Fuzzy judgment of edge features under dynamic constraints in pedestrian tracking

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Abstract: In order to improve the pedestrian tracking and recognition ability, it is required to conduct fuzzy judgment to edge features. Therefore, a fuzzy judgment method of edge features under dynamic constraints in pedestrian tracking based on local motion planning and edge contour segmentation was proposed. In this method, a geometry mesh area model for pedestrian tracking and recognition was constructed, and the fuzzy dynamic feature segmentation method was adopted to reconstruct dynamic edge feature points in pedestrian tracking to extract the greyscale pixel set under dynamic constraints in pedestrian tracking. The simulation results show that in pedestrian tracking and recognition, this method has strong fuzzy judgment ability of edge features and can provide results with error below 10 mm and relatively stable fluctuation, so this method can provide relatively high recognition accuracy and good robustness.

Keywords: pedestrian tracking; dynamic constraint; edge feature; recognition; image fusion.

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1 Introduction

Pedestrian tracking is one of the most active research topics in the field of computer vision. It can be widely used in many research fields, such as night intelligent monitoring, vehicle assisted driving, military target search and so on (Hu et al., 2018). As the development of image processing technology, the image processing method is adopted for dynamic pedestrian tracking and recognition, and dynamic features of pedestrians are analysed based on pedestrian's posture information and environmental information to extract edge contour feature points and posture details of pedestrians, so as to realise dynamic tracking and recognition to pedestrians and judgment to posture features

(Tengfei and Weili, 2014). Research on pedestrian tracking and recognition methods has good application value in the fields of sky-eye monitoring, criminal investigation, anti-terrorism and anti-riot (Siwei et al., 2014; Liu et al., 2010). The dynamic tracking and recognition of pedestrians is based on extraction and fuzzy judgment of edge features of pedestrians. Based on three-dimensional motion features of pedestrians, dynamic constraint planning is carried out for pedestrian tracking, and the three-dimensional dynamic space area for pedestrian tracking is constructed, and then fuzzy judgment is carried out to edge features in the three-dimensional space area to improve the dynamic tracking and self-adaptive recognition performance to pedestrians. Related research on fuzzy judgment of edge features under dynamic constraints in pedestrian tracking has drawn great attention (Grimm et al., 2016).

In traditional fuzzy judgment and learning methods of edge features of moving pedestrians, the autocorrelation quantification analysis method and matching filtering fuzzy learning method (Chen, 2016) are mainly adopted to construct an image fusion model reflecting the three-dimensional dynamic feature quantity of pedestrians to extract the set feature quantity for pedestrian tracking and recognition, so as to establish a three-dimensional dynamic flow field for fuzzy judgment and recognition of pedestrian edge features. Certain research results have been achieved in this aspect. In Huang et al. (2014), an edge feature fuzzy judgment method based on adaptive learning algorithm is proposed. In this method, the histogram distribution feature extraction method is adopted for fuzzy judgment and dynamic recognition of edge features under dynamic constraints in pedestrian tracking, and the fuzzy learning algorithm is adopted for fuzzy judgment of edge features of moving bodies; the detection ability for edge contour features of pedestrians is improved through the pattern recognition method. However, this method is computationally expensive and performed well in fuzzy orientation of edge feature fuzzy judgment under dynamic constraints in pedestrian tracking and in real-time dynamic tracking recognition of pedestrians. In Meher (2014), a fuzzy judgment learning algorithm for edge features of pedestrians based on deep learning and fuzzy feature decomposition is proposed. In this algorithm, the body imaging is performed based on the distribution similarity features of histograms of pedestrian three-dimensional dynamic images; a dynamic vector library for pedestrian tracking and recognition is constructed and fuzzy judgment of edge features is carried out according to the pedestrian's posture information and environmental information. This method improves the accuracy of pedestrian tracking and recognition, but it is also computationally expensive, poor in anti-interference ability, and is prone to cause tracking errors. In Wang et al. (2016), a pedestrian tracking method combining multi-feature histogram and mean shift algorithm is proposed, the colour and edge features of the target are described by histogram model, and the colour is corrected by the motion information, and the kernel function of the edge histogram is used to reduce the influence of the object deformation, background interference and local occlusion on the algorithm, the multi-feature histogram information is integrated to construct the target and candidate target model, which is embedded into the mean shift tracking framework to achieve pedestrian tracking, but the robustness of this method is poor.

