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Improvement of Maximum Variance Weight Partitioning Particle Filter in Urban Computing and Intelligence

LI HUANG[1,2], QIAOBO FU[1], GONGFA LI[3,4], (Member, IEEE), BOWEN LUO[5], DISI CHEN[6], AND HUI YU[7]

[1]College of Computer Science and Technology, Wuhan University of Science and Technology, Wuhan 430081, China
[2]Hubei Province Key Laboratory of Intelligent Information Processing and Real-Time Industrial System, Wuhan University of Science and Technology, Wuhan 430081, China
[3]Key Laboratory of Metallurgical Equipment and Control Technology of Ministry of Education, Wuhan University of Science and Technology, Wuhan 430081, China
[4]Institute of Precision Manufacturing, Wuhan University of Science and Technology, Wuhan 430081, China
[5]Research Center of Biologic Manipulator and Intelligent Measurement and Control, Wuhan University of Science and Technology, Wuhan 430081, China
[6]School of Computing, University of Portsmouth, Portsmouth PO1 2UP, U.K.
[7]School of Creative Technologies, University of Portsmouth, Portsmouth PO1 2UP, U.K.

Corresponding author: Bowen Luo (378401869@qq.com)

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ABSTRACT At present, urban computing and intelligence has become an important topic in the research field of artificial intelligence. On the other hand, computer vision as a crucial bridge between urban world and artificial intelligence is playing a key role in urban computing and intelligence. Conventional particle filter is derived from Karman filter, which theoretically based on Monte Carlo method. Sequential importance resampling (SIR) is implemented in conventional particle filter to avoid the degeneracy problem. In order to overcome the shortcomings of the resampling algorithm in the traditional particle filter, we proposed an optimized particle filter using the maximum variance weight segmentation resampling algorithm in this paper, which improved the performance of particle filter. Compared with the traditional particle filter algorithm, the experimental results show that the proposed scheme outperforms in terms of computational consumption and the accuracy of particle tracking. The final experimental results proved that the quality of the maximum variance weight segmentation method increased the accuracy and stability in motion trajectory tracking tasks.

INDEX TERMS Maximum variance weight division, particle filter, resample algorithm, urban computing and intelligence.

I. INTRODUCTION

The emerging of the first applicable Particle filter algorithm raised the research trend of Particle filter until now [1]. With the intensive researches on optimizing traditional Particle filter, the performances of proposed models have been greatly improved. Especially in tracking tasks, the results witnessed leaps in both accuracies and stabilities, which in turn enhances the real-time capability. Particle filter has been widely applied in many areas, such as target tracking [2], speech recognition, fault detection, radar positioning, video monitoring, parameter estimation and system identification [3]. According to the tracking process in real world, specific image processing and pattern recognition algorithms are designed. By analyzing the application environment of hand motion tracking tasks in urban Computing and Intelligence, the particle filter method is most suitable algorithm in the situations. Considering the shortcomings of traditional particle filter [4], we proposed the improved Particle filter in this paper and the experimental results proves that the effectiveness of each stage in hand motion tracking [5]. We further optimized the tracking process and enhanced the self-adaptability, which result in improvements of tracking accuracy and real-time capability [6]. In the hand tracking experiments, we customized the improved particle filter in hand motion tracking framework [7] and verified the tracking

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accuracy, real-time capability and the self-adaptability [8]. In the hand tracking framework, hand detection method was applied in labeling the hand area in the initial frame, in which the color histogram in HSV color space are applied as hand feature. According to the improved particle filter process [9], the state transformation between each continue frame is carried out sequentially, from which the hand position in each frame is estimated for tracking purpose [10]. It is theoretically and experimentally proved that the resampling method with maximum variance weight segmentation improves the performance of traditional particle filter algorithm [11], which not only saves computational time but also improves the accuracy of in real-time tracking [12].

The main contributions of this paper are as follows: firstly, the theoretical basis of particle filter is analyzed, and the importance probability density and resampling mechanism are introduced; secondly, a new method based on the most variance weight segmentation sampling method is proposed, which can find the combined weight threshold adaptively and avoid the degradation of particle diversity; finally, the experiment proves that the resampling square with the largest variance weight segmentation can be used. The new algorithm of traditional particle filter is improved. The proposed method not only saves measurement and time consumption, but also improves the accuracy of particle tracking.

