Abstract

3D face analysis has been researched intensively in recent decades. Most 3D data (so called range facial data) are obtained from 3D range imaging systems. Such data representations have been proven effective for face recognition in 3D space. However, obtaining such data requires subject cooperation in a constrained environment, which is not practical for many real applications of video surveillance. It is therefore in high demand to use regular video cameras to generate 3D face models for further classification. The goal of our research is to develop a method of tracking feature points on a face in multiple views in order to build 3D models of individual faces. We proposed a three-view based video tracking and model creation algorithm, which is based on the Active Appearance Model and a generic facial model. We will describe how to build useful individual models over time, and validate the created dynamic model sequences through the application of face recognition. Tracking multiple view fiducial points of a face in a time sequence can also be used for facial expression analysis. Our experiments demonstrated the feasibility of the proposed work.

1. Introduction

3D range data has been intensively used for face analysis (3D face recognition [8-20] and 3D face expression recognition [21-25]). Most of the existing 3D imaging systems require a cooperative individual and often under a controlled environment. While these techniques are much more capable of identifying cooperative subjects, they are hard to identify non-cooperative subjects for applications such as surveillance. The significant implication and practice of the video surveillance system lie in:

(1) The system may be installed in a public place, e.g., the check point for a court house; controlling a passage volume such that any person’s movement within the volume can be tracked and recognized.

(2) Analyzing spontaneous expression requires installing un-cooperative camera systems so that the expression data can be captured in a nature way, which could reflect a person’s true emotion more accurately.

This paper reports our new development for identifying uncooperative individuals based on 3D face models. Although there have been many successful systems for face recognition, automatic face recognition is still a very challenging task, partly due to variations in pose, illumination and aging from one image of a face to another. For example, the task of recognizing people from views different than the views used for training in an uncooperative imaging circumstance is still unsolved. The use of 3D models for representing a face enables having one model to include the facial features of the person’s face, resulting in the easy creation of arbitrary views of the face.

There are some existing works to construct face models from single [31] or two views of a face [29, 30, and 18]. However, two orthogonal views of a face may not be able to generate facial surfaces in arbitrary views, especially for the part which is originally invisible by cameras. Adding an extra view may provide additional information to compensate for other parts of a face.

In this paper, we propose to build a 3D face analyzer using regular CCTV videos. We propose to use a three-view tracking approach to build 3D face models over time. The proposed system is designed to detect, track and estimate the facial features. After the tracking stage, a generic model is then adapted to the different views of the face accordingly. Finally, the multiple views of models are combined to create an individualized face model. The tracking and modeling process is elaborated through the video sequences. The facial shape features will be explored for increasing the accuracy of face matching and identification, not only for face recognition, but also for facial expression identification.

Tracking specific feature points or landmarks on the human face is a challenging task. We use our predefined fiducial points to track the facial motion under three different views, i.e., front view, side view, and angle view.
Our dynamic face modeling system utilizes the facial features exhibited in three different views, and customizes a generic model to each view separately. As a result, the individual 3D models for each frame can be generated by combining the three models across the video sequences.

For the tracking, we decide to adapt an Active Appearance Model approach to our work in order to decrease the amount of manual work that must be done. In the past few years, the Active Appearance Model (AAM) approach to face tracking has achieved a lot of attention for both speed and accuracy [1-7]. Originally proposed by Edwards et al. [4] as an extension of Active Shape Models, AAM's make use of texture data in the model in order to improve the fitting algorithm.

To fit the generic model to separate views of facial sequences, we developed a face adaptation algorithm, which includes two steps: feature point adaptation and non-feature point interpolation. A Cardinal spline curve interpolation approach is applied to infer the non-feature points. A local-region based mesh model adjustment is developed.

Finally, the generated dynamic 3D model sequences are validated through applications of face recognition and facial expression recognition. As shown in Figure 2, we created a dynamic 3D face database from multiple views video’s input. Each subject has models with six universal expressions. The classification of facial expression is carried out through the facial surface labeling and motion vector estimation approach. Note that the creation of 3D facial models from 2D imagery has practical implications. For example, image pairs (frontal and profile views) are found in most commonly used data sources, such as persons’ records, which are available from existing police and federal government database.

The organization of the paper is as follows: the facial feature tracking for three-view videos is described in Section 2. In Section 3, we explain the generic model adaptation algorithm and the approach for model creation. Experiments on 3D face recognition and facial expression recognition are reported in Section 4, followed by a final section for discussion of the limitations and future work as the conclusion.

2. Multiple-View Face Tracking

2.1 Feature point definition

We designed a three camera (see figure 1) system able to capture videos of the human face at a resolution of 640x480 pixels and at a rate of 30 frames per second.

