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Face Contour Tracking Based on Mean Shift and GVF Snake

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Abstract: GVF Snake algorithm can't extract an accurate image edge if the face has a large scale change. And it is difficult for GVF Snake algorithm to solve deep depression problem and the occlusion problem which is more complex. A method of extracting the contour of face is proposed in this study, which combines Mean Shift, grey prediction and improved GVF Snake algorithm. Firstly it employs the Mean Shift algorithm and the grey prediction tracking technologies to get the initial area of the face and then the improved GVF Snake algorithm is used to get the accurate face contour. It effectively solves the problems of initialization and being unable to iterate into deep depression in the GVF Snake algorithm. When the face is partially occluded, the Mean Shift and GM (1,1) will be used to solve it. When the face is totally occluded, the grey forecasting model will be used. The experimental results show that the algorithm can achieve the face contour accurately and has strong robustness to the irregular movement and serious occlusion of the face in both static and dynamic scenes.

Key words: Face contour tracking, mean shift, GVF Snake, GM(1,1) model

INTRODUCTION

Face tracking has important application value in many areas such as the safety monitoring, face recognition, identification, artificial intelligence interaction, video phone and video retrieval and so on and therefore it becomes a very active research direction in the domain of computer vision. Due to the uncertainty of the scale change of the face, the diversity of face expression, the variability of illumination condition and the complexity of human body movement and imaging environment for the video object, the face tracking becomes a challenging work.

Oka and Shakunaga (2012) put forth a method of face tracking and recognition with the combination of an augmented eigenface and a 3D tracker controlled by particle filter. Yao *et al.* (2012) presented a new adaptive PSO particle filter face tracking algorithm. Tian *et al.* (2010) proposed the method of face tracking based on particle filter which mixed the color and texture features. This method uses the particle filter to deal with the non-linear and non-gauss effectively, describes the features of face by combining the rotated complex wavelet and the weighted color histogram and adopts the particle filter mixed color and texture features to track the face. Yu and Wang (2011) suggested a 3D face expression tracking method based on an adaptive statistic model, incorporating improved particle filter into the transition model. This method did decrease the influence of illumination changes and the relevance between different individualities. But in the facial motion tracking, the particle filter needs a large number of samples to simulate the posterior distribution for higher tracking precision. Therefore, this algorithm would result in more complicacy and poor real-time performance.

Comaniciu *et al.* (2000) proposed the Mean Shift algorithm which employed color as the characteristic, adopting the convergence approach where the testing center is continuously approximating the centroid image. This algorithm has made a great improvement of the computational efficiency. After constant improvements, Li *et al.* (2011) introduced a better method of time-variable and weighted-variable histogram, which, to some degree, has corrected the deficiency of histogram algorithm with single color, but by no means did it solve the occlusion problem completely.

Active contour model is another common method for face tracking. Huang *et al.* (2003) proposed one method combined both Kalman filter and the Level Set algorithm, tracking the contour of face in an image sequence. But the contours were merely extracted from the simple background in an image sequence, irrespective of the effectiveness of face occlusion. It can not track the contour of face under pose variations. Xu and Prince (1998a) proposed the Gradient Vector Flow Snake (GVF Snake) algorithm, which is often used in target tracking. While it is difficult to solve the problems of the large scale variations and the deep depression, affecting the

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accuracy largely while extracting the face contour. In order to solve the above-mentioned contour tracking problems, the face contour will be first roughly located with Mean Shift and grey prediction. An improved GVF Snake algorithm is applied to track the face then, at the same time the initialization problem of GVF Snake algorithm would be solved in our study.

Face tracking based on mean shift: Assume that each pixel position in face model is represented by $\{x_i\} i = 1,... n$, then $q(y) = \{q_u(y)\} u = 1,..., m$ and:

$$\sum_{\mu=1}^{m} q_u = 1$$

will represent the face mode. Its feature distribution can be expressed as:

$$\hat{q}_u(y) = C_h \sum_{i=1}^{n} k\left(\left\| \frac{x_i - y_0}{h} \right\|^2\right) \delta[b(x_i) - u] \quad (1)$$

where, C_h stands for the normalization constant, y_0 stands for the center pixel position of face model area and h stands for the Kernel window width. Kernel function k(x) is a monotonic decreasing convex function which is used to set weight for the pixel in face model area. In our study, Epanechnikov kernel is chosen. δ stands for Kronecker delta kernel which is used to determine whether the pixel color value in the face model exists in the quantitative feature space.