To solve the above problems, a fuzzy judgment method of edge features under dynamic constraints in pedestrian tracking based on local motion planning and edge contour segmentation is proposed in this paper. Firstly, a geometry mesh area model for pedestrian tracking and recognition is constructed, and the fuzzy dynamic feature segmentation method is adopted to reconstruct dynamic edge feature points in pedestrian tracking to extract the greyscale pixel set under dynamic constraints in pedestrian tracking; and then edge feature quantity is fused based on the distribution intensity of greyscale pixels to realise pedestrian tracking image fusion and information enhancement processing; the three-dimensional dynamic constraint method is adopted to realise local motion planning of pedestrian tracking, and then fuzzy judgment is carried out to edge features in pedestrian tracking based on the edge contour segmentation results. Finally, a simulation tests is performed, which demonstrates the superior performance of this method in improving the fuzzy judgment ability of edge features under dynamic constraints in pedestrian tracking.

2 Geometric mesh area model for pedestrian tracking and recognition and imaging

2.1 Geometric mesh area model for pedestrian tracking and recognition

In order to realise fuzzy judgment of edge features under dynamic constraints in pedestrian tracking, it is necessary to first construct a geometric mesh area model for pedestrian tracking and recognition, and to design a dynamic area mesh model for pedestrian tracking and recognition through the bottom-up modelling method. In order to improve the accuracy of geometric mesh area model, the designed dynamic area mesh model should be a three-dimensional mesh area. The spatial distribution of the mesh area is V_2. The multi-vision geometric mesh for pedestrian tracking and recognition is obtained as follows through the uniform mesh partition method:

$$V_2 = \{P(x, y, z) \big| x \in (0, Width), y \in (0, Length), \mathrm{z} \in (0, Height)) \tag{1}$$

where $Width \times Length \times Height$ is the definitional domain of coordinate. Pedestrian tracking and recognition in coordinate $P(x, y, z)$ and fuzzy judgment of edge features are performed in the mesh with *Width* as target width, *Length* as target depth and *Height* as target height, and a mesh model is obtained as shown in Figure 1.

In edge feature recognition and reconstruction of the mesh area according to construction of the multi-vision geometric mesh for pedestrian tracking and recognition, based on the pheromone in the environment, quantitative tracking and recognition are done to pedestrians by taking $u^{(2)} = (u_1^{(2)}, u_2^{(2)}, u_3^{(2)}, u_4^{(2)}, u_5^{(2)}, u_6^{(2)})$ and u^2 as the sequence of a pixel intercepted within the three-dimensional mesh area to extract geometric feature quantity reflecting the dynamic posture information of pedestrians (Hsieh et al., 2013). The pedestrian's movement rule is calculated with the formula of $u = (x_0, y_0, z_0, \lambda, \phi, \alpha)^T$, where all of λ, ϕ, α represent the edge features of pedestrians in the coordinate of the three-dimensional mesh. The greyscale pixel set for geometric features sites of pedestrian tracking and recognition is obtained to be $u^{(3)} = (u_1^{(3)}, u_2^{(3)}, u_3^{(3)}, u_4^{(3)}, u_5^{(3)}, u_6^{(3)})$ through the autocorrelation feature matching method. The edge block structure for pedestrian tracking and recognition is obtained as shown in Figure 2 based on the dynamic parameters obtained by the vector bevel angle and the above designed geometric grid area model:

Figure 1 Multi-vision geometric mesh model for pedestrian tracking and recognition (see online version for colours)

