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Goal-oriented and Map-based People Tracking Using Virtual Force Field

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Abstract—**Estimation of people tracking may become divergent in the presence of occlusion. Since the interactions between people and environments can be mathematically modeled and probabilistically estimated, stream field based tracking provides the solution where the state of the occluded people is estimated by inferring the interactive force between the virtual goal of a person and environmental features. Such tracker suffers from high computation complexity because of the multi-hypotheses of the person's goal and feature-based map. Therefore, this paper proposes a novel virtual force field (VFF) based tracking algorithm that can be realized with a single hypothesis for the person's goal and grid-based map. The occupied grids generate repulsive forces while the person's goal generates attractive force in the virtual force field. Since the virtual force field based tracking integrates map, person, and the person's goal, the position of the person sheltered by the environment can be accurately estimated in unknown environments. Compared with the Kalman filter with constant acceleration (CA) model and stream field based algorithms, our proposed scheme significantly improves the tracking accuracy in case of occlusion.**

I. Introduction

People tracking is a key technique for human robot interaction. Most tracking algorithms aim at estimating the position, velocity, and acceleration of moving objects based on the prior states and sensor measurement [1]. Object tracking can be realized with Kalman filter (KF) with constant velocity model and/or constant acceleration model [2]. Although it is with low time complexity, it does not consider the map and goal information. For objects with nonlinear transition and observation models and non-Gaussian distribution, they can be tracked with higher accuracy using particle filter (PF) although the price is the computational complexity.

Several interactive motion models between a person and a environment have been proposed in the past years. Since a person's motion is highly influenced by the person's goal, other persons' motion, and environments, the interaction force can be generated due to person's goal, other persons, and environmental features. For example, in [3], the social force model (SFM) models the pedestrians' dynamics using Langevin equation, where the interactive force between people is considered. In [4][5], the visual tracking algorithms tackle the problem of occlusion in crowded environments using the pedestrian dynamics. Considering the interactive force between a person and an environment, the non-homogeneous spatial Poisson process is adopted to model the person's motion given a known map in [6]. In [7], Bennewitz et al. propose an algorithm to learn the motion patterns of people by using the expectation maximum (EM).

The interaction between a person, person's goal, and an environment are further considered in [8]. With the concept of frontiers, the location of potential gateway is predicted as a person's goal, in a partially known environment. In [9], the social force motion model was integrated into a multi-hypothesis tracker for crowed people tracking. In [10], a person's motion is deemed as passive in a stream field, where the attractive and repulsive forces are resulted from the person's goal and an environment, respectively. The stream field based tracking algorithm can use a known map and an estimated goal even if a person is occluded [10]. In [11], SLAMSAT further extends the stream field base tracking to estimate the robot and the person's position and the map, even if the person is occluded.

In [10], the computational complexity of the stream field based tracking increases with the size of the map and the number of goals. The reason is that a multi-hypotheses tracking system will become more complex if it simultaneously considers a person's goal, other persons, and an environment. Another problem of [10] is that the aliasing of obstacle shape arises due to the feature based map. For example, the object shape is modeled as a circle (Fig. 1(b)) although the ground truth is a rectangle.

There have been various robotic applications of potential field developed in the past years. For example, virtual force field (VFF) and vector field histogram (VFH) are adopted for path planning [12][13]. Enhanced versions of VFF such as VFH, VFH+, and VFH* are further proposed where most of them are designed for kinematics and obstacle avoidance [14][15]. In this paper, we propose a novel tracking scheme where the VFF is incorporated into the motion model of the probabilistic tracking with grid map. With VFF, we can model the interactions among the states of a goal, updated grid map, and a person's position more accurately. There are three advantages of the adoption of VFF based motion model. First, the assumption that the attractive force and repulsive force are mutually independent significantly reduces the computational complexity of the stream field based tracking in case of multiple goals. Secondly, multiple obstacles can be simplified as independent repulsive forces generated by each grid in the map. Third, according to the stream field based motion model in [11], there will be an infinite force at the position of the obstacle. Accordingly, it is impossible for a

