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REGULAR ARTICLE

RBF network based motion trajectory optimization for robot used in agricultural activities

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ABSTRACT

At present, the efficiency of the method to track and predict motion trajectory of fruit and vegetable picking robot was low and the realization process was complex. Therefore, a research on motion trajectory optimization of fruit and vegetable picking robot based on RBF network was proposed. After analyzing the reason for data class imbalance of fruit and vegetable picking robot, this paper introduced the processing technology MWMO in RBF network. Then, the MWMO technology was embedded in the tracking and prediction research of motion trajectory optimization of fruit and vegetable picking robot. Moreover, the semi-supervised learning algorithm was used as the framework and integrated the processing technology of data class imbalance of motion trajectory to improve the efficiency of tracking and prediction of fruit and vegetable picking robot. According to the integration result, combined with the idea about the calculation of spatial function and the tracking and prediction of motion trajectory in RBF network, we designed the matching principle of trajectory similarity of time and space and realized the matching between the predicted position and the actual position, so that the tracking and prediction of fruit and vegetable picking robot could be completed. Experimental results show that the average calculation time of proposed method is 2.0S, which is only half of average time of traditional tracking and prediction method. It fully proves that the proposed optimization method can accurately track and predict the motion trajectory of fruit and vegetable picking robot. The prediction efficiency is higher and the time consumptionis shorter.

Keywords: RBF network; Fruit and vegetable picking robot; Trajectory; Tracking prediction; Optimization

INTRODUCTION

At present, the mobile robot has been widely used in the field of agricultural production. The fruit and vegetable picking robot has become an Indispensable equipment to improve the yield of fruit and vegetable. Due to the non-linearity and non-completeness of fruit and vegetable picking robot, to efficiently track and forecast motion trajectory of fruit and vegetable robot has been a challenging research (Maddi et al., 2018; Yadav et al., 2018). In order to realize the tracking and prediction of motion trajectory of fruit and vegetable robot, the relevant scholars and experts track and predict the overall moving trajectory of robot manipulator. The results can improve the working efficiency. But the tracking process is complex and the calculation time of tracking prediction is too long, which cannot meet the real-time tracking of motion trajectory of fruit and vegetable robot and high efficient prediction (Zheng & Wang 2017, Cui & Tian 2016). In order to solve this problem, some scholars and experts have got some achievements (Huang et al., 2016).

In achievement one, a method to track and predict flux linkage trajectory based on model prediction is proposed. This method uses the optimized pulse-width modulation model (PWM) to predict the trajectory of magnetic chain (Karim et al., 2017; Nyemb et al., 2018; Rahman et al., 2018). It does not need to estimate the fundamental components of stator flux linkage and voltage in real time, and realizes the high performance closed-loop control of optimized PWM. The effective set method is used to solve the numerical value. The optimal PWM switch angle is corrected as little as possible and the deviation of tracking magnetic chain is eliminated. Thus, the tracking prediction of flux linkage trajectory based on optimized PWM is realized. But this method has a large error in tracking prediction (M.M. 2017).

In achievement two, a method to design trajectory tracking model predictor is proposed. A nonlinear space model with only two control inputs and interference is built (Borogayary et al., 2018; Khan et al., 2017; Kylili et al., 2018; Sanchez Camacho and Martinez Morales, 2017; Wu et al., 2018). But,

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this method has a large amount of computation, leading to the complex process of tracking and forecasting(Wang et al., 2017). In achievement three, a method to track and predict trajectory based on support vector machine is proposed. The input and output data of network system are collected and designed. The generalized inverse system is obtained by support vector machine, which is decoupled from the original system (Litwin et al., 2017; Liu, 2018; Mo et al., 2018; Peng et al., 2017). For the decoupled system, the identification prediction model based on support vector machine and the predictive function control method based on PSO optimized control sequence are used to realize the tracking and prediction of motion trajectory. But, this method does not consider noise interference in social network, resulting in low accuracy of trajectory prediction (Zheng & Wang 2017). In achievement four, a method to track and predict motion trajectory of fruit and vegetable picking robot based on dynamic characteristic is proposed. This method has high accuracy for the tracking and prediction, but it costs a lot of prediction time due to calculation error, leading to low efficiency of tracking and prediction (Xue et al., 2016). In achievement five, a method to track and predict motion trajectory of robot based on reinforcement learning and self-organizing topology control algorithm of neural network is proposed. According to the reinforcement learning, we can intelligently probe the environment and accumulate the probe result into experience. Combined with the neural network topology control algorithm, we can realize the accurate tracking and prediction of motion trajectory of robot. This method achieves intelligent tracking and prediction, but the efficiency is low (Jiang J et al., 2017). In achievement six, a research on path planning of mobile picking robot based on visual path planning is proposed. This method has high accuracy in path control, but it can only play an auxiliary role in tracking and forecasting, and it cannot achieve accurate and high-efficient tracking and monitoring.