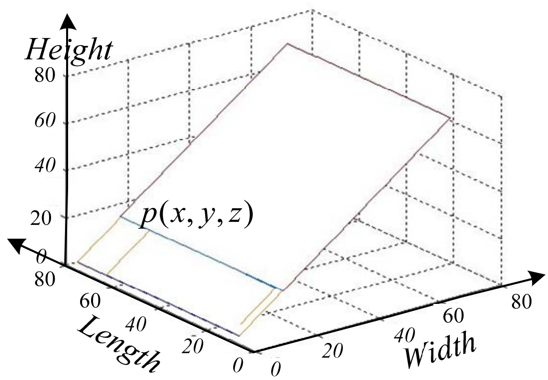
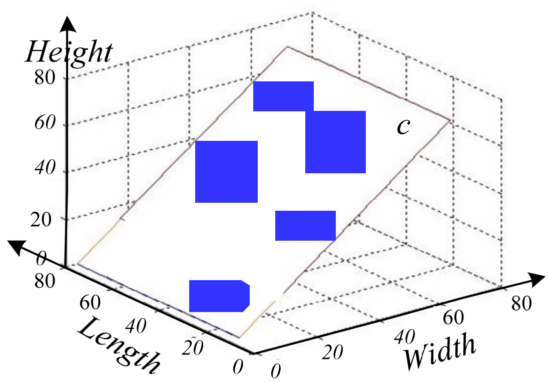


Figure 2 Edge block structure for pedestrian tracking and recognition (see online version for colours)



2.2 *Pedestrian tracking imaging, fuzzy dynamic feature segmentation and principle of reasoning*

The dynamic edge feature points in pedestrian tracking are reconstructed through the fuzzy dynamic feature segmentation method. Under dynamic constraints, the formula for calculating the joint angle and dynamic elastic force constraints in human body movement in dynamic tracking of several edges for pedestrians is as follows:

$$X_{RL} = R \times \theta_{RL} \tag{2}$$

where θ is the joint movement angle in unit time; R is the elastic force in unit time and X_{RL} is the trajectory of the joint angle in unit time.

$$X_{RR} = R \times \theta_{RR} \tag{3}$$

where θ_{RR} is the maximum value of the joint motion angle in unit time and X_{RR} is the maximum interval of the joint trajectory change in unit time.

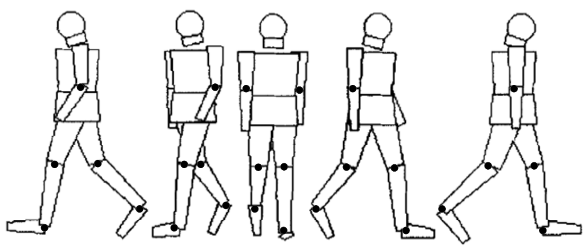
$$X_P = X_{RR} + X_{RL} L \cos \theta_P \tag{4}$$

$$Y_P = X_{RR} + X_{RL} L \sin \theta_P \tag{5}$$

where X_P represents the change trajectory coordinate of the predicted joint activity on the axis X, and Y_P represents the change trajectory coordinate of the predicted joint activity on the axis Y.

It can be seen that according to the movement feature quantity of the moving pedestrian, the trajectory of the same joint in the three-dimensional space can be tracked; the joint activity interval under the human body movement can be understood, and the pedestrian travel route can be calculated cyclically according to the movement speed of the pedestrian and the change of the joint angle. Based on the above, boundary layer fusion and three-dimensional dynamic information reconstruction of the moving pedestrian can be reconstructed.

Figure 3 Distribution of edge feature points in pedestrian tracking imaging



The reconstructed results are obtained as shown in Figure 3. According to the geometric invariance of each reconstructed feature point, fuzzy judgment is carried out to edge features (Di and Crawford, 2012), and the output geometric invariant moment is obtained as follows:

$$\left.\begin{aligned} EX^{(cs2)} &= \{x \mid x \in [0, h]\} \\ EY^{(cs2)} &= \rho^e \cos \theta^e \\ EZ^{(cs2)} &= \rho^e \sin \theta^e \end{aligned}\right\} \tag{6}$$

The fuzzy dynamic feature segmentation method is adopted to reconstruct the dynamic edge feature points in pedestrian tracking, and the greyscale pixel set under the dynamic constraint of pedestrian tracking is extracted. Vector translation is performed in the direction of axial x by taking ρ^e as the rotation invariant moment and θ^e is the horizontal and vertical coordinate motion angle. In this way, pedestrian tracking imaging and fuzzy dynamic feature segmentation are realised.