The three cameras are set up to capture three main views of the human face, the front, the profile, and a low angle view (Figure 3a). It has been reported that the front view and profile view are commonly used views [18, 14], and many databases of such data already exist (e.g., persons’ records in police departments). However, due to occlusion, pose, and lighting variations, sometimes the front or profile view may not provide all of the information expected, especially in the chin part due to shadows. The low angle camera setup allows us to capture more information (e.g., areas of side face and lower chin) in order to reconstruct the pose and head shape. Three cameras could help locate many of the same features in the front, the side, and the angle view. They can be useful as a subject moves or the face becomes occluded in one line of sight because we can rely upon the other to provide a better view of the subject’s face.

For the first frames of three videos, we defined key features on the faces with front view (92 points), profile view (49 points), and the angle view (92 points) (as shown in Figure 3b). According to our previously developed work for face detection and facial feature detection using deformable template based approaches [27], we applied the same algorithm to detect facial features in the first frames of the video sequences. As a result, the feature
points defined in the three views are determined [27]. In case of the detection errors, we manually correct the error points for the first frame of each video sequence.

\[ x = \bar{x} + P_{s}b_{s} \]  

where \( \bar{x} \) is the mean shape, \( P_{s} \) and \( b_{s} \) are the eigenvectors and eigenvalues which describe the variations across the set of training shapes [2].

According to the defined feature points, each training shape is warped to the mean shape for all training data [3]. The warping is done on the triangulated feature points [4]. The result is a set of images which can be directly compared for color and intensity variations which have the same shape. Then, the PCA can be performed on the images to provide a model to explain the variations in color or intensity across the data set. Note that another PCA is performed on the shape and image vectors simultaneously because some image intensity changes may correlate with changes in shape.

As a result, the model is then stored as the set of eigenvectors and eigenvalues for the training data. The eigenvectors are truncated by PCA to explain a certain percentage of shape and image variation, usually between 95 and 98 percent, to achieve a more compact model. In our testing we used 95 percent.

Once the model has been saved, it is then possible to perform tracking of the video sequences, and find the feature points within each frame automatically. An efficient fitting algorithm, described by Cootes et al. [3] is used by the AAM-API [1] classes, by which we used to perform the feature tracking. Since we intend to retain the original images, and only wish to keep the detected feature points, we do not need to save the AAM model, only the feature point locations for each frame. These feature point locations are then converted back to the coordinate system used by our application. We also take advantage of the temporal similarity of successive frames in the video sequence by using the previous frame’s parameters and shape as a starting point for fitting the next frame. This provides significant savings in the time it takes to achieve convergence of the fitting algorithm.

2.2. Active appearance model based tracking

The Active Appearance Model algorithm uses principal component analysis (PCA) on the face image shapes and image intensities to generate a statistical model to describe the variations in shape and image intensity across the training images. The fitting algorithm then attempts to find the best parameters, \( b \), to describe the new images [2].

\[ x = \bar{x} + P_{s}b_{s} \]  

2.3. Feature point expansion by spline approximation

In order for subsequent generic model adaptation, we expand the AAM-tracked feature points (92 for front, 49 for profile, and 92 for angle view) to a large set (459 for front, 237 for profile, and 459 for angle view). The expanded feature space is based on the feature vertices defined on our 3D generic facial model. To do so, we apply a feature point interpolation procedure using a Cardinal Spline approximation approach.

2.3.1. Cardinal Spline Interpolation

Because most of the feature points are located to
indicate the facial features’ area or shape in each facial image, those regions or shapes can be drawn with multiple curve lines as an artist would draw a human face. Motivated by this idea, we defined 42 curve lines in order to infer 459 feature points from 92 feature points in the frontal view facial region. The 42 curve lines are derived from 92 feature points using the cardinal spline interpolation algorithm. One curve line is determined by four key points, as illustrated in Equation (2) and Figure 4:

\[
P(u) = p_{k-1}(-s u^3 + 2s u^2 - su) + p_k[(2-s)u^3 + (s-3)u^2 + 1] + p_{k+1}[(s-2)u^3 + (3-2s)u^2 + su] + p_{k+2}(s u^3 - su^2)
\]  

The same procedure is also applied to the side view and angle view face images.

To draw \( n \) points using this method, the space between two key points are divided equally by \( n+1 \) pieces along the curve line. As a result, the non-key points can be determined along the curve line (as illustrated in Figure 5 for an example), and the facial feature space is eventually expanded to 459 feature points from the initially defined 92 feature points. Note that the AAM-based tracking outputs the 92 feature points of the front view video sequences. The feature space expansion is performed for each frame individually. The same procedure is also applied to the angle view and side view video sequences.

It is worth noting that although the above procedure for feature point expansion does not introduce new information, the expanded three sets of feature points make it easy to conduct the subsequent model adaptation because the three sets of points (459 for front, 237 for profile, and 459 for angle view) correspond to the predefined feature vertices on the generic model in three views exactly, and less non-feature points need to be determined in the later model adaptation stage.

