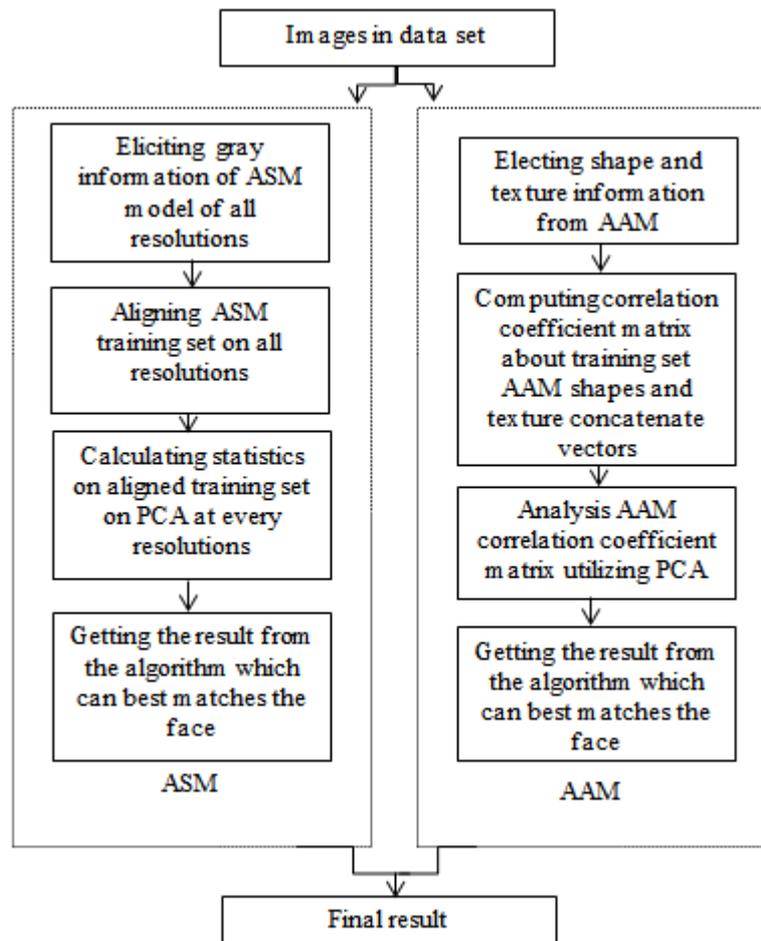


Figure 3. Flowchart of experiment.

The weighing vector is specified by the experiment. It changes with several training set and request many of experiments. Moreover, there is no obvious criterion to estimate the effectiveness of the weight vector. The algorithm of AAM model consists of three steps: (i) connecting shape and texture vectors to each AAM in training set, jointly shape and texture vectors are connected in the same vector: $C_i = (T_i, X_i)^T$, where T_i is a texture vector for m_t pixel, X_i is the position of n landmark point. (ii) Computing the correlation coefficient matrix about connected shape and texture vectors in training set. (iii) Analysis correlation coefficient matrix utilizing PCA. The eigenvectors P of C_{cor} are the hybrid parameters, and they are necessary to monitoring the shape and texture of AAM model. Each pattern in the training group can be proposed as: $C_i = \bar{C} + A \cdot (P \cdot b)$
 A represents a diagonal matrix and i element in diametrical contrast correspondent to coefficient of i dimension of C .

2.3. Data sets

We performed the experiments of the ASM and AAM on one data set taken from LFPW database. The data sets contained 100 face images, each marked with 68 points. We did search experiments on the data set, computing the accuracy to relocate the points, how well the texture could be matched and the time consumed to do so.

LFPW database provides us with only the web links and not the real images. Due to broken links, we were able to download only a subset of about 800 out of 1.100 and 224 out of 300 images were obtained for testing and training.

2.4. System requirement

Our experiments were conducted on MATLAB R2016a, PC with processor Intel(R) Core(TM) i5, 4.00 GB RAM memory and Operating System: Windows 7 64-bit.

3. Results

LFPW image database is used to test the efficiency of both algorithms. Total of 100 face images are chosen as training set, each marked with 68 points. The number of searching positions has the most primary influence on the location result. We compared the performance between both algorithms. The experimental results are shown in Figure 4.