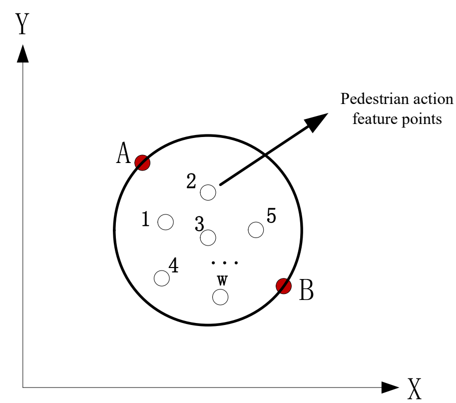
3 Fuzzy judgment optimisation of edge features in pedestrian tracking

In the process of pedestrian tracking, it is easy to be affected by human walking environment and dynamic edge features of human body, which results in the lower accuracy of pedestrian tracking. Therefore, it is necessary to make fuzzy judgment on the edge features of pedestrian tracking. In this paper, the traditional fuzzy evaluation method of edge features is improved and optimised to improve the accuracy of pedestrian recognition.

3.1 Reconstruction of dynamic edge feature points in pedestrian tracking

In order to reconstruct edge feature points more clearly, the design of fuzzy judgment of edge features in pedestrian tracking is optimised based on the construction of geometric mesh area model for pedestrian tracking and recognition (Dou et al., 2016). The three-dimensional geometric mesh area is made to be planar, and the fuzzy dynamic feature segmentation method is adopted to reconstruct dynamic edge feature points in pedestrian tracking as shown in Figure 4.

Figure 4 Reconstruction of dynamic edge feature points in pedestrian tracking (see online version for colours)



Assuming that in the spatial coordinate system, the dynamic feature data set of geometric dynamic constructs in pedestrian tracking is

$$\left(\theta^{e}, \rho^{e}\right) = EFA\left(\theta^{*}, \rho^{*}\right) \tag{7}$$

The dynamic edge feature points in pedestrian tracking are reconstructed through fuzzy dynamic segmentation method by taking the pixel point (θ^e, ρ^e) as quantisation centre based on the three-dimensional dynamic region planning method, so as to extract the greyscale pixel set under dynamic constraints in pedestrian tracking:

$$\sigma(Z; D_X) = \sum_{i>j} \left| d_{ij}(Z) - d_{X}\left(x_i, x_j\right) \right|^2 \tag{8}$$

where $d_{ij}(Z)$ is the Euclidean distance between pixel points and $d_x(x_i, x_j)$ is the combined spatial distribution distance of multiple key points. The edge feature point reconstruction area is divided into $M \times N$ 2×2 sub-blocks $G_{m,n}$ through the greyscale quantisation method. Finally, the reconstruction output of edge feature points is obtained as follows:

$$G_{m,n} = \begin{pmatrix} g_{(m,n)}(1,1) & g_{(m,n)}(1,2) \\ g_{(m,n)}(2,1) & g_{(m,n)}(2,2) \end{pmatrix} \quad m = 1, 2, \ldots, M; n = 1, 2, \ldots, N; \tag{9}$$

where

$$g_{(m,n)}(u, v) = I_{(k)g}[2(m-1)+u, 2(n-1)+v] \tag{10}$$

where $u \in \{1, 2\}$; $v \in \{1, 2\}$ represent the global learning operators for pedestrian tracking. Fuzzy judgment of edge features is done based on the reconstruction results.

3.2 Local motion planning and fuzzy judgment output of pedestrian tracking

According to the distribution intensity of gray pixels, edge feature quantity is fused. Assuming that there are K critical points around pedestrian coordinate P_1, P_2 and $p_{(k)g}$ is the sub-block of the critical points of the pedestrian coordinate, $p_{(k)g}^*$ the sub-block under the maximum threshold of the critical point and (i, j) the pixels on the Euclidean distance, the fusion output of the pedestrian image is recorded as:

$$P_1 = \sum_{k-1}^{h} p_{(k)g}(i, j) \times 2^{k-1} \tag{11}$$

$$P_2 = \sum_{k-1}^{h} p_{(k)g} *(i, j) \times 2^{k-1} \tag{12}$$

The three-dimensional dynamic constraint method is adopted for local motion planning for pedestrian tracking (Bian et al., 2016; Li et al., 2014). The feature point distribution set for motion planning $H(z)$ is obtained as follows:

$$H(z) = P_1 \cdot \sum_{k=1}^{h} p_{(k)g}(i, j) \times 2^{k-1} \Big/ P_2 \cdot \sum_{k=1}^{h} p_{(k)g}^*(i, j) \times 2^{k-1} \tag{13}$$