In order to match the face tracking accurately in the current frame, it's necessary to get the probability model of the candidate region of the face. Assume that each pixel position in the candidate region of the face is represented by $\{x_i\} i = 1,...n$, where *y* stands for the center position of the current frame and the candidate face model is represented by $p(y) = \{p\mu(y)\} u = 1,...m$ and:

$$\sum_{\mu=1}^{m} p_u(y) = 1$$

then the feature distribution of the candidate region of the face can be expressed as:

$$\hat{p}_u(y) = C_h \sum_{i=1}^{n} k\left(\left\| \frac{x_i - y}{h} \right\|^2\right) \delta[b(x_i) - u] \quad (2)$$

After getting the probability density functions of face template and candidate region, the position of target in current frame will be determined with a criterion of the similarity between p_u (y) and p_u (y). Then the Bhattacharyya coefficient will be adopted to measure the similarity between the face model and the candidate face, that is:

$$\hat{\rho}(y) \equiv \rho[\hat{p}(y), \hat{q}(y_0)] = \sum_{\mu=1}^{m} \sqrt{p_u(y_0) q_u} \quad (3)$$

Improved GM(1,1): The initial condition of traditional GM(1,1) model can be represented by $x^{(0)}$ (1) but the predictive value of traditional GM(1,1) model has not relation with the original sequence $x^{(0)}$ (1). Liu *et al.* (2004) proposed it didn't meet the basic principle of the grey system theory to take full advantage of the possessed minimum information to improve the prediction accuracy of the grey model. Dang *et al.* (2005) proposed if the initial condition of traditional GM(1,1) model was changed from $x^{(0)}$ (1) to $x^{(1)}$ (n) which was one of components in $x^{(1)}$sequence, the predictive value would be more consistent with the actual situation and the predictions are more accurate. The whitenization model of GM(1,1) can be expressed as:

$$\frac{dx^{(1)}}{dt} + ax^{(1)}(k) = b \quad (4)$$

The corresponding function is expressed as:

$$x^{(1)}(t) = \left(x^{(1)}(n) - \frac{b}{a}\right)e^{-a(t-n)} + \frac{b}{a} \quad (5)$$

After discretization, let t = k, such that:

$$\hat{x}^{(1)}(k) = \left(x^{(1)}(n) - \frac{b}{a}\right)e^{-a(k-n)} + \frac{b}{a}, k = 1, 2, \cdots, n \quad (6)$$

After inverse accumulated operation, the predictive result is:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad (7)$$

Then:

$$x^{(0)}(k) = (\beta - \alpha x^{(1)}(n))e^{-a(k-n-1)} \quad (8)$$

To avoid the effect of exponentiation computation in Eq.8 on the real-time tracking, $e^{-a(k-n-1)}$ will be expanded with the Maclaurin formula, that is:

$$e^{-a(k-n-1)} \approx 1 - (k-n-1)a + \frac{((k-n-1)a)^2}{2!} - \frac{((k-n-1)a)^3}{3!} + \cdots + (-1)^m \frac{((k-n-1)a)^m}{m!} \quad (9)$$

Taking the first four terms, Eq.8 will be transformed into:

$$x^{(0)}(k) = (\beta - \alpha x^{(1)}(n))(1 - (k-n-1)a + \frac{((k-n-1)a)^2}{2!} - \frac{((k-n-1)a)^3}{3!}) \quad (10)$$

If $k \le n$, $x^{(0)}$ (K) is called the simulation value of the model. If $k>n$, then $x^{(0)}$ (k) is called the prediction value of the model. As tracking the face, it is very necessary to race against time, so it is suitable to make use of the Maclaurin formula to expand $e^{-a(k-n-1)}$ and take the first four terms instead.

Improved GVF Snake algorithm: The minimum energy equation of GVF Snake proposed by Xu and Prince (1998a) is:

$$E = \iint u\nabla^2 V + |\nabla f|^2 |V - \nabla f|^2 \, dx dy \tag{11}$$

where, V(x,y) = (u(x,y),v(x,y)) is the external force field of GVF, u is the control parameter, Δ^2 is the Laplace operator and Δf is the gradient of f at (x, y). When Δf is small, E is decided by the first term which is the smoothing term. When Δf becomes big, E is decided by the second term.