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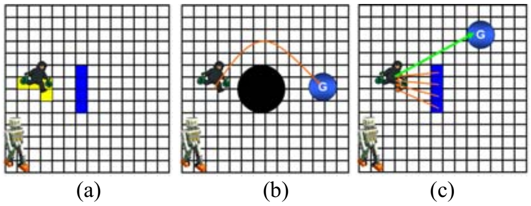


Fig.1 Comparison between the stream field based tracking with feature map and VFF based tracking with grid map. (a) Simulated environment. (b) Streaming field based tracking with feature map. (c) VFF based tracking with grid map. Blue and yellow grids depict obstacles and leg features, respectively.

person to be modeled to be close to an obstacle. On the contrary, a person can be modeled to be quite close to an obstacle using VFF based motion model as a person walks towards to an obstacle. The remainder of the paper is organized as follows. Section II describes the motion model of VFF based tracking. In Section III, we propose the VFF based tracking algorithm using grid map. The experimental results are given in Section IV. Finally, Section V concludes this paper.

II. Virtual Force Field Based Motion Model for People Tracking

SLAMSAT estimates the position of an occluded person by constructing the search path using the known stream field [11]. This algorithm suffers from high computation complexity since it has to estimate the multi-hypotheses of a person's goal and a feature-based map. In this paper, we reduce the computational complexity of [11] by adopting a novel virtual force field based motion model that can be realized with a single hypothesis of a person's goal and a grid-based map.

The purposes and the given information of people tracking using VFF and path planning using VFF quite differ from each other. Path planning is to compute the action that a robot should take given the environmental information, a robot's position, and a robot's goal. Kinematics and obstacle avoidance are its focuses. On the other hand, VFF based tracking is that a robot estimates a person's position and the goal of a person given the robot position, sensor information, and map information. How to track a moving person accurately by modeling the attractive and repulsive forces is the focus of VFF based tracking.

In the following, we will introduce the stream field based motion model in [10] and our proposed VFF based motion model in this paper.

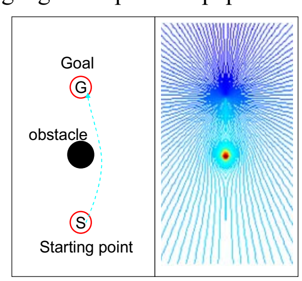
A. Stream field based motion model

To achieve the on-line prediction of motion model according to an estimated map and a virtual goal, stream field based motion model is proposed in [10]. For an irrational and incompressible flow, there exists a complex potential consisting of the potential function $\phi(x, y)$ and stream function $\psi(x, y)$, where (x, y) is a 2-D location. A stream field consists of a sink flow $\psi_{\sin k}(x, y)$ and a doublet flow $\psi_{doublet}(x, y)$, and it is defined by

$$\begin{aligned}
&\psi(x, y) \\
&= \psi_{\sin k}(x, y) + \psi_{doublet}(x, y) \\
&= -C \tan^{-1}\left(\frac{y - y_s}{x - x_s}\right) + \\
&\quad C \tan^{-1}\left(\frac{\dfrac{a^2 (y - y_d)}{(x - x_d)^2 + (y - y_d)^2} + (y_d - y_s)}{\dfrac{a^2 (x - x_d)}{(x - x_d)^2 + (y - y_d)^2} + (x_d - x_s)}\right),
\end{aligned} \tag{1}$$

where (x_s, y_s) is the center of sink, (x_d, y_d) is the center of doublet, a is the radius of doublet, and C is the constant proportion to the flow velocity. Details of stream fields can be found in [16]. Stream functions can be computed if a robot position, a person's goal, and obstacle positions are known. People velocities are computed by the partial derivative of (1).