The Euclidean distance between the feature points of gray-scale pixel set distribution is calculated. For k neighbouring points, the tracking quantisation function of motion movement point is:

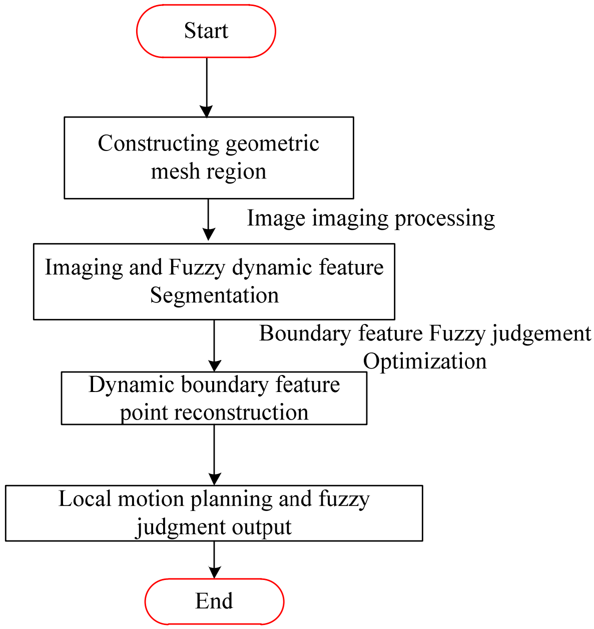
$$x_i(t) = \left[w_{i1}^{lk}, \cdots, w_{in}^{lk} \right] \left[x_1(t-k), \cdots, x_n(t-k) \right]^T \tag{14}$$

where $[w_{i1}^{lk}, \cdots, w_{in}^{lk}]$ is the weight coefficient of edge feature fuzzy judgment. The fuzzy judgment SSIM output of edge feature points is obtained as follows through local motion planning and edge contour segmentation:

$$SSIM(x, y) = [l(x, y)]^{\alpha} \cdot [c(x, y)]^{\beta} \cdot [s(x, y)]^{\gamma} \tag{15}$$

Based on the above formula, the edge geometric feature quantity and sample sets for pedestrian tracking and recognition can be obtained. The dynamic tracking and recognition of pedestrians can be realised through the dynamic edge feature point reconstruction and recognition method. The overall flow chart is as follows:

Figure 5 Overall flow chart of dynamic tracking and recognition of pedestrians (see online version for colours)



Pseudo code for positioning for pedestrian target tracking is as follows:

```
Function main
% edge initialisation
Length = 50; % the target depth of the space where the pedestrian is in, unit: meter
Width = 50; % the target width of the space where the pedestrian is in, unit: meter
Height = 50; % the target height of the space where the pedestrian is in, unit: meter
Node_number = 4;% the number of pedestrian detections
For i = 1:Node_number% Fuzzy obtain of pedestrian edges
    Node(i).x = Width * rand;
    Node(i).y = length * rand;
End
Target..x = Width * rand;
Target.y = Length * rand;
X=[ ];
For i = Node_number
if DIST(Node(i), Target) <= d
X = [X; Node(i).x, Node(i).y];
End
N = size(X, 1); % The number of pedestrians tracked
Est_Target.x = sum(X(:,1))N; % Pedestrian position x
Est_Target.y = sum(X(:,2))N; % Estimated pedestrian position y
Error_Dist = DIST(Est_Target,Target) % Deviation distance between the actual position of the
```

```
pedestrian and the estimated position
Hold on;box on;axis([0 100 0 100]); % Output pedestrian edge frame
Postion','Estimate postion');
function dist = DIST(A,B)
dist = sqrt(A.x-B.x)^2 + (A.y – B.y)^2);
% Subfunction for pedestrian tracking
function circle(xO, yo, r)
sita = 0:pi / 20:2 * pi; Output pedestrian tracking positioning results
```