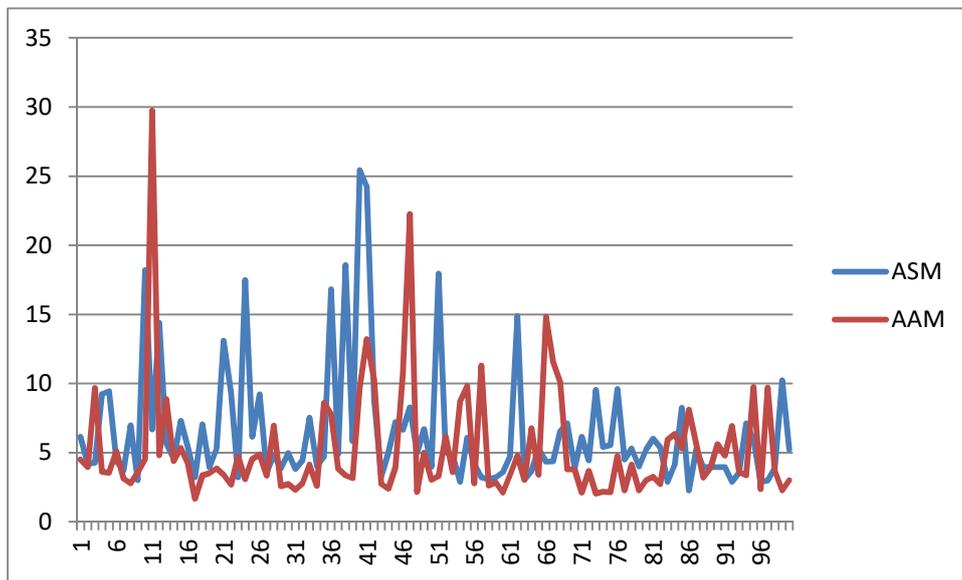


Figure 4. Shows the normalized mean point-to-point error (Euclidean) for AAM and ASM models.

Figure 4 displays resulting point to point errors (the distance between model points and the corresponding points marked in images), the length of point to point error is from 1.6679 to 29.7505. The vertical axis is the point to point error between two algorithms and the Horizontal axis is the image number, the line is the point to point error of all feature points. From above results, it can be seen that, under all conditions, the line of the ASM algorithm is more accurate than AAM algorithm except some cases.

Table 1. summarizes the average of point-to-point error for 100 images using AAM and ASM models.

Model	Point to Point error
ASM	6.502441
AAM	5.238626

Table 1 compare the average of point to point error for 68 landmarks of training set using both algorithms, the result shows that the difference between ASM and AAM equal 1.263815 so the ASM algorithm locates the points more accurately than the AAM algorithm.

In our experiments, 68 landmark points are labeled on every face image to describe the shape. Figures 5, 6 show the facial feature extraction using ASM, AAM model.



Figure 5. Example of shape composed of landmarks using ASM



Figure 6. Examples of facial feature extraction using AAM model.

3.1. Efficiency

The efficiency was taken regarding time-measurements for running each algorithm on 100 images sequentially. Table 2 shows Time measurements for ASM and AAM algorithms:

Table 2. Comparison of Time measurements for ASM and AAM algorithms.

Model	Time
ASM	133.368243 seconds.
AAM	337.959374 seconds.

Table 2 compare the time measurements for ASM and AAM algorithms, each algorithm performed separately and applied for 100 image sequentially, the experiment conducted on MATLAB R2016a, PC with processor Intel(R) Core(TM) i5, 4.00 GB RAM memory and Operating System: Windows 7 64-bit, The result shows that ASM model takes 133.368243 seconds to perfume full process, AAM model takes 337.959374 seconds to perfume full process, so ASM is faster than AAM.

4. Discussion

As shown in our experiment, see Figure 4, the ASM algorithm is more accurate and faster than AAM algorithm, but AAM algorithm is better in texture matching. ASM algorithm just processes data around the model points and does not take all the information obtainable through an object as the AAM algorithm. So ASM model may be less reliable. The model points proceed to be places of interest (borders or angles) where there is the extreme information. We could train the AAM model to just search using information in areas around strong borders; this would need less image sampling through search so a potentially faster algorithm.

One feature of the AAM is that we can construct a masked model with a comparatively little number of landmarks. Any additional shape variation is extracted in extra methods of the texture model. The ASM requires points about boundaries so as to set appropriate directions for search. Fewer landmarks are required because the significant work only needs to obtain credible image labelling.

5. Conclusion

In this paper, the facial feature extraction using AAM, ASM Algorithms with LFPW face databases. In the experimental results, we found that the ASM model is faster and attains more precise traits point location than the AAM model, and AAM model gives a better match to the image texture. There are three key differences between the ASM and AAM algorithms:

- The AAM attempts to minimise the difference between the target image and the synthesized model image, while the ASM attempts to reduce the distance between model points and the corresponding points found in the image.
- The AAM employs a model of the appearance of the whole of the region, while the ASM employs models of the texture in small regions around every landmark point.
- The AAM model samples the image only under the current position, whereas the ASM model searches around the current position, typically along profiles normal to the boundary.

In the future work this results can be compared to other Models which concerns with face recognition also the researchers can improving and build a combined model using ASM and AAM model that jointly optimizes a precise traits point location and gives a better match to the image texture.

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