The reminder of the paper is as follows, the second part reviews the basic methods of gesture recognition in human-computer interaction, including vision-based recognition, snake model-based recognition and mean shift-based recognition. In the third part, we first analyze the traditional particle filter algorithm, which includes four parts: Bayesian, Monte Carlo, Sequential Importance Sampling Probability Density Function Selection and Resampling. Aiming at the shortcomings of resampling algorithm in traditional particle filter method, a resampling algorithm based on maximum variance weight segmentation is proposed, and an improved algorithm of particle filter is given. Through experiments, the effectiveness of the proposed improved algorithm is verified. The fourth part introduces the recognition experiment based on the algorithm and summarizes the experimental.

II. RELATED WORK

With the development of computer technologies, human-computer interaction is no longer limited to the operation like tedious keyboard inputs, mouse clicks but can be finished in diversified ways [13]. Waving hands, lip-language, human gaze and human facial expression to name but a few, can be the means of human-computer interaction [14]. The new intelligent interaction mode makes the operation and control of computer simple but efficient [15]. At the same time, this interaction mode is more friendly for human users. Therefore, they will become profound research scopes for multi-mode human-computer interaction in the future [16].

Urban computing and intelligence is an emerging field for the application of artificial intelligence where machine vision plays an important role [17]. The reminder of this paper is as follows, firstly, we analyzed the conventional particle filter algorithm, which includes four parts: Bayesian formula, Monte Carlo method, Sequential Importance Sampling (SIS), Probability Density Function Selection and Resample. Experiments show that the performance of resample method affects the accuracy and stability of trajectory tracking [18]. Historically, Kalman filter and extended Kalman filter are most frequently applied in tracking tasks, Both the motion equation and the observation equation are assumed to be linear Gaussian processes [19], [20]. In reality, the tracking results of the linear Gaussian model is not acceptable, due to the interferences of external factors such as noises from camera shaking and ambient light [21]. Therefore, in order to adapt to the nonlinear non-Gaussian state under actual conditions to improve the accuracy of target tracking, Isard and Blake proposed the Condensation algorithm in 1996 [22].

The function of computer vision in hand tracking is mapping image features to gestures, which simplifies the descriptions of states [23]. However, due to the non-rigidity and changeability of the original algorithm, it is necessary to combine the unique characteristics of gestures to develop a new algorithm for tracking [24]. The method based on region feature mainly considers the whole tracking region and searches the target position of the current frame according to gray scale, textures and contours [25]. The vision-based algorithm is simple, but the tracking accuracy is relatively low. At the same time, the real-time performance is poor when the template is too large. When the target itself changes greatly or is partially occluded, it is easy to cause error tracking [26]. The method based on edge features mainly uses the target or contour information. When the contour is relatively single rule, the extraction effect is better, but for the changeable target, the effect and real-time performance are poor [27]. For the feature extraction method based on region and edge combination, one or more of the features such as edge, contour color and texture are usually selected as the target features, and usually used in combination with classical methods [28].

Based on Snake model method, the contour optimization problem is modeled as a curve energy function, and the partial differential equation of contour curve evolution is derived by variational method [29]. The objective contour is the extremum of the equation, but it cannot converge to concave edge very well, and the solution of the partial differential also greatly increases the computational complexity [30]. The gradient vector flow is introduced into the active contour model to enlarge the reachable real boundary and improve the accuracy of contour fitting, but there is still a ''critical point'' problem in initialization and it does not have real-time property [31]. In order to improve the accuracy of contour extraction in the initial frame, contour tracking can achieve higher accuracy by iterating layer by layer, but it will cost more time. Snake's jump model is suitable for fast moving target tracking, it is better not to cover the image in two frames [32]. The matching and tracking methods based on Snake model are of higher precision, which is robust in tracking the targets in changing environments and adaptive with the changing models [33]. However, partial differential equations are introduced to obtain the contours, so the calculation is complex, the calculation speed is low and the model updating process is even complex. At the same time, Snake model also has the shortcomings of variability and poor real-time [34].

Target tracking method based on Mean-shift is a kind of gradient descent algorithm. It will run iteratively until the similarity function converging to the local maximum [35]. It can accurately approximate the real location of the target and takes less time for a convenient application [36]. However, Mean-shift is vulnerable to the external interference, such as noises and it cannot easily converge to the global optimal [37]. Annealed Mean-shift algorithm is an improved Mean-shift method, whose cost function can be easily minimized globally [38]. There are many improved algorithms, such as fusing the image edge information and color histogram information with Mean-shift, which promotes the target tracking performance [39]. Although the above algorithm based on Mean-shift can solve the shortcomings of the algorithms to a certain extent, it is still difficult to track the postures of moving objects, especially non-rigid objects, because the targets are affected by their positions, angles, scales and other factors in the tracking process [40].