By (1), we assume that a person will avoid a known obstacle (doublet) and move toward a virtual goal (sink) in the stream field (Fig. 2). Since a stream field constructs an active field where a person is moved inactively by attractive and repulsive forces, we can predict a person's position and the goal position and construct the search path using the known stream field. To estimate the position of the virtual goal of an unobservable moving person, the RBPF based tracking algorithm is adopted. One problem with this algorithm is that it suffers from high computation complexity and lower tracking accuracy since it adopts a feature map. Therefore, we propose a fast virtual force field based tracking algorithm using a grid map in this paper.



(a) (b)

Fig. 2 An example of a real environment and its virtual stream field. (a) Obstacle avoidance. (b) Stream field.

B. The proposed virtual force field based motion model

In tracking algorithms, the people position at time k can be modeled by $X_k = AX_{k-1} + Bu_k + \varepsilon_k$, where u_k is a person's motion at time k and ε_k is motion noise. A robot may fail to track a moving person when this person is unobservable. To solve this problem with low computation complexity, this paper proposes to incorporate the VFF into Kalman filter with constant acceleration model (CA model) using grid map. The virtual force field consists of an attractive force and multiple repulsive forces [12]. We take a person's goal to be an attractive force and occupied grids to be repulsive forces, respectively. The force summation is formulated as

$$F_{sum} = F_a + F_r, \tag{2}$$

where F_a is an attractive force of a goal, and F_r is the total repulsive force of an occupied grid map. The attractive force of a person's goal F_a can be computed by

$$F_a = \lfloor F_{ax} i + F_{ay} j \rfloor, \tag{3}$$

where F_{ax} and F_{ay} are attractive forces along the *x*- and *y*-axes, respectively. (i, j) is the unit vector.

Details of VFF designed for motion planning can be found in [12]. The extended VFF that models a repulsive force for motion planning is proposed in [17]. Since the number of occupied grids is not fixed, a repulsive force models in [12] and [17] is not suitable for people tracking. Therefore, we design a repulsive force model for tracking as

$$F_r = \sum_{n=0}^{N-1} F_{vr,i} \left[(\cos\theta_i) i + (\sin\theta_i) j \right], \tag{4}$$

$$F_{vr,i} = f_r \left[\tanh\left(\frac{2}{3}(d_i) - 1\right) - 1 \right], \tag{5}$$

$$\theta_i = \tan^{-1}\left(\frac{y_i - y_o}{x_i - x_o} \right), \tag{6}$$

where f_r is the intensity of the repulsive force, $F_{vr,i}$ is the repulsive force of the *i*-th doublet, (x_i, y_i) is the grid position, and θ_i is the angle between the person and the *i*-th obstacle. N is the number of occupied grids. d_i is the distance between the *i*-th occupied grid map and a person. For example, an attractive force and repulsive forces are represented by green arrow and orange arrows in Fig. 1(c), respectively. Since a person naturally avoids known obstacles and moves toward a virtual goal in a virtual force field, a person's motion can be computed. That is, a person is moved due to an attractive force and repulsive forces in an active field constructed by VFF, and thus we can easily predict a person's position.

Although a repulsive force can be estimated using map information, an attractive force is unknown. To simultaneously estimate a person's position and the goal states of a person, we design the motion model as

$$\begin{aligned} X_k &= A X_{k-1} + B u_k + \Gamma \varepsilon_k, \\ \begin{bmatrix} x \\ y \end{bmatrix}_k &= \begin{bmatrix} A_x & 0_{4,4} \\ 0_{4,4} & A_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}_{k-1} + \\ & \begin{bmatrix} B_x & 0_{4,1} \\ 0_{4,1} & B_y \end{bmatrix} \begin{bmatrix} F_{rx} \\ F_{ry} \end{bmatrix}_k + \begin{bmatrix} \Gamma_x & 0_{4,2} \\ 0_{4,2} & \Gamma_y \end{bmatrix} \varepsilon_k, \end{aligned} \tag{7}$$