Although, GVF Snake can segment the objects with a sunken edge, the object segmentation results of the objects with depth depression are not very good. In order to highlight the role of the amplitude, u(x,y) and v(x,y) will be normalized before solving the diffusion equation of force field:

$$u' = \frac{u - u_{min}}{u_{max} - u_{min}}, v' = \frac{v - v_{min}}{v_{max} - v_{min}} \tag{12}$$

In this condition, the result that each point in the sunken region is impacted by other points around it will be reduced greatly and the impact on the force direction will be weakened, too. In Eq.11, assume that:

$$u = g(|\nabla f|) \tag{13}$$

$$|\nabla f|^2 = h(|\nabla f|) \tag{14}$$

when, u is a constant, the same smoothing is done in the whole region. However, it needs less smooth in some of regions with larger gradient of the edge in order to get a better face contour segmentation. According to the improvement of the energy function E proposed by Xu and Prince (1998b):

$$g(|\nabla f|) = e^{-\left(\frac{|\nabla f|}{k}\right)^2} \tag{15}$$

$$h(|\nabla f|) = 1 - g(|\nabla f|) \tag{16}$$

where, K is the adjustable parameter. When Δ is large, the smooth item decreases and thus it is able to segment edge and narrow zone better. When Δ fis small, the smooth item increases, which increases the range of the force field and speeds up the spread of the force field to the contour direction. In our study, the location of face region would be granted as the initial iteration basis of improved GVF Snake algorithm with the Mean Shift. It has solved the initialization problem of GVF Snake and avoided the problem of shrink in iterative deformation when the GVF Snake contour escapes from the face contour edge. It turns out that the numbers of GVF Snake model iterations would be reduced and the efficiency of the algorithm would be improved accordingly.

Face contour tracking based on mean shift and GVF snake: If only GVF Snake and GM(1,1) is used to track the face contour, when the size of the face contour model changes greatly, the effect will not be good by using GVF Snake algorithm iteration to take the face contour of the last frame as initial contour of the current frame. Besides, it is difficult to deal with occlusion. In order to solve these problems, the face contour tracking method based on the combination of Mean Shift, the improved GM(1,1) and GVF Snake will be proposed in our study. It can reduce the iteration times and the search matching time of algorithm by taking the predictive value of the GM(1,1) predictive model as the starting point of the Mean Shift algorithm in an iterative search in the next frame. After obtaining the position of the face contour using Mean Shift, it can obtain the accurate position of the face contour with the improved GVF Snake iteration and take the iterative center of mass as the current value of the improved GM(1,1) model. When total occlusion happens, it can close Mean Shift algorithm and GVF algorithm and only use two GM(1,1) models to predict the positions of the face contour in next frame along the horizontal and vertical directions of the moving face, respectively.

Prediction and location of the face position: In our study, the region of face model would be obtained with Mean Shift algorithm firstly. And through taking the region as initial position of improved GVF Snake, the real position of face contour would be denoted next with the iteration of improved GVF Snake. After obtaining the real positions of the face contours in the last four frames, the GM(1,1) model can be initialized and two GM(1,1) models are used to respectively predict along the x and y directions. Then the predictive results are taken as the initial position of Mean Shift algorithm iteration and at the same time the information of the position is taken as the initial face area of the improved GVF Snake. At last the face contour is obtained with the improved GVF Snake iteration. Because the region of face model is made through Mean Shift, it is just necessary to calculate the force field within the face region instead of within the whole frame, which will accelerate the improved GVF Snake iteration and increase the real-time performance of tracking. The improved GVF Snake iterated result will be used as the updated value of GM (1,1). The same steps are repeated until the end of tracking.

Model updating: While tracking the face contour in a complex background, it is very possible to meet such changes as light, noise, occlusion and so on. Also the pixel characteristics of the human face are constantly changing, so updating the face model is inevitable in the process of tracking. When occlusion doesn't happen, using the algorithm which combines Mean Shift, the improved GVF Snake and GM(1,1) could make a stable tracking of face contour. As ρ, the Bhattacharyya coefficient, meets the condition $\rho > T_{rem}$, the template update mechanism is opened. In our study, when the threshold is set as T_{rem}= 0.90, the updating equation of the model will express as:

$$q_k = (1-\rho+T_{rem})q_{k-1} + (\rho - T_{rem})p_k \tag{17}$$

Experimental results and analysis: In order to test the performance of the algorithm mentioned above in real-time tracking, it is necessary to carry out the face tracking tests of multiple video sequences.