The filtering-based method mainly refers to the estimation problem of transforming the target tracking process into probability function [41]. It is an important method of moving target tracking. The best condition for Kalman filter to track is that the state estimation is assumed to be a linear Gaussian process, which is completely determined by mean vectors and covariance matrix [42]. So Kalman filter is mostly used in linear Gaussian system. For gestures, the non-linearity is introduced by the unconstructed motions of the target itself and noise in the image or the change of illumination. Later on, the Extended Kalman filter fixed the shortages aforementioned but this method needs the calculation of Jacbian comparable matrix, which is a second order equation and cannot meet the requirement of speed in real-time tracking [43]. The traditional Kalman filter cannot express the multi-Gaussian distribution model, then the condensation algorithm, also known as particle filter, is used to bridge this gap. Because this method is well adapted to non-linear, non-Gaussian systems and transform the high-dimensional integration problems into the weighting problems of discrete samples (particles), which greatly reduces the computational complexity and is able to track the moving targets. In real world application, Particle filter is of better tracking accuracy and stability [44], [45].

III. PROPOSED SCHEMES

A. TRADITIONAL PARTICLE FILTERING ALGORITHMS

The target tracking method based on filter theory is mainly to transform the problem into the optimal estimation problem of probability density function in time series. This method uses three probability density functions: the optimal estimation problem over the sequence. This method uses three probability density functions: the first is the prior probability, which is also called the motion equation in the physical sense. The known target is derived from the state of the previous frame image according to the state of the target in the frame; the second is the observation probability. This is also called the observation equation, which estimates the state value of the target in the current image; finally, the posterior probability, based on the previous prior probability and observation probability, namely the motion equation and the observation equation, then uses Bayesian theory to derive the true estimation state of the target.

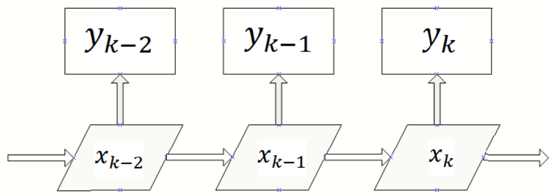

FIGURE 1. Dynamic spatial structure diagram.

Bayesian statistical theory is the theoretical basis for obtaining the optimal estimations. Bayesian filter introduces the probability distribution into the estimation of the target state and uses the target tracking process as the update process of the posterior distribution after the prior probability then the observation probability derived. At this time, the optimal estimate of the posterior distribution is the final target status. In the target tracking problem, and the dynamic spatial model is shown in Figure 1:

The dynamic equation corresponding to the spatial structure diagram is shown in Equation 1 and 2:

$$x_k = f(x_{k-1}) + u_{k-1} \tag{1}$$

$$y_k = h(x_k) + v_k \tag{2}$$

Among them, $\boldsymbol{f}()$ and $\boldsymbol{h}()$ are state transition equations and observation equations respectively, $\boldsymbol{x_k}$ is the target state, $\boldsymbol{y_k}$ is the observation value, $\boldsymbol{v_k}$ and $\boldsymbol{u_k}$ respectively transfer the noise and observed the noise. $\boldsymbol{X_k} = \boldsymbol{x_{0:k}} = \{\boldsymbol{x_0}, \boldsymbol{x_1}, \ldots, \boldsymbol{x_k}\}$ And $\boldsymbol{y_k} = \boldsymbol{y_{0:k}} = \{\boldsymbol{y_0}, \boldsymbol{y_1}, \ldots, \boldsymbol{y_k}\}$ represent all states and observations value from 0 to k respectively. When solving the target tracking problem, it is usually assumed that the state transition process of the target obeys the first-order Markov process. At this time, the current state $\boldsymbol{x_k}$ is only related to $\boldsymbol{x_{k-1}}$, and the observation value $\boldsymbol{y_k}$ is only related to the state $\boldsymbol{x_k}$ at the time k. The most basic Bayesian formula is shown in Equation 3 below. Most of the formulas are derived from this:

$$P(x\,|\,y) = \frac{P(y\,|\,x)\,P(x)}{P(y)} = \frac{P(y\,|\,x)\,P(x)}{\int P(y\,|\,x)\,P(x)\,d_x} \tag{3}$$

To obtain an optimal estimate of the target state, Bayesian filter includes two stages of prediction and update. The prediction process uses the system model to predict the prior probability of the current state, and the update process uses the latest measured values to correct the prior probability to obtain the posterior probability. Assuming that the probability density function at time k-1 is known to be $\mathbf{p}\left(\boldsymbol{x_{k-1}} \,|\, \boldsymbol{y_{k-1}}\right)$, the two processes of Bayesian filter are is shown in Equation 4:

Predicted process, First, get $\mathbf{p}\,(\boldsymbol{x_k} \mid \boldsymbol{Y_{k-1}})$ from $\mathbf{p}\,(\boldsymbol{x_{k-1}} \mid \boldsymbol{Y_{k-1}})$. Obtained by integrating $\boldsymbol{x_{k-1}}$:

$$p\,(x_k \,|\, y_{k-1}) = \int p\,(x_k \,|\, x_{k-1}) p\,(x_{k-1} \,|\, y_{k-1}) \tag{4}$$

Update process, get $\mathbf{p}\left(\boldsymbol{x_k} \,|\, \boldsymbol{y_k}\right)$ from $\mathbf{p}\,(\boldsymbol{x_k} \mid \boldsymbol{Y_{k-1}})$, after obtaining the measured value $\boldsymbol{y_k}$ at time k, the Bayesian formula is used to update the prior probability density to obtain the posterior probability, is shown in Equation 5

$$p\,(x_k \mid Y_k) = \frac{p\,(y_k \,|\, x_k, Y_{k-1})\, p\,(x_k \mid Y_{k-1})}{p\,(y_k \mid Y_{k-1})} \tag{5}$$

Assuming that $\boldsymbol{y_k}$ is only determined by $\boldsymbol{x_k}$, then there is shown in Equation 6:

$$p\,(x_k \mid Y_k) = \frac{p\,(y_k \,|\, x_k)\, p\,(x_k \mid Y_{k-1})}{p\,(y_k \mid Y_{k-1})} \tag{6}$$

where A is the normalization constant is shown in Equation 7:

$$p\,(x_k \mid Y_{k-1}) = \int p\,(y_k \,|\, x_k)\, p\,(x_k \mid Y_{k-1}) \tag{7}$$

In the target tracking process, the target state optimal estimation is the best solution for Bayesian recursive posterior probability. The currently used methods for estimating the optimal state of the target state are the Maximum a Posteriori (MAP) criterion and the Minimum Mean Square Error (MMSE) criterion, both of which are states or conditional mean values with a large posterior probability density Estimated status is shown in Equation 8:

$$\widehat{x}_k^{MAP} = arg \min_{x_k} p\,(x_k \mid Y_k) \tag{8}$$

Bayesian filter uses integral operations in both the prediction and update phases. In addition to special system models such as linear Gaussian systems and finite-state discrete systems, it is difficult for nonlinear non-Gaussian systems to obtain correct solutions due to the complexity of the derivation process and multivariate causes Bayesian filter to calculate posterior probabilities. For the integral problem, because the posterior probability A has a higher dimension, so most of them use the approximate solution to obtain the estimated suboptimal solution.

B. POSTERIOR ESTIMATION USING MONTE CARLO METHOD

The basic idea of Monte Carlo method is to reflect the geometric characteristics by using the frequency of the occurrence of the event or the expected mean value by repeated experiments as many times as possible, and as a solution of the problem. When the target tracking is solved, a large number of sample points in the state space are used to approximate the posterior probability distribution of the estimated variables, and the integral problem is converted to the weighted sum problem of the finite sample point. The concrete steps of the Monte Carlo method are as follows: First, the construction of the probability model is carried out: the deterministic problem without random properties is transformed into a probability model with random properties, so that some parameters are exactly the required solutions. Second, conduct random sampling: The probabilistic model constructed in the first step is generally composed of known common probabilistic models. The next step is to sample the random variables in the probability distribution. Finally, the solution: after obtaining the probability model and random sampling, basically has the experimental basis of the Monte Carlo method, and then the search for the appropriate random variable as the unbiased estimate of the problem solution, so as to continue to try Test and calculate, get the real solution to the problem. The process of the Monte Carlo method is shown in Figure 2.

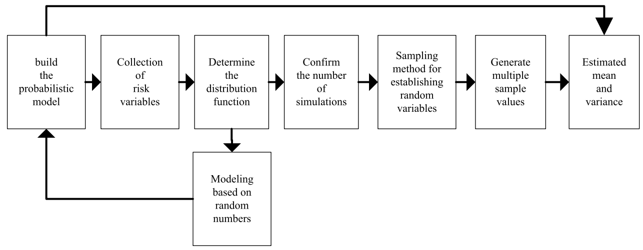

FIGURE 2. Process of the monte carlo method.