where

$$x = \left[O_x \quad V_{ax} \quad V_{rx} \quad F_{ax} \right]^T, \tag{8}$$

$$y = \left[O_y \quad V_{ay} \quad V_{ry} \quad F_{ay} \right]^T, \tag{9}$$

$$A_x = A_y = \begin{bmatrix} 1 & \Delta t & \Delta t & 0.5\Delta t^2 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{10}$$

$$B_x = B_y = \left[0.5\Delta t^2 \quad 0 \quad \Delta t \quad 0 \right]^T, \tag{11}$$

$$\Gamma_x = \Gamma_y = \begin{bmatrix} 0.5\Delta t^2 & 0.5\Delta t^2 \\ \Delta t & 0 \\ 0 & \Delta t \\ 1 & 0 \end{bmatrix}, \tag{12}$$

$$\begin{aligned} &\varepsilon_k \sim N(0, \sigma^2) \\ &\sigma^2 = \left[\sigma_{ax}^2 \quad \sigma_{rx}^2 \quad \sigma_{ay}^2 \quad \sigma_{ry}^2 \right]^T, \end{aligned} \tag{13}$$

where (O_x, O_y) is a person's position, (V_{ax}, V_{ay}) is the velocity of an attractive force (F_{ax}, F_{ay}), (V_{rx}, V_{ry}) is the velocity of a repulsive force, $(\sigma_{ax}, \sigma_{ay})$ is the standard deviation of an attractive force, and $(\sigma_{rx}, \sigma_{ry})$ is the standard deviation of a repulsive force.

The basic idea of the proposed motion model is that it estimates (O_x, O_y), (V_{ax}, V_{ay}), (V_{rx}, V_{ry}), and (F_{ax}, F_{ay}) by the CA model in [2]. This model consists of the attractive force (F_{ax}, F_{ay}) and a repulsive force (F_{rx}, F_{ry}). In our design, the action term u_t is replaced by a repulsive force (F_{rx}, F_{ry}). ε_k denotes Gaussian noise. Γ is noise gain matrix.

Next, a sensor model is defined as

$$Z_k = C X_k + \delta_k, \tag{14}$$

$$\begin{bmatrix} Z_x \\ Z_y \end{bmatrix}_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} O_x \\ V_{xx} \\ V_{rx} \\ F_{ax} \\ O_y \\ V_{xy} \\ V_{ry} \\ F_{ay} \end{bmatrix}_k + \delta_k \tag{15}$$

where Z_k is the measured position of a person, and δ_k is the sensor noise modeled by Gaussian. The predicted states are corrected by the sensor measurement. In case of occlusion, the person's states can be estimated according to an attractive force F_a and a repulsive force F_r. In the next section, we will propose our grid map based tracking algorithm.

III. The Proposed Virtual Force Field based Tracking Algorithm using Grid Map

Detection is a necessary stage prior to tracking. In our proposed VFF based tracking algorithm using grid map (Fig. 3), the moving points at time k are inferred from the difference of sensor scans at time k and the first moment. The association between the points and the points from a person's position prediction at time k are then computed based on Mahalanobis distance. A point will be deemed as a leg point if the distance is small (Fig. 4). Finally, a person's position $(z_x^O, z_y^O)_k$ by people detection is the average position of all leg points.

We estimate the map state m_k at time k using the grid mapping algorithm proposed in [18]. The incremental update equation for mapping is

$$\begin{aligned}&\log o(occ(i,j)\,|\,r=D)\\&=\log o(occ(i,j))+\log\lambda(r=D\,|\,occ(i,j))\end{aligned} \tag{16}$$

where $occ(i, j)$ is an occupied grid cell at position (i, j), r is the range reading from a sensor, and λ is the likelihood ratio. The logarithmic operation that represents odds of each grid cell is updated using laser measurement at the correction stage.