Face contour tracking without occlusion: When tracking the non-occluded face contour sequences, the initial area of human face is first determined through the Mean Shift algorithm. Due to the tracking error caused by the Mean Shift algorithm, it is possible that not all parts of the face are included into the initial area. The first stage of tracking results through the Mean Shift algorithm is shown in Fig. 1. In order to enhance the real-time tracking, the improved GM(1,1) algorithm is introduced to track. It is used to predict the initial position of the face contour in next frame of image and take it as the iterative basis of the Mean Shift model. This method not only reduces the iterative times of Mean Shift model, but also reduces the interference from other moving targets. Ears and chins are not included totally in part of the tracking result figures in the first stage. Thus the force field region of the improved GVF Snake will be set as twice the size of the face area determined by Mean Shift. Then using the improved GVF Snake algorithm iteration to get the exact location of the face would reduce the iterative times of the improved GVF Snake algorithm and improve the stability of extracting the face contour. The result of tracking the non-occluded face of a person who is walking straight using the algorithm proposed in this study is shown in Fig. 2. The average tracking time of each frame is 2.3693 s with the proposed algorithm in this study, while the average time of each frame is 4.3756 s with GVF Snake algorithm and it is 5.6933 s with Level Set algorithm. The comparative experiment results are shown in Fig. 3. The comparison between the experimental average error of the proposed algorithm in this study and that of the Mean Shift algorithm is carried out. And the result shows that the average error of the proposed algorithm in this study is 0.7410 pixels/frame and the average error of Mean Shift algorithm is 4.9381 pixels/frame. The experimental results of error comparison are shown in Fig. 4.

When the human body begins to walk upright from the squat, it is necessary to track the face with different body movements. The proposed algorithm in this study firstly predicts tracking based on Mean Shift and GM(1,1)

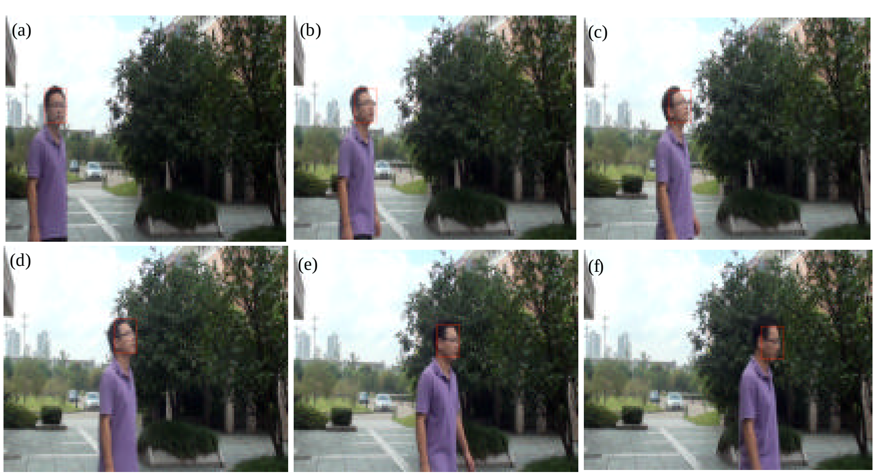

Fig. 1(a-f): Results of face tracking when walking straight with mean shift algorithm (Frame 15, 30, 45, 60, 75 and 90)

Fig. 2(a-f): Results of face tracking when walking straight with the proposed algorithm (Frame 15, 30, 45, 60, 75 and 90)