C. HAND MOTION TRACKING ALGORITHM BASED ON IMPROVED PARTICLE FILTER

Color is the most common feature of an object, and it is easier to obtain. It is simple and visually intuitive. The current color-based target detection and tracking has become a hot research top. Particle filtering achieved satisfactory accuracy in simulation in a nonlinear Gaussian tracking system. Hand skin colors as a sign for tracking are clustering in certain color spaces. Therefore, in the paper, we use skin color and improved particle filter to perform motion tracking of hands in color video footages.

The color-based particle filtering algorithm refers to a particle filtering algorithm that uses a histogram or a probability difference as a target feature for tracking. Particle filtering refers to discrete samples as a weighted sum of state posterior probabilities at each time. Physically, the particle is simulated as a target feature. A target can be represented by multiple particles plus certain weights, in another word, each particle represents a possible target, which can be position, shape or other features. In this paper, the motion tracking of the hand is mainly to obtain the final estimated position and the covariance to obtain the trajectory of the target motion. Because the particles reflect the possible targets through the features, in order to get the target position estimation of the optimal position, the target feature is very important. Compare with longitudinal, mirroring, partial occlusion and shape, color, as a more common and easily obtained feature, reduced the time consumption and simplified calculation. Therefore, color-based particle filtering algorithms are widely used.

The basic idea of resample is that when the effective particle number is less than a threshold value, it is considered that there is a particle degeneration. According to the weight threshold, the particles with small weights are eliminated, while particles with higher weights are retained and the weights of particles are updated. The traditional resample method eliminates the effectiveness of small-weight particle enhancement calculations. This method also makes the particles with larger weights be copied multiple times, and the particles with lower weights gradually disappear, resulting in the loss of diversity of the particles. In order to solve the phenomenon of particle degradation and depletion, this paper proposes a resample algorithm based on maximum variance weight division. The maximum variance weight segmentation resample algorithm calculates an intermediate value from all particle weights in each iteration of particle generation and division all particle weights into two groups and obtains the average weights differences between the two groups of particles value. Judging the selected intermediate value is realized by comparing it with $\frac{1}{2}\boldsymbol{N}$. If it is greater than $\frac{1}{2}\boldsymbol{N}$: then it is not considered that the particle is degraded and all particles remain unchanged and continue to the next iteration; when the intermediate value is less than $\frac{1}{2}\boldsymbol{N}$, the description: There are large differences in the particles that must be eliminated with a weight less than $\frac{1}{2}\boldsymbol{N}$ to avoid calculation and time waste and to retain the weights of $\frac{1}{2}\boldsymbol{N}$ particles in all particle weights. Through analysis, the resample decision proposed in this paper has a good balance on the usual particle degradation and particle dilution. Under these circumstances, it is possible to ensure that particles are not sampled blindly for resample, reducing particle diversity and causing particle impoverishment. The maximum variance weight segmentation comes from the threshold segmentation of image processing which is only the gray value segmented in the image, and the normalized particle weight in the particle filter. The basic principle of the maximum variance weight division is as follows:

Mean value of all particles is:

$$\mathrm{u} = w_0 u_0 + w_1 u_1 \tag{9}$$

Define the variance between classes is:

$$\sigma^2 = w_0(u_0 - u)^2 + w_1(u_1 - u)^2 = w_1 w_0 (u_0 - u_1)^2 \tag{10}$$

Let T be in the range of [0, 1], and increment in a certain step. When $\boldsymbol{\sigma^2}$ is maximum, the corresponding T is the optimal segmentation weight. The T obtained at this time is the above-mentioned intermediate weight. Sequential Importance Resample uses the prior probability function as the importance probability density function in the SIS method, and introduces the resample algorithm which is the standard algorithm of particle filter is:

$$\left[\left\{x_k^i, w_k^i\right\}_{i=1}^N\right] = \mathrm{PF}\left[\left\{x_{k-1}^i, w_{k-1}^i\right\}_{i=1}^N, y_k\right] \tag{11}$$

SIS algorithm is:

$$\left[\left\{x_k^i, w_k^i\right\}_{i=1}^N\right] = \mathrm{SIS}\left[\left\{x_{k-1}^i, w_{k-1}^i\right\}_{i=1}^N, y_k\right] \tag{12}$$

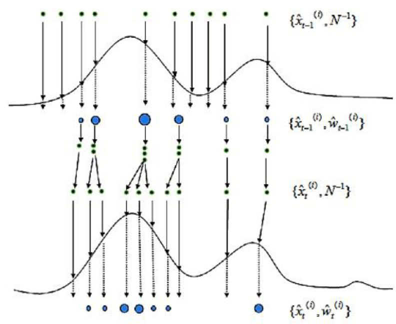

FIGURE 3. Implementation of SIR algorithm.