Next, the person's state O_k and goal state G_k is predicted based on the person's state O_{k-1}, goal state G_{k-1} and map state m_k. Let the state of VFF based tracking be $S_k=\langle O_k,G_k,m_k\rangle=\langle\langle O_x,O_y\rangle_k,\langle V_{ax},V_{ay},V_{rx},V_{ry},F_{ax},F_{ay}\rangle_k,m_k\rangle$, where O_k is the person's state at time k that consists of the mean $(O_x,O_y)_k$. The person's goal G_k consists of the repulsive velocity, the attractive velocity, and the attractive force. m_k, the grid map information, generates the repulsive forces (F_{rx},F_{ry}) by (4). Kalman filter is employed to simultaneously estimates the goal state G_k and person's state O_k. The states of people tracking using VFF based motion model is factorized into the VFF state distribution and grid map distribution at time k-1 as

$$\begin{aligned}&bel(\mathbf{S}_k)\\&=P(m_{1:k},O_{1:k},G_{1:k}\,|\,z_{1:k})\\&=P(m_k,O_k,G_k,m_{1:k-1},O_{1:k-1},G_{1:k-1}\,|\,z_{1:k})\\&=P(G_k,O_k\,|\,m_k,m_{1:k-1},O_{1:k-1},G_{1:k-1},z_{1:k})\times\\&\quad P(m_k\,|\,m_{1:k-1},O_{1:k-1},G_{1:k-1},z_{1:k})\times\\&\quad P(m_{1:k-1},O_{1:k-1},G_{1:k-1}\,|\,z_{1:k})\\&\overset{DBN}{=}\underbrace{P(G_k,O_k\,|\,m_k,O_{1:k-1},G_{1:k-1},z_{1:k})}_{\text{VFF state distribution}}\times\\&\quad\underbrace{P(m_k\,|\,m_{1:k-1},z_{1:k})}_{\text{Grid map distribution}}\times\\&\quad\underbrace{P(m_{1:k-1},O_{1:k-1},G_{1:k-1}\,|\,z_{1:k})}_{bel(\mathbf{S}_{k-1})}\end{aligned} \tag{17}$$

In (17), the VFF state distribution and grid map distribution can be derived based on Dynamic Bayesian Networks (Fig. 5). Thus, VFF based tracking conditioned on grid map can be formulated as

$$\begin{aligned}&P(G_k,O_k\,|\,m_k,O_{1:k-1},G_{1:k-1},z_{1:k})\\&=\eta\underbrace{P(z_k\,|\,O_k)}_{\text{Correction}}\underbrace{P(G_k,O_k\,|\,m_k,O_{1:k-1},G_{1:k-1},z_{1:k-1})}_{\text{Prediction}}\end{aligned} \tag{18}$$

where the prediction stage and correction stage are computed according to (7) and (15), respectively.

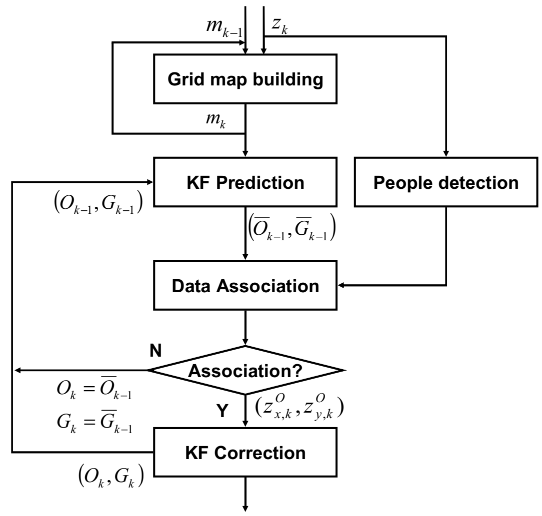


Fig. 3 The system architecture of people tracking using VFF based motion model.

Fig.4 Thresholds for classification of moving points in data association.