4 Simulation experiment and result analysis

Experimental scheme:

1. Experimental motivation: in order to test the application performance of the method proposed in this paper in fuzzy judgment of edge features under dynamic constraints in pedestrian tracking, a simulation experiment was carried out.
2. Experimental environment and parameter setting: the experiment was designed with MATLAB; two groups of pedestrians (man and woman) were taken as test objects; the matching coefficient of template target of dynamic pedestrian tracking was set to be 0.23; the histogram $Hm = 0.12$; the template size $M_s = 2$. For the i^{th} frame, the pixel level intensity was 24dB; the centre position C_p was (0.25, 0.32). A total of 10 frames of image were read continuously to perform fuzzy judgment of edge features under dynamic constraints in pedestrian tracking.
3. In the process of experimental analysis, it is necessary to pre-process the experimental data. Data pre-processing: because real-world data may be incomplete, noisy, inconsistent, the data needs to be pre-processed as follows:
   a. data cleaning: noise and irrelevant data removal
   b. data Integration: combine data from multiple data sources in one consistent data store
   c. data conversion: converting raw data into a form suitable for data scheduling.
4. Experimental indicators: firstly, the fuzzy evaluation and tracking results of pedestrian edge feature are given, and then the centre position error of pedestrian object is selected as the index, TM (time-frequency analysis tracking algorithm) and CBWH (localised square tracking algorithm) method) was compared with paper method.

According to distribution intensity of greyscale pixels, edge features were fused to realise pedestrian tracking image fusion and information enhancement processing. The three-dimensional dynamic constraint method was adopted to realise local motion planning for pedestrian tracking. The method proposed in this paper, MS (Minimum mean square error), TM (time-frequency analysis tracking algorithm) and CBWH (localised square tracking algorithm) were adopted for fuzzy judgment of edge features under dynamic constraints and the results were obtained as shown in Figures 6 and 7. In the figures, from top to bottom, the results were obtained by the algorithm proposed in this paper, MS (minimum mean square error), TM (time-frequency analysis tracking algorithm) and CBWH (local two-square tracking algorithm) respectively.

Figure 6 Results of edge feature fuzzy judgment and tracking of pedestrian with pedestrian tracking sequence man (see online version for colours)

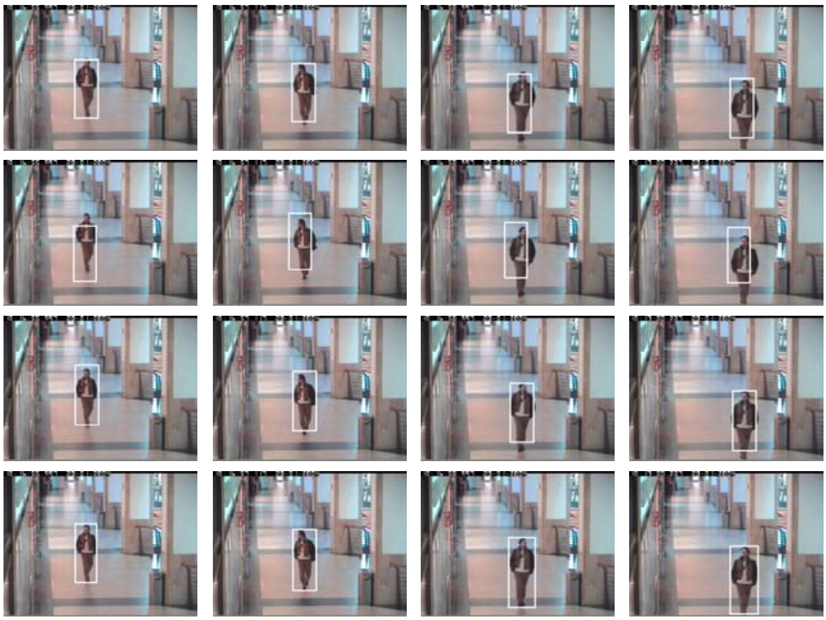
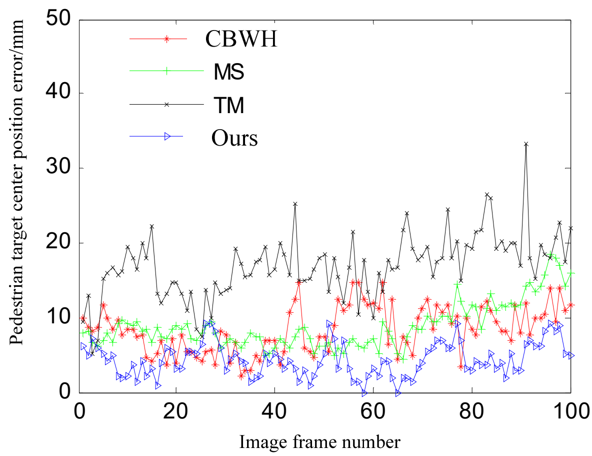