Mean and equation estimates is:

$$\widehat{x_k} = \sum_{i=1}^N w_k^i x_k^i \tag{13}$$

The implementation of SIR algorithm is shown in Figure 3:

There are many particle filter tracking methods based on color. Because the particle filter algorithm needs to judge the characteristics of each particle and calculate the weights. The calculation cost is very expansive, so in order to save time and accelerate the object tracking in videos or sequential images, researchers mostly use color as the only feature to get fewer particles. We proposed a maximum variance weight segmentation algorithm in this paper to optimize resampling process, solve particle degradation problem and avoid particle depletions. The main process of the hand motion tracking algorithm based on improved particle filter are in five stages, input and detection hand, sampling, weight calculation, resample and output. For color-based hand motion tracking, the HSV color histogram is detailed and the improved particle filtering hand motion tracking algorithm is introduced. Firstly, sampling particle filtering needs to find the initial position of the target to obtain the registration characteristics of the target. Then convert the original image from RGB color space into an HSV color space, sprinkle a certain number of particles in the ellipse range of the hand and obtain a color histogram of the HSV with three independent channels, H, S and V respectively. A quasi-color histogram and copy this probability to the total number of particles. Secondly, in the first frame, the center of the large ellipse of the hand range defined in the second chapter is the center of the random scattering particle. There are two random particles commonly used, one is a pseudo-random number and the other is a quasi-random number. A dot plot of two random numbers as shown in Figures 4 and 5. Quasi-random numbers generally also become physical random numbers, which are actually generated by physical phenomena, which have certain requirements on hardware. In the practical application of computers, most of them use pseudo-random numbers, which is the basis of the Monte Carlo method.

Particles are generated around the hand by pseudo-random numbers. Over time, through the observation equation and state transition equation, the HSV color histogram in the

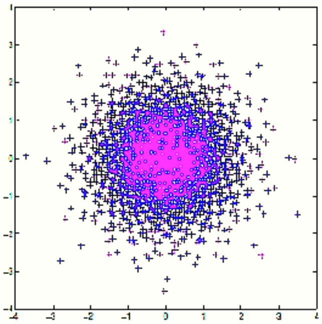

FIGURE 4. Quasi-random number.

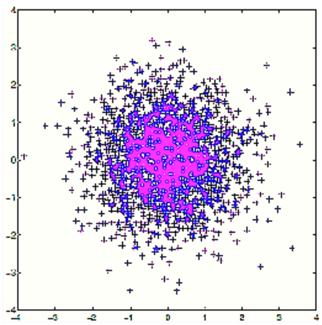

FIGURE 5. Pseudo random number.

small ellipse of each particle in the new frame image is calculated, and then the color square of the registration is applied. The graph obtains the similarity by the Pap singer distance, which is the observed value and the normal distribution calculation obtains the normalized weight. After the particle weights obtained in each frame, the mean values and covariance of the position are calculated to estimate the position of the hand. Then, according to the maximum variance weight division resample algorithm in this paper, it is judged whether resampling is performed. If the requirement is fulfilled, the weight whose weight is less than the threshold is updated to 1/N (N is the number of particles), the weights remaining unchanged, and the remapping is performed. In order to solve the problems of particle degradation, since the particles with larger weights have no change in value, particle depletion can be avoided. Finally, according to the mean and covariance of all the particles in each frame, the rendering path of the hand and the 3D histogram of the hand distribution are output.

IV. EXPERIMENTAL RESULTS ANALYSIS

Experimental settings with random particle points were designed for both conventional particle filter and the improved particle algorithm. The number of the particles increases from 100 to 500 and set the particle weight threshold to 12N, which is convenient for us to find out the mean errors of x coordinate or y coordinate. Then comparison of average values, time consumption and the experimental results are shown in Table 1 and Table 2.

From the above table, when the number of particles, average value and the weight depreciation is the same,

TABLE 1. Traditional particle filter algorithm tracking error.

	Particle	Average Value	Weight Depreciation	X-axis error Average	Y-axis error Average	Time
Original algorithm	100	0.01	0.005	2.3	2.26	80.11
	200	0.005	0.0025	1.36	1.4	82.42
	300	0.0032	0.00164	1.5	1.46	83.25
	400	0.00124	0.000626	1.74	1.82	85.6
	500	0.00019	0.0001	3.64	4.02	88.81

TABLE 2. Improved particle filter algorithm tracking error.