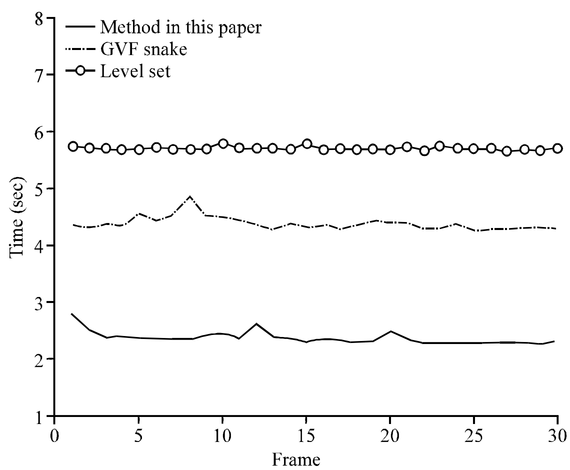

Fig. 3: Comparison of the tracking time

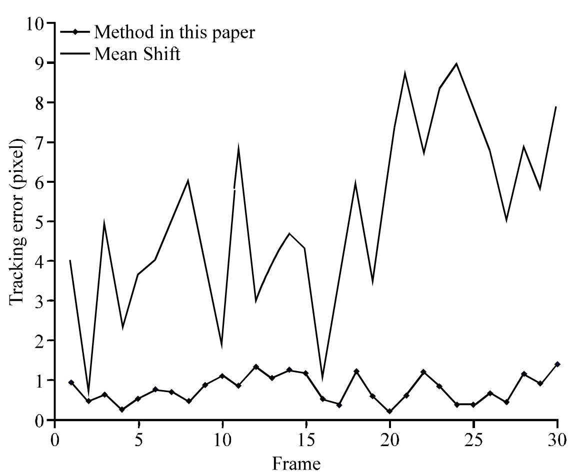

Fig. 4: Comparison of the tracking error caused by the proposed algorithm and Mean Shift algorithm

model and then tracks using the improved GVF Snake algorithm. The result of experiment is shown in Fig. 5, where it is clear that the result of tracking through the proposed algorithm in this study is better and this algorithm adapts to the pose variation better.

When the change of face scale is large, this algorithm can be able to adapt well to this situation because it takes face region of the Mean Shift algorithm as a basis for the initial outline of the region of the GVF Snake model. In this study, the experiment is conducted on a group of human faces from far to near which is an image sequence of changeable face size. The result is shown in Fig. 6.

Although, the original GVF Snake algorithm can deal with the image with depression edge, it can't deal with the image with long and narrow depression edge. In order to highlight the effect of amplitude, the improved GVF Snake tries to normalize the force field before getting the diffusion equation of force field to make the energy function adapt to the change of image gradient. Also, through changing the constant u of the size distribution of the control energy function, it is more suitable to the size change of image gradient. In this study, the comparison is made between a set of image sequences dealt with by the original GVF Snake algorithm and the improved GVF Snake algorithm. To make experimental results of the comparison more convincing, the same number of iteration to the original GVF Snake algorithm and the improved GVF Snake algorithm will be utilized. The experimental result carried out by the improved GVF Snake algorithm is shown in Fig. 7 and the experimental result carried out by the original GVF Snake algorithm is shown in Fig. 8. It's seen that the iteration processing of the hair region with deep depression on the head is not

Fig. 5(a-f): Results of face contour tracking under pose variation (Frame 15, 30, 45, 60, 75 and 90)

Fig. 6(a-f): Results of face contour tracking when the size of face is changing (Frame 15, 30, 45, 60, 75 and 90)

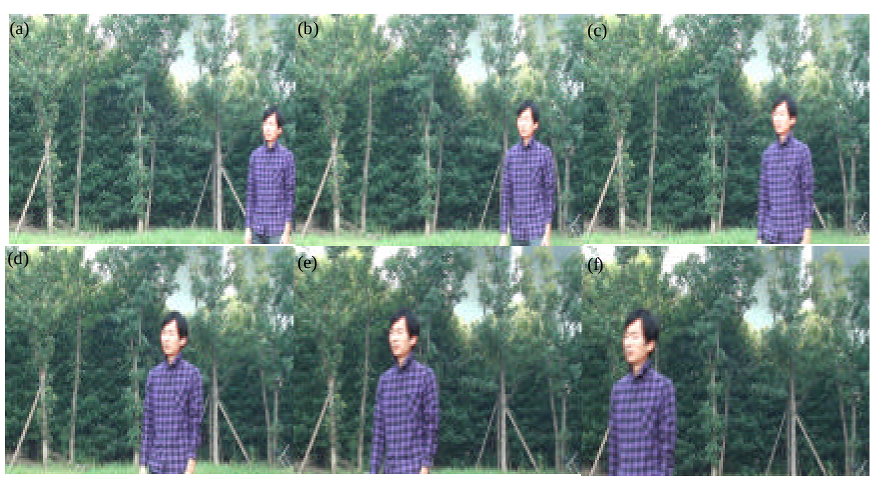

Fig. 7(a-f): Results of face contour tracking using the improved GVF Snake algorithm (Frame 5, 20, 35, 50, 65 and 80) good in Fig. 8. But the proposed algorithm in this study can solve this kind of problem better.

Face contour tracking with occlusion: In this study, the face contour tracking is carried out when the faces in different sequences are occluded partly and totally at different directions of movement. During the tracking, the occlusion is judged mainly according to the Bhattacharyya coefficient.