For above problems, a method on the motion trajectory optimization of fruit and vegetable picking robot based on RBF network was proposed. Experimental results show that the proposed optimization method can accurately track and predict the motion trajectory of fruit and vegetable picking robot, and the realization process is simple, which provides a theory basis for development of this subject in the application field. The overall implementation framework of proposed method is as follows:

Analyze the reasons for imbalance of trajectory data of fruit and vegetable picking robot. MWMO processing technology for imbalance of motion trajectory data class in RBF network is applied to the research of tracking and predicting the motion trajectory of fruit and vegetable picking robot.

Take the semi supervised learning algorithm as the framework to integrate the imbalance of motion trajectory data class.

According to the integration result of motion trajectory data class, the idea about the calculation of space function and the prediction of trajectory track in RBF network is fused to design the matching principle which comprehensively considers trajectory similarity between time and space.

The tracking prediction optimization method is verified by experiment and analysis.

Discussion.

Summarize the whole article and pointing out the way of future development.

METHODS AND MATERIALS

Research on imbalance of motion trajectory data classes for fruit and vegetable picking robot

For the data class imbalance of motion trajectory of fruit and vegetable picking robot, this paper uses semi-supervised learning method. The semi supervised learning method is a method of probabilistic trajectory tracking based on classifier. It transforms the trajectory tracking problem into the problem of binary classification(Yang et al., 2016). The essence of semi-supervised learning: a learning algorithm between unsupervised learning (training data without any marks) and supervised learning (training data which is completely marked). The unprocessed data set of motion trajectory tracking prediction of fruit and vegetable picking robot is $X=(x_i)i=1,2,\cdots,N$, which can be divided into two parts: the part $X_l=(x_1,\cdots,x_l)$ is the marked motion trajectory data, the corresponding mark is $Y_l=(y_1,\cdots,y_l)$, and the unmarked motion trajectory data is $X_u=(x_{l+1},\cdots,x_{l+u})$. The main idea of algorithm: first, the initial classifier is obtained from the data set (X_l,Y_l) of motion trajectory. In each step, the unlabeled data X_u is classified based the decision function, and its pseudo labels and weights are obtained, which are added in the training set. In view of the characteristic of semi-supervised learning method, the semi-supervised learning method is better than the full-supervised learning method and unsupervised learning method, which can improve the accuracy of learning algorithm and tracking performance. The Semi-Boosting learning method is an important method of semi supervised learning. The data set in Semi-Boosting training not only contains the unmarked data set X^U of motion trajectory but also contains the marked data set X^L of motion trajectory. To classify the unmarked motion trajectory data and incorporate it into the training process is the key of Semi-Boosting tracking algorithm (Atikuzzamman, M et al., 2018).

$$q_n(x) = e^{2H_{n-1}(x)} \frac{1}{|X^L|} \sum_{x_i \in X^-} S(x, x_i) + \frac{1}{|X^U|} \sum_{x_i \in X^U} S(x, x_i) e^{H_{n-1}(x) - H_{n-1}(x_i)} \quad (1)$$

$$p_n(x) = e^{-2H_{n-1}(x)} \frac{1}{|X^L|} \sum_{x_i \in X^+} S(x, x_i) + \frac{1}{|X^U|} \sum_{x_i \in X^U} S(x, x_i) e^{H_{n-1}(x_i) - H_{n-1}(x)} \quad (2)$$