	Particle	Average Value	Weight Depreciation	X- axis error Average	Y-axis error Average	Time
Original algorithm	100	0.01	0.005	2.02	2.26	76.02
	200	0.005	0.0025	1.11	0.98	79.22
	300	0.0032	0.00164	1.26	1.15	80.78
	400	0.00124	0.000626	1.12	1.42	80.71
	500	0.00019	0.0001	1,56	1.64	83.12

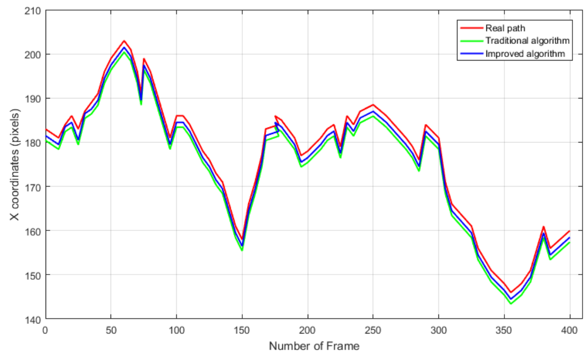

FIGURE 6. X-coordinate filtering algorithm for tracking the particle.

the mean error of x, y-axis are lower and the time consumption of the improved algorithm are generally smaller than those of the traditional algorithm, which proves that the improved algorithm increased the tracking accuracy and real-time capabilities. As the number of particles increases, the average error of the x and y-axis witness a steady decrease. When the number of particles is 200, the position error of both algorithms is the smallest. When the number of particles is 500, it increases. Because the tracked particles have the most suitable number of particles, which means that 200 is the most suitable. When the number of particles is 500, although the number of particles is large, but since the range of tracking is too large or the influence of noise or the like is likely to occur abnormal particles, thereby affecting the accuracy of tracking. When the number of particles is 200, the tracking effect of the traditional particle filter algorithm and the improved particle filtering algorithm on the particle is shown in Fig 6 and Fig 7. Although the tracking effect of the improved particle filter algorithm is not as good as real path, the effect is better than the traditional particle algorithm.

Aiming at several evaluation indexes, the motion tracking situation based on single hand is analyzed. Figure 8 shows the X coordinate error and Figure 9 shows the Y coordinate error. Figure 10 shows the average standard deviation of

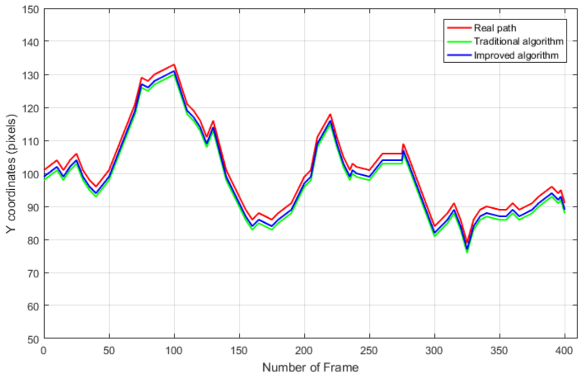

FIGURE 7. Y-coordinate filtering algorithm for tracking the particle.

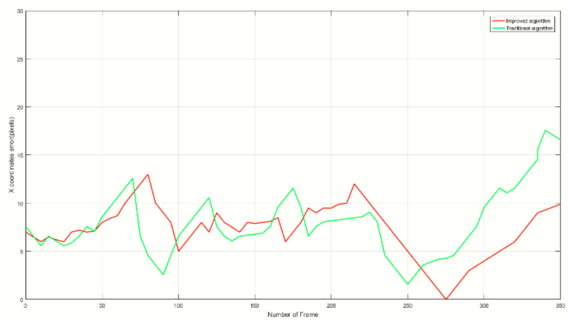

FIGURE 8. X coordinate error.

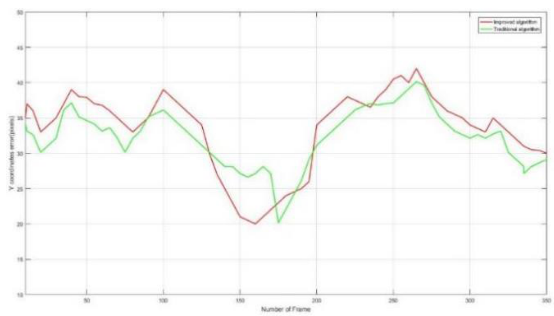

FIGURE 9. Y coordinate error.