When the face contour occluded totally by the tree in the sequence, the ρ [p (y), q (y_0)] value of the occlusion critical is the threshold 0.9, which is set in advance. After face occluded is judged, the iteration process of GVF Snake algorithm should be stopped and so should the template updating of Mean Shift algorithm. When Bhattacharyya coefficient is less than 0.5, then the face will be determined as being occluded totally. At this time the iteration of Mean Shift algorithm should be terminated, the improved GM(1,1) will be used alone to predict the face position in the next frame. Through a prediction from the horizontal and vertical direction, ρ [p (y), q (y_0)] is to be calculated and saved. When ρ [p (y), q (y_0)] increases more than 0.9, the face is not occluded any more. Then the algorithm can restart Mean Shift and GVF Snake and also make combination with the GM(1,1) predictive model again. The experimental results of tracking the faces occluded totally by the tree are shown in Fig. 9. The change of Bhattacharyya coefficient is shown in Fig. 10. The experimental results turn out that our proposed algorithm performs better when the face is occluded totally by a tree.

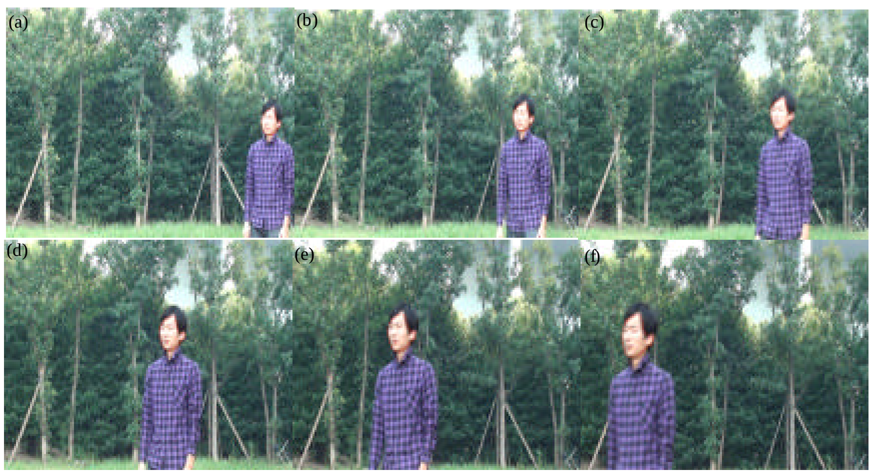

Fig. 8(a-f): Results of face contour tracking using the original GVF Snake (Frame 5, 20, 35, 50, 65 and 80)

Fig. 9(a-f): Results of face contour tracking with complete occlusion (Frame 15, 30, 45, 60, 75 and 90)

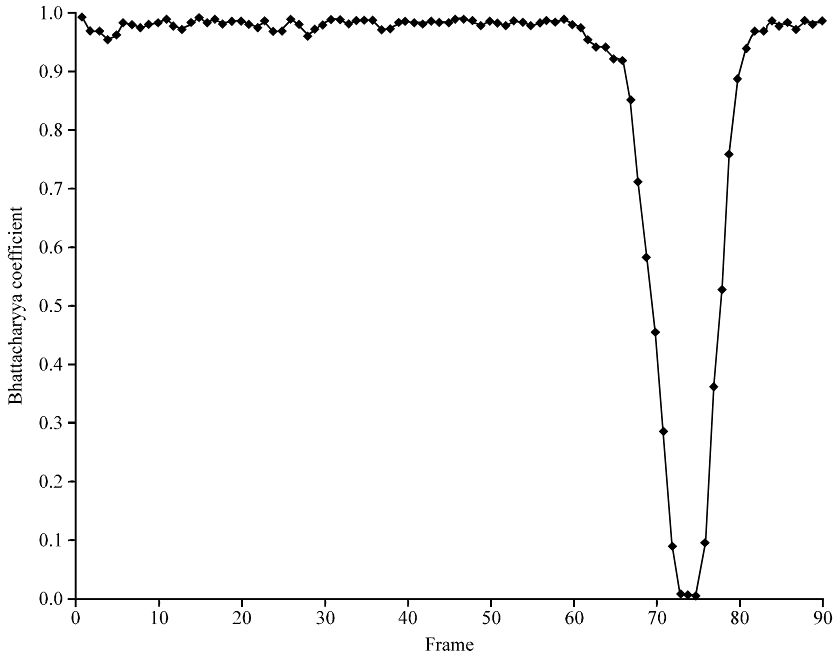

Fig. 10: Bhattacharyya coefficient with complete occlusion

Fig. 11(a-f): Results of face contour tracking of movement direction change with part occlusion (Frame 15, 30, 45, 60, 75 and 90)