3. Generic Model Adaptation to Three Views

3.1. Feature point adaptation

The displacement vector \( V \) of a facial view (i.e., front, profile, or angle view) is defined as a vector from the position in the generic model to the corresponding position in the actual image when the model is projected to that view. Model adaptation of the feature points is simply done by placing the feature vertices of the model to the positions of feature points of the image.

Let vector \( V_i^e \) of feature vertex \( i \) be defined by

\[
V_i^e = M_i^e - P_i^e
\]

where \( M_i^e, P_i^e \) are the positions of \( i \)th key point in the face image and the generic model.

Figure 5: Key points (left) and non-key points (right) which are generated by spline interpolations.

Figure 6: Feature and non-feature points adaptation using dynamically updated interpolation.
3.2. Non-feature point adaptation

The displacement vectors of non-feature vertices \( V^i \) can be derived by interpolating the displacement vectors of feature vertices \( V^k \) (as shown in Figure 6):

\[
V^i = \sum_{j=1}^{N} w(d_{i,j}) V^j
\]

where \( N \) is the number of nearest feature vertices surrounding the non-feature vertex (e.g., \( N = 10 \)). \( d_{i,j} \) is the distance between vertex \( i \) and vertex \( j \). The weight value depends on the distance of the two vertices. The shorter the distance is, the higher the weight is to be assigned:

\[
w(d_{i,j}) = \frac{1}{\sum_{j=1}^{N} d_{i,j}^{-1}}
\]

Note that the estimated \( V^i \) of vertex \( i \) is added to the set of feature vertices, and can be used for the estimation of the remaining non-feature vertices. This dynamic growing method infers the displacement vectors of non-feature vertices based on the updated feature vertices list. The newly added feature vertices will influence the non-feature vertices of the local region. Therefore, the region of influence on a non-feature point is dynamically changed. While more feature points are considered, the calculation turns more complex. Because control points which are far from the current vertex have less influence on the vertex displacement, we could use only those features that contribute significantly to the movement of current vertex. In our experiment, ten nearest features points are considered for achieving the satisfactory results.

4. Experiments

4.1. Creation of facial models

We captured video streams from 150 subjects with a variety of racial background, e.g., Black, White, Asian, Latino/Hispanic, etc.). Each subject has seven sets of video clips, which show the six basic expressions (anger, disgust, fear, smile sad, and surprise) plus one additional video with arbitrary motion and expressions for testing. With three separate views, we captured a total of 31,500 (=150*7*3) video clips, with each expression lasting a few seconds. Using our three-view 3D face modeling algorithm, 10,500 3D dynamic model sequences, in total, are created. Figure 7 illustrates one example of a male model sequence, which shows the adapted models in three view planes and the synthesized individual models across frames.

We evaluated the quality of our generated models by comparing to the 3D range data captured from a 3DMD structure lighting imaging system [28]. Each subject has
one 3D range model with a neutral expression. We then compare the range models to our generated models (which are selected from neutral expression as well). Given 63 feature points, which are manually selected from the range models and our generated models, we compute the mean square error of these points. The result shows that the MSE of these feature points are averagely 5.17 units in the condition of all the models are normalized to a 128*128*128 cubic space.

4.2. Application for 3D face recognition

To validate the usefulness of the generated 3D model sequences, we conducted a model classification experiment for face recognition. Since a model sequence contains various facial expressions, we warp them to a standard shape which exhibits a neutral expression. Then, the entire warped frame models of the sequence are averaged, resulting in the individual’s representative model, based on which the subsequent face recognition is carried out. We used 1,000 3D model sequences to test our face recognition algorithm. Based on the existing approach reported in [14], we implemented the optimal feature selection algorithm, and compared the individual’s representative models to the database models. The recognition is based on the feature correlation criterion. The average correct recognition rate is 95.7%. As compared to the range data used in [14], our generated 3D models are accurate enough to distinguish from person to person, even outperforming the range data used in [14]. We also implemented the ICP+LDA based surface matching approach used in [16] for 3D model classification. The result shows an 87.7% rank-one recognition rate. The result is degraded as compared the results reported in [16] where 90% correct recognition rate was achieved when high resolution range models were used. However, our data offers more practical and flexible applications when regular surveillance video cameras are used instead of range scanners.