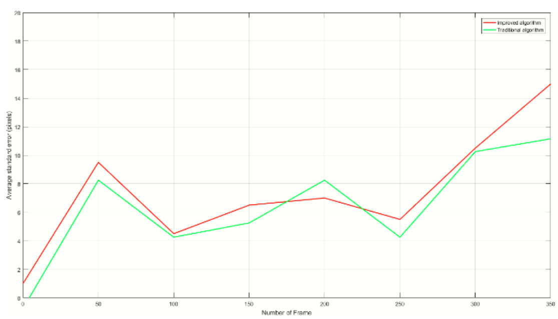

FIGURE 10. Average standard error.

hand position. The X coordinate and Y coordinate of improve algorithm in every frame is not good than traditional algorithm, but the average standard deviation of hand position is better than traditional algorithm in almost time.

For the average tracking time of each frame, this paper uses the maximum variance weight segmentation algorithm to resample, so that each frame can self-adaptively decide when to resample and which particles need to resample. Compared with the fixed threshold in the conventional Particle filter, resampling is effectively conducted and particle dilution is avoided, thus ensuring the tracking accuracy. Although there is a waste of time in using HSV color space 4×4×4 grouping feature matching but getting the weight of each particle color matching in each frame saves the time. Compared with the conventional particle filter algorithm, our proposed method has a higher tracking accuracy and a better real-time performance. For the average standard deviation, we take one frame for every 50 frames, totaling 8 frames. There are 300 particles in each frame. The distance between each particle and the center of the target is calculated and multiplied by the weight of each particle. The average standard deviation of each frame is calculated by dividing 300 weighted distances and the number of particles, and the average standard deviation of each frame is calculated by dividing the distances with the number of particles. As shown in Figure 8, the standard deviation of the improved particle filter is smaller than that of the traditional particle filter. It shows that 300 particles do not deviate from the real position of the target, which ensures the accuracy and stability of tracking. By comparing the above experimental data, it is proved that the improved particle filter algorithm based on HSV color histogram is effective.

V. CONCLUSION

This paper proposes a resampling method based on maximum variance weight segmentation which can adaptively find the optimal weight threshold values and avoid particle diversity degradation. It has been theatrically and experimentally proved that the resampling method with maximum variance weight segmentation improves the performance of traditional particle filter algorithm, which not only saves computational time but also improves the accuracy of object tracking. On the other hand, this paper analyzed the performance of improved particle filter based on HSV color histogram and improves the particle filter resampling method with the maximum variance weight segmentation, which can avoid the particle degradation and dilution and improve the accuracy of target tracking. Finally, in the experimental environment, the movements of the hand can be tracked. We compared our improved particle filter algorithm with the conventional one and verified its improvements in tracking accuracy, stability and real-time capabilities.

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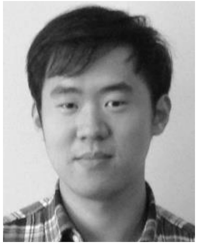
LI HUANG is currently pursuing the Ph.D. degree in computer science. She is currently a Lecturer of computer science with the School of Computer Science and Technology, Wuhan University of Science and Technology, Wuhan, China. Her research interests include data management, semantic web, and knowledge.

QIAOBO FU was born in 1995. He is currently pursuing the M.E. degree with the Wuhan University of Science and Technology. His research interests include deep learning and data analysis.

GONGFA LI received the Ph.D. degree from the Wuhan University of Science and Technology, Wuhan, China, where he is currently a Professor. His current research interests include robotics, human–computer interaction, vision, intelligent control, computer-aided engineering, and optimization design.

BOWEN LUO received the B.S. degree in mechanical engineering and automation from the Wuhan University of Science and Technology, Wuhan, China, where he is currently pursuing the M.S. degree in mechanical design and theory. His current research interests include mechanical CAD/CAE, signal analysis, and processing.



DISI CHEN received the B.S. degree in mechanical engineering and automation from Wuhan Textile University, Wuhan, China, and the M.S. degree in mechanical engineering from the Wuhan University of Science and Technology, Wuhan, in 2017. He is currently pursuing the Ph.D. degree in intelligent robot control with the University of Portsmouth, Portsmouth, U.K. His research interests include robot learn from demonstration and machine learning.

HUI YU is Professor with the University of Portsmouth, U.K. His research interests include vision, computer graphics and application of machine learning, and AI to above areas, particularly in human–machine interaction, image processing and recognition, virtual and augmented reality, 3D reconstruction, robotics, and geometric processing of facial performances. He serves as an Associate Editor for the IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS and *Neurocomputing*.