When tracking the face contour of another group in special circumstance where the face is not occluded totally by a tree and a person suddenly changes direction and walk out from the occlusion region, it will not so ideal if only using GM(1,1) model to track since the movement direction changes while occlusion happens. In this study, our method is to set two threshold values of Bhattacharyya coefficient to deal with this kind of problem. When the Bhattacharyya coefficient is less than 0.9 but more than 0.5, the face is determined as part occlusion. Under this situation, the GVF Snake iteration is closed and the Mean Shift algorithm combing with GM(1,1) model is used to track. In this way, tracking the face contour would be carried out better when part occlusion exists, even if the movement direction changes. The result of tracking is shown in Fig.11 and the change of Bhattacharyya coefficient is shown in Fig. 12.

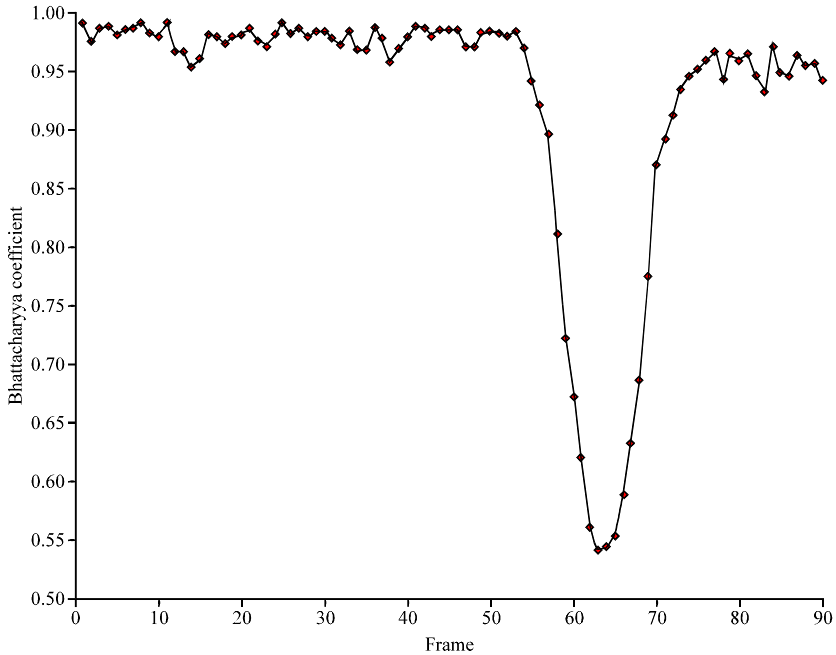

Fig. 12: Bhattacharyya coefficient with part occlusion

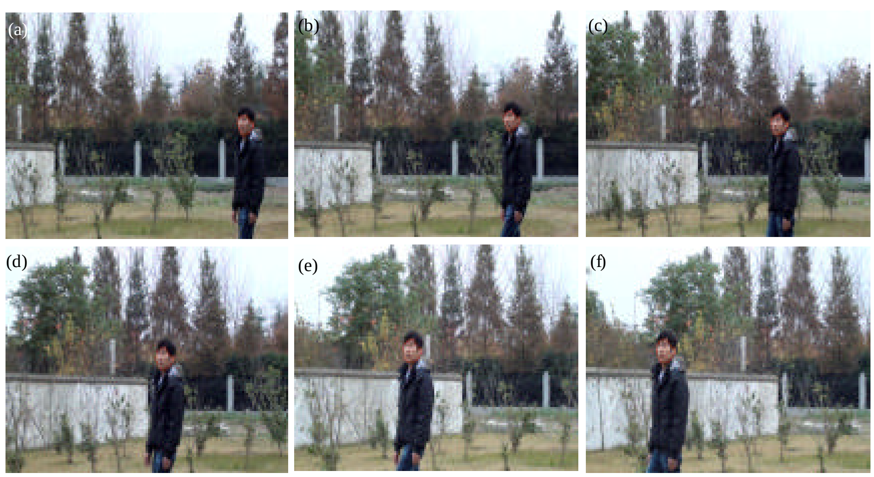

Fig. 13(a-f): Results of face contour tracking with the proposed algorithm in dynamic background (Frame 5, 20, 35, 50, 65 and 80)