4.3 Application for facial expression recognition

We further investigate the usage of such data for facial expression recognition. Since all the models generated for individual frames have same number of vertices and same geometric topology, they have inherently established the correspondence across the model sequences. As such, the 3D motion trajectories are estimated by vectors from the tracked points of the current frame to the corresponding points of the first frame of a neutral expression. Each motion trajectory is represented by a three-tuple vector $u_i = (dx, dy, dz)$. We selected 63 feature points on the facial regions (e.g., eyes, nose, mouth, eyebrows, and chin), and construct a facial expression motion vector $u$ for each instant model by the 63 components: $u = [u_1, u_2, ..., u_{63}]$. It represents the temporal facial expression information. Similar to the approach reported by Yin et al. in [24], the facial expression label map (FELM) is created using small scale labeling. It captures the small surface variation during the facial surface movement. The different label distributions show the different facial expression characteristics. For each expression, a FELM vector $e = [e_1, e_2, ..., e_n]$ is generated after the model is labeled. Each element $e_i$ of a FELM is a ratio of the number of vertices with a specific label type to the number of vertices in the whole facial region. $n$ denotes the number of label types ($n=12$). Given the same facial expression from different subjects, the FELMs of expressive regions exhibit the similar characteristics of

![Figure 7](image-url): From Left to Right: 3D model tracking in three individual views separately (Column 1 – 3: front view, angle view, and side view), and the generated 3D models (Column 4) and the textured mapped models (Column 5). From top to bottom: frame #5, 53, 80, 151, 209, 235, 319, and 325.
histograms. The FELM can be used as a descriptor of facial expression, which reveals the spatial expressive information and decreases the variation of diverse individuals.

To this end, we have constructed a spatial-temporal facial expression descriptor \( F = [u, e] \) for each expression model, which is a vector concatenating both \( e \) and \( u \). We conducted person-independent facial expression recognition experiments using our created dynamic 3D facial expression database, and applied linear discriminant analysis (LDA) to classify the six prototypic facial expressions. The data from 80 subjects are used for training. The remaining 70 subjects are for test. The average correct recognition rate is 83.7%. The result is better than the result (around 80%) reported in [24], where the synthesized range data has a low frame rate.

5. Conclusion

In view of the existing technology development in face information processing [12, 16, 19, 26], especially for face recognition, the big challenge still remains as to how to handle the complex environment in various imaging conditions, such as low resolution, various pose change, viewing point, illumination, aging, etc. Although some systems based on 2D face images have been successfully applied to frontal faces with limited ranges of view angles, they are inherently incapable of handling the large head rotation. The performance degradation remains in the situation of large pose and expression variations. 3D model based face analysis is promising to handle the face rotation in depth [8, 13, 19, 20].

There are existing systems utilizing 3D range data captured by 3D imaging sensors (e.g., laser based or structured lighting based 3D scanner) to perform the face recognition. However, these raw data contain a large number of 3D points and are very difficult to perform the comparison from person to person, due to the lack of correspondence between two compared model structures. Moreover, the 3D range imaging system requires special hardware (e.g., laser device, structured lighting projector), and requires a close distance setup and user cooperation, it is thus not feasible in many practical environments (such as surveillance). The high cost of 3D range scanner and low processing speed limit its real application.

In view of the major obstacles in face information processing, we developed a dynamic multi-view based face tracking and modeling system based on regular cameras, and used the generated 3D dynamic models for performing the tasks of face recognition and facial expression recognition.

5.1 Limitation and future work

There is still more work to be done in this area, among the questions we found during our research is how to select the best key frames for training. We would like to have a more automatic and meaningful approach to the selection process. We intend to look at ways to find frames which contain the greatest variations from the mean and present a list of training candidates to the user for selection. Ultimately, the user should be able to override the system’s selection, but we believe this is one more way we could provide time savings to the user.

We also want to look into ways in which we could incorporate tracking data from 2 or 3 different streams together to improve performance and accuracy. Some previous work has been done in this area, also with Active Appearance Models, using 3-D models and projecting them into a 2-D space as a means of face recognition. We believe a similar approach would work just as well for feature tracking.

Another area of further investigation is whether or not we could build generic Active Appearance Models capable of performing tracking reasonably well on a previously unseen subject [7]. Investigation of current literature suggests that the use of image intensity have been moderately successful in fitting to data not in the training set. We plan to further investigate similar approaches for future versions of this research.

The feature detection for the first frame image is currently based on the deformable template approach, which is not very robust. In case of failure of detection, a manual correction (add/remove/modify feature points) is necessary. We will investigate more reliable approach for feature points localization not only from one frame but from a number of sequential frames (e.g., Kalman filter based or RANSAC based approach).

We proposed a simple yet effective dynamic face modeling system using multiple-view regular cameras. The current camera setting works well in the condition that the roles of the three cameras are fixed. To handle the large pose variations, it is demanded to design an algorithm to automatically update the roles of three cameras. For example, when a subject changes the face orientation dramatically, the frontal view camera can function like a side view camera, and vice versa. Such a dynamic functionality is expected to be added in our system as our future work. Moreover, a better integration of three view models is also a future research direction in order to improve the facial model accuracy.
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