Figure 7 Results of edge feature fuzzy judgment and tracking of pedestrian with pedestrian tracking sequence woman (see online version for colours)

Analysis of Figures 6 and 7 show that the method proposed in this paper can provide higher accuracy and good tracking and recognition performance in judgment of edge features under dynamic constrains in pedestrian tracking. Different methods are adopted to analyse tracking errors and test position errors in the centre of pedestrian objects respectively, and then test results are obtained as shown in Figure 8.

Figure 8 Testing results of position error in the centre of pedestrian objects (see online version for colours)



Analysis of Figure 8 shows that in dynamic pedestrian tracking and edge feature judgment, the method proposed in this paper provides results with lower error controlled less than 10 mm and relatively stable fluctuation. This is mainly because that this method fully considers the dynamic constraints in pedestrian tracking and can effectively track pedestrian features despite some interference in the tracking. The fluctuations caused by MS, TM and CBWH are large, indicating that those methods are highly interfered during pedestrian tracking. Especially for the TM method, with the increase of the number of image frames, the average value of the centre position error of the pedestrian target is about 20 mm, which is higher than that of the 17 mm method in this paper, which shows that the performance of this method is superior. In those methods, the dynamic edge feature points in pedestrian tracking are not reconstructed, leading to relatively low accuracy in the tracking of dynamic pedestrians and relatively high fluctuation.

5 Discussion and analysis

Fuzzy and accurate judgment of pedestrian edge features under dynamic constraints is the basis for improving the accuracy of pedestrian tracking and recognition. In judgment of edge features, it is difficult to study image segmentation and feature point reconstruction. Due to the large number of feature points of pedestrian images, the three-dimensional dynamic region planning method can effectively shorten the reconstruction time in reconstructing the image with pixel as the quantisation centre. In further research, in order to improve the accuracy of image reconstruction, under the constraints of the simplification algorithm, the image can be further detailed into three-dimensional dynamic pedestrian movement area.

In the experiment, it is found that experiment results of centre position error of pedestrian object has a certain degree of volatility, which may be due to the fact that pedestrian tracking dynamic image processing process contains a certain noise interference. In order to make the processing result more stable and accurate, in the next study, denoising pre-processing can be considered to remove the influence of noise on the experimental results to further improve the accuracy and stability of edge feature judgment in pedestrian tracking.

6 Conclusions

Due to the fact that the movement environment and dynamic constraints of pedestrians limit the accuracy of pedestrian tracking and recognition, easily resulting in tracking errors, in order to improve the capability of pedestrian tracking and recognition, it is required to perform fuzzy judgment to edge features. Based on three-dimensional motion features of pedestrians, dynamic constraint planning for pedestrian tracking is carried out, and a three-dimensional dynamic space area is established for pedestrian tracking to carry out fuzzy judgment to edge features in the space area, so as to improve the dynamic pedestrian tracking and adaptive recognition performance. A fuzzy judgment method of edge features under dynamic constraints in pedestrian tracking based on local motion planning and edge contour segmentation was proposed in this paper. Firstly, a geometry mesh area model for pedestrian tracking and recognition was constructed to shorten the dynamic tracking distance, perform quantitative tracking and recognition, extract the geometric features reflecting pedestrian's dynamic posture information and reduce pedestrian tracking and recognition time. And then the results are quantified to improve the recognition accuracy. Then the fuzzy dynamic feature segmentation method was adopted to reconstruct dynamic edge feature points in pedestrian tracking to extract the greyscale pixel set under dynamic constraints in pedestrian tracking. Based on the distribution intensity of greyscale pixels, edge feature quantity was fused to realise pedestrian tracking image fusion and information enhancement processing. The three-dimensional dynamic constraint method was adopted to realise local motion planning of pedestrian tracking, and then fuzzy judgment was carried out to edge features in pedestrian tracking based on the edge contour segmentation results. The study shows that the method proposed in this paper can provide higher accuracy and good tracking and recognition performance in judgment of edge features under dynamic constrains in pedestrian tracking, and the tracking error of this method is less than 10 mm, relatively stable fluctuations, which is better than that of other methods, so it has good application value.