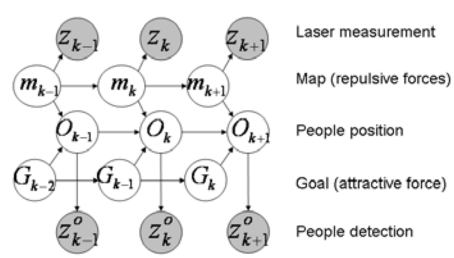


Fig. 5 Dynamic Bayesian Networks (DBNs) of our proposed grid map based tracking algorithm.

After the states of a goal and a person are computed, the tracking algorithm is divided into two cases.

$$\begin{aligned}&P(O_k,G_k\,|\,O_{1:k-1},G_{1:k-1},m_k,z_{1:k})\\&=\begin{cases}P(O_k,G_k\,|\,O_{1:k-1},G_{1:k-1},m_k,z^O_{1:k}), & \text{tracking case.}\\P(O_k,G_k\,|\,O_{1:k-1},G_{1:k-1},m_k), & \text{predicting case.}\end{cases}\end{aligned}$$

It will be the tracking case if the robot detects the people successfully, otherwise it will be the predicting case.

IV. Experimental Results

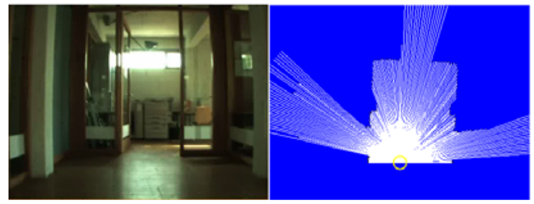
In the experiments, our computing platform is a 2.4 GHZ IBM X200 laptop with 2G RAM. We adopt COLD – Freiburg dataset of COLD database as our test data [19]. This dataset was acquired at the Autonomous Intelligent Systems Laboratory at the University of Freiburg in Germany. A laser range finder with angular resolution of 1 degree is mounted on the mobile platform, ActivMedia Pioneer-3. The ground truth of a person's trajectory is hand labeled. Figure 6 shows the experimental environment, where the yellow circle represents the position of the laser.

We compare the performance of VFFT with CAKFT and RBPFT. VFFT is our proposed VFF based tracking with 120 occupied grids of grid map. CAKFT is Kalman filter based tracking with constant velocity model [2]. RBPFT is stream field based RBPF tracking with 1000 particles and a feature map of three doublets [10]. In Fig. 7(a), black points represent occupied grids of VFF based tracking (VFFT). Doublets of RBPFT are represented by three black circles (Fig. 7(b)). The number of doublets in VFF based tracking depends on the grid map at runtime. In our experiments, the size of each grid cell is 2cm×2cm. Figure 8 gives the tracking trajectories of VFFT, CAKFT, and RBPFT. The average tracking errors of CAKFT, RBPFT, and VFFT are 1.94cm, 0.27cm, and 1.89cm, respectively (Table I). RBPFT outperforms CAKFT and VFFT since RBPF combines Kalman Filter and particle filter. However, VFFT is better than CAKFT because the map information is considered in VFFT.

In case of occlusion, the probabilistic tracking algorithm believes the result of the prediction stage but not that of the correction stage. Hence, to demonstrate the performance of our proposed scheme in the presence of occlusion, we define a measurement called N-Prediction performance for verification. We compare the predicted data with the ground truth. We set the prediction step N to be 5 in the tests. Thus, we propose the N-Prediction performance formulated as

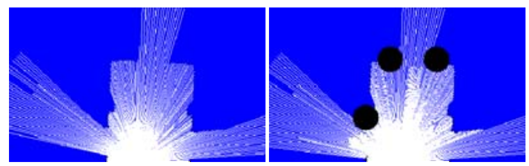
$$5P\_error = \frac{1}{5}\sum_{i=k}^{k+5}\left((x_k^G - x_k^P)^2 + (y_k^G - y_k^P)\right)^{0.5} , \quad (19)$$