Face contour tracking in dynamic background: The experiment of tracking face contour in previous context is conducted in the case that the camera is fixed. To verify the robustness of this method in the dynamic background, two sets of face contour will be tracked when both cameras and human body move. Due to the dynamic change of the background caused by the movement of camera, it is difficult to track the face contour well. However, the tracking result of the algorithm in our study is good and is shown in Fig. 13. If using the traditional Mean Shift algorithm and GM(1,1) to predict tracking, the effect of tracking of the thirty-fifth frame and the eightieth frame becomes bad, as shown in Fig. 14. The fact that our algorithm can track the face contour with occlusion in sequence in dynamic background proves that the algorithm proposed here is more suitable than other

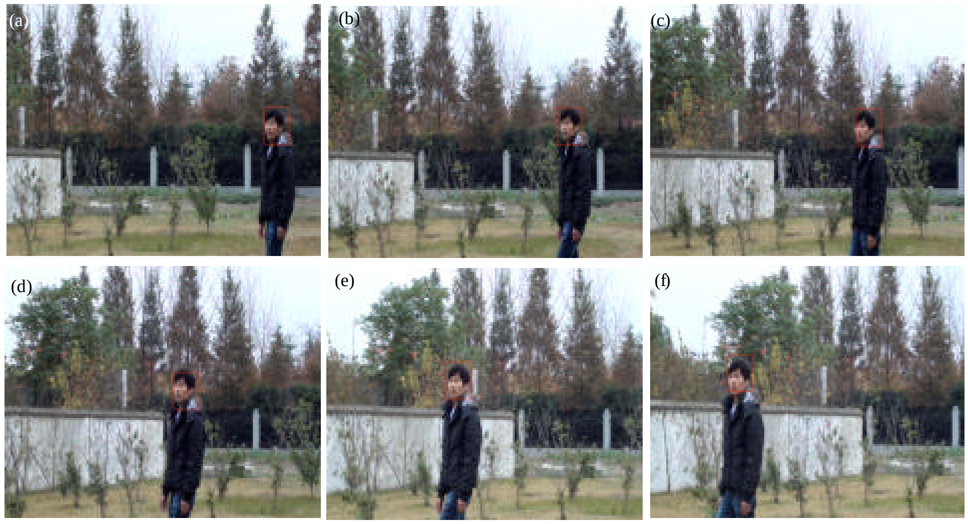

Fig. 14(a-f): Results of face contour tracking with mean shift algorithm in dynamic background (Frame 5, 20, 35, 50, 65 and 80)

Fig. 15(a-f): Results of sheltering face contour tracking with the proposed algorithm in dynamic background (Frame 5, 20, 35, 50, 65 and 80)

algorithms. The result is shown in Fig. 15. Although the traditional Mean Shift algorithm uses the color character in object tracking, but it can't deal with the problem that the low contrast object has similar color with the background. Even though the object is greatly different from the background, the result of tracking based on the color characteristic still inevitably has a difficulty to acquire the exact contour of the object. Although the combination of color and moving characteristic can provide the tracking in some cases, problems will still exist in some complex cases. The effect of tracking is not so good if using the traditional Mean Shift algorithm combining with GM(1,1) model to conduct contrastive experiments. The tracking result is shown in Fig. 16. The contrastive experiments show that the method proposed here combining with color, moving and edge characteristics can accurately locate the face contour and overcome the shortcomings existing in the color characteristic.

Fig. 16(a-f): Results of sheltering face contour tracking with mean shift algorithm in dynamic background (Frame 5, 20, 35, 50, 65 and 80)

CONCLUSION

Comparing with the quick and rough location of human face by color characteristic, the edge characteristic can partly provide more precise information about face shape. The proposed algorithm in our study combines Mean Shift algorithm, the improved GM(1,1) model and the improved GVF Snake to solve the problem that the accurate edge can not be extracted and the depression problem which is difficult to be solved by GVF model. When the part occlusion exists, it closes GVF Snake iteration. When the total occlusion exists, it can use the improved GM(1,1) model to predict the position of mass center of the face contour according to the completeness of the face contour movement in order to effectively solve the occlusion problem. Compared with the experimental result of the face tracking with Mean Shift algorithm, our proposed algorithm is proved with more precision in tracking and more robust.

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