Where, $S(x, x_i)$ denotes the similarity measure of tracking and prediction sample of motion trajectory of fruit and vegetable picking robot. Respectively, X^+ and X^- denote the positive sample set and negative sample set. $e^{H_{n-1}(x)}$ denotes the similarity coefficient of tracking prediction sample. $H_{n-1}(x_i)$ denotes the index function of unprocessed data set. $H_{n-1}(x)$ denotes the index function of unmarked training sample x . $p_n(x)$ denotes the reliability degree that unmarked training sample x belongs to normal sample. $q_n(x)$ indicates that the reliability degree that unlabeled training sample x belongs to negative sample. $p_n(x)$ and $q_n(x)$ can be calculated directly. The key problem is to estimate the value in the online case and introduce the boosting method: firstly, to train H^p (a priori classifier), which will be rough, and then to calculate the approximate value of $p_n(x)$ and $q_n(x)$ by the estimation method, as shown in formula (3) and formula (4).

$$\tilde{p}_n(x) = \frac{e^{-H_{n-1}(x)} e^{H^P(x)}}{e^{H^P(x)} + e^{-H^P(x)}} \quad (3)$$

$$\tilde{q}_n(x) = \frac{e^{H_{n-1}(x)} e^{-H^P(x)}}{e^{H^P(x)} + e^{-H^P(x)}} \quad (4)$$

According to above formulas, the pseudo label and weight of unmarked motion trajectory data are calculated in the trajectory tracking prediction of fruit and vegetable picking robot. After getting the pseudo label and weight, we add them in the training set, and then they can participate in the updating of classifier (S.N. and Hanafiah 2017.)

The semi-supervised online learning method shows the good adaptability in the tracking process. The positive sample which is adjacent to the current target location and the negative sample which is far away from the current target location are used to update the tracker and model. Generally, it has good adaptability to new apparent change and new background change. The classifier training only has only a marked sample and unlabeled samples of all subsequent frames. In the framework of semi-supervised algorithm, the focus of class imbalance is the class imbalance processing (CI) module in Fig. 1 (the framework of P-N tracking algorithm). The meaning of each module: (i) classifier marks unlabeled samples, (ii) correct the sample that violates the constraint condition, (iii) training set after joining a new sample, (iv) use the class imbalance technique to balance the training set, (v) retrain the classifier.

The class imbalance method has two aspects of purposes: improve the sample selection mechanism of motion trajectory tracking prediction and improve the mechanism of minority class sample synthesized by artificial interpolation in over-sampling(Artaud et al., 2016). The class imbalance process method has three steps: firstly, in the minority class $S_{\min}$ of previous training set, the majority class weighting and minority class over-sampling technique are used to recognize minority class $S_{\min}$ that is difficult to learn; secondly, based on its importance in data set, a weight S_w is given for each $S_{i\min}$; thirdly, the class imbalance processing technology MWMO is used to combine weight S_w from $S_{i\min}$ to generate synthetic sample trajectory data and add it in $S_{\min}$ to form an output set $S_{o\min}$. The principle of equalization technique of majority class weight and minority sample oversampling is as follows:

Supposing that $NN(x)$ denotes the nearest neighbor set of sample points of user location, and $N_{maj}(x)$ denotes the nearest set of minority class, and $N_{\min}(x)$ denotes the nearest set of majority class, and their respective elements are $k1, k2, k3$. When $k1 = k2 = k3 = 5$, $N_{maj}A$ of minority class A is (P, Q, R, S, T) . For the sample of majority class P , $N_{\min}P$ is (A, B, C, D, E).

The detailed process to construct $S_{i\min}$ is described as follows:

MWMO firstly filters the minority class $S_{\min}$ in initial data set of motion trajectory tracking prediction, and the set minority class is labeled as $S_{\min f}$: in implement process, we calculate its $NN(x)$ for each $x_i \in S_{\min}$ element. If $NN(x)$ only contains the majority class, the corresponding x_i should be filtered out.