where (x_k^G, y_k^G) and (x_k^P, y_k^P) are the ground truth and predicted data at time *k*, respectively. In this case, the average tracking errors of CAKFT, RBPFT, and VFFT are 12.54cm, 7.90cm, and 6.22cm, respectively (Table II). CAKFT diverges faster than RBPFT and VFFT while RBPFT and VFFT can keep predicting a person's position based on the stream field and virtual force field, respectively (Fig. 8). Therefore, the accuracy of CAKFT is lower than those of RBPFT and VFFT. However, the repulsive forces modeled by VFFT are more accurate than those by RBPFT. As a result, the predicted person's position of VFFT is more accurate than that of RBPFT (Fig. 9). The average cycle time for RBPFT and VFFT are compared in Fig. 10. As we can see, the average cycle time of RBPFT increases with the number of doublets. However, the average cycle time of VFFT is always short.



(a) (b)

Fig. 6 The images of the experimental environment. The yellow circles represent the position of the robot.



(a) (b)

Fig. 7 The grid map and feature map. (a) The grid map for VFF based tracking. (b) The feature map for stream field based tracking. Grids and features of doublets are represented by black points and circles, respectively.

TABLE I.
Comparisons of tracking errors among CAKFT, RBPFT, and VFFT.

	Total mean (cm)
CAKFT	1.94
RBPFT	0.27
VFFT	1.89

TABLE II.
Comparisons of tracking errors among CAKFT, RBPFT, and VFFT in 5 steps case.

	Total mean (cm)
CAKFT	12.54
RBPFT	7.90
VFFT	6.22

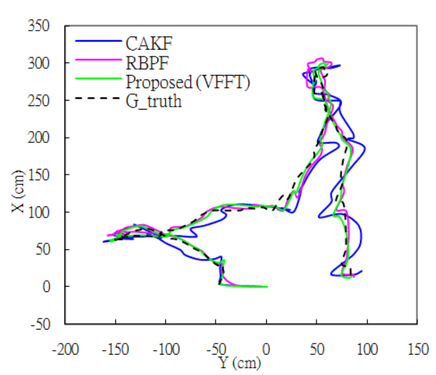


Fig. 8 Trajectories of CAKFT, RBPFT, VFFT, and ground truth in 5-step prediction case.

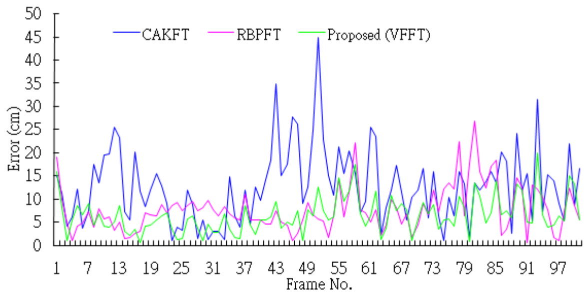


Fig. 9 Errors of CAKFT, RBPFT and, VFFT in case of 5-step-prediction.

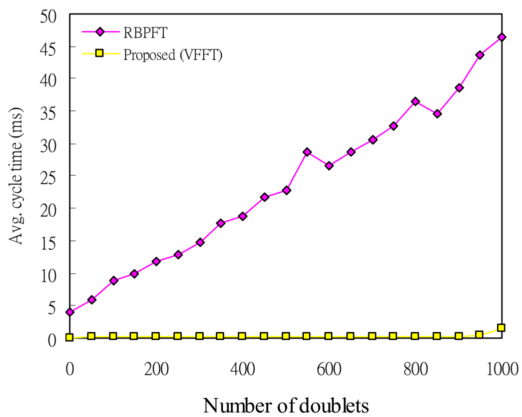


Fig. 10 Comparisons of average cycle time of RBPFT tracking with feature map and VFFT with grid map.

V. Conclusions

This paper proposes a fast virtual force field based tracking algorithm. The tracker adopts the efficient Kalman Filter as the estimator. With VFF, the interactions among the states of a goal, a grid map, and a person's position can be modeled more accurately. The experimental results show that our algorithm can track a moving person effectively and fast.

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