However, the research results of this paper are still not comprehensive; the influence factors of the dynamic edge characteristics of human body are not analysed in detail that is the interference of external factors to the results of this study can not be completely eliminated. In the next step of the research, it is necessary to carry out a further study in order to obtain a more complete experimental conclusion and provide a reference for the further improvement of human body tracking technology, and promote the better application of human body monitoring technology in automobile driving, night monitoring and social safety prevention and so on.

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References

Bian, L., Huo, G. and Li, Q. (2016) 'Multi-threshold MRI image segmentation algorithm based on Curevelet transformation and multi-objective particle swarm optimization', *Journal of Computer Applications*, Vol. 36, No. 11, pp.3188–3195.

Chen, F. (2016) 'Color image information characteristics in digital image library search optimization', *Computer Simulation*, Vol. 33, No. 8, pp.430–433.

Di, W. and Crawford, M.M. (2012) 'View generation for multiview maximum disagreement based active learning for hyperspectral image classification', *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 50, No. 5, pp.1942–1954.

Dou, H., Wang, Q. and Zhang, X. (2016) 'A joint estimation algorithm of TDOA and FDOA based on wavelet threshold de-noising and conjugate fuzzy function', *JEIT*, Vol. 38, No. 5, pp.1123–1128.

Grimm, F., Naros, G. and Gharabaghi, A. (2016) 'Closed-loop task difficulty adaptation during virtual reality reach-to-grasp training assisted with an exoskeleton for stroke rehabilitation', *Frontiers in Neuroscience*, Vol. 10, p.518.

Hsieh, M.H., Cheng, F.C., Shie, M.C. et al. (2013) 'Fast and efficient median filter for removing 1–99% levels of salt-and-pepper noise in images', *Engineering Applications of Artificial Intelligence*, Vol. 26, No. 4, pp.1333–1338.

Hu, M., Li, C., Lu, R. and Huang, H. (2018) 'Performance analysis of motor imagery training based on 3D visual guidance', *Journal of Computer Applications*, Vol. 38, No. 3, pp.836–841.

Huang, Y., Wu, Z., Wang, L. et al. (2014) 'Feature coding in image classification: a comprehensive study', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 36, No. 3, pp.493–506.

Li, J.Y., Dang, J.W. and Wang, Y.P. (2014) 'Medical image segmentation algorithm based on quantum clonal evolution and two-dimensional Tsallis entropy', *Journal of Computer-Aided Design & Computer Graphics*, Vol. 26, No. 3, pp.465–471.

Liu, C., Zhao, H.B., Li, C.S. et al. (2010) 'CSP/SVM-based EEG classification of imagined hand movements', *Journal of Northeastern University (Natural Science)*, Vol. 31, No. 8, pp.1098–1101.

Meher, S.K. (2014) 'Recursive and noise-exclusive fuzzy switching median filter for impulse noise reduction', *Engineering Applications of Artificial Intelligence*, Vol. 30, pp.145–154.

Siwei, L., Xunyu, P. and Xing, Z. (2014) 'Exposing region splicing forgeries with blind local noise estimation', *International Journal of Computer Vision*, Vol. 110, No. 2, pp.202–221.

Tengfei, L. and Weili, J. (2014) 'Automatic line segment registration using Gaussian mixture model and expectation-maximization algorithm', *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 7, No. 5, pp.1688–1699.

Wang, A., Dong, B., Sun, Y. et al. (2016) 'Research on pedestrian tracking method based on joint multi-feature histogram and mean shift', *Journal of the China Railway Society*, Vol. 38, No. 12, pp.76–85.