For each $x_i \in S_{\min}$, the corresponding $N_{maj}(x_i)$ is calculated. When the value of $k2$ is very small, the samples

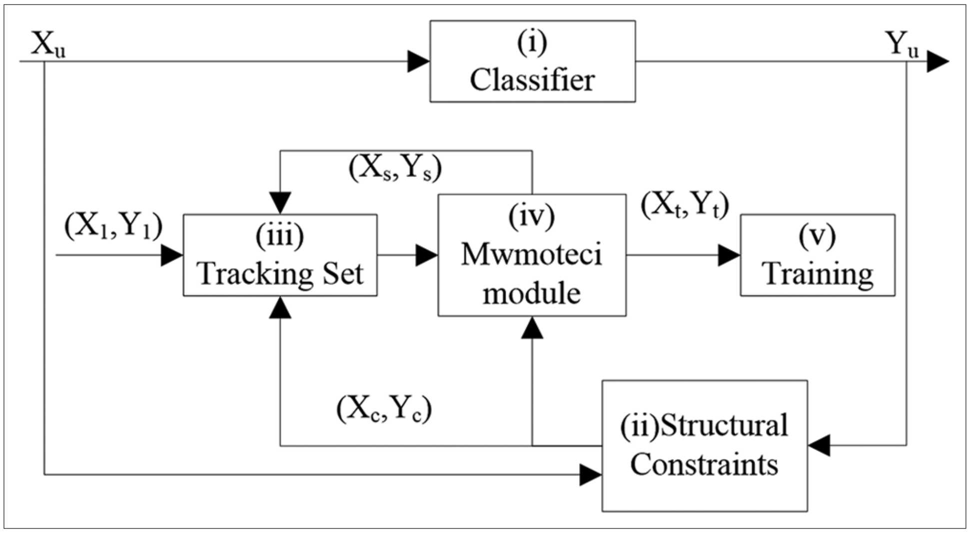


Fig 1. Imbalance module of motion trajectory data class.

in $N_{maj}(x_i)$ will be the majority class sample S_{bmaj} on the edge. They are at the decision boundary. S_{bmaj} is obtained by adding all $N_{maj}(x_i)$.

For each $y_i \in S_{bmaj}$, MWMO calculates $N_{\min}(y_i)$ and combines the calculation results to get $S_{i\min}$.

The big weight value denotes the important minority class. Correspondingly, composite value should be generated around it. The process of using MWMO to calculate weight value is as follows: each majority class of $y_i \in S_{bmaj}$ sample gives each minority sample a weight (information weight). $I_w(y_i, x_i)$ is defined as the product of adjacent factor $C_f(y_i, x_i)$ and density factor $D_f(y_i, x_i)$ of fruit and vegetable picking robot.

$$I_w(y_i, x_i) = C_f(y_i, x_i) \times D_f(y_i, x_i) \tag{5}$$

Where, the calculation for adjacent factor $C_f(y_i, x_i)$ of motion trajectory of fruit and vegetable picking robot needs two steps.

$$d_n(y_i, x_i) = \frac{dist(y_i, x_i)}{l} \tag{6}$$

$$C_f(y_i, x_i) = \frac{f(1/d_n(y_i, x_i))}{C_f(th)} * CMAX \tag{7}$$

The formula (6) denotes the normalized Euclidean distance y_i from to x_i. l is the dimension of feature space. In formula (7), $C_f(th)$ and $CMAX$ are parameters defined by user. $f(\bullet)$ is a cut-off function. The purpose is to ignore the high value and limit the maximum value as $C_f(th)$. Therefore, the range of $C_f(y_i, x_i)$ value is $[0, CMAX]$. Then, $f(\bullet)$ is defined as follows:

$$f(\bullet) = \begin{cases} x & x \le C_f(th) \\ C_f(th) & otherwise \end{cases} \tag{8}$$

Because the distance from the decision boundary to the two ethnic groups is equal, the density factor $D_f(y_i, x_i)$ should have such function: when the sample is synthesized again, the sparse group and the dense group should be distinguished. Meanwhile, more and more synthetic samples should be formed around the sparse ethnic group. $D_f(y_i, x_i)$ can be defined as:

$$D_f(y_i, x_i) = \frac{C_f(y_i, x_i)}{\sum_{q \in S_{i\min}} C_f(y_i, q)} \tag{9}$$

MWMO uses the improved multilevel clustering algorithm to find minority class $S_{\min}$ and initializes the output set $S_{o\min}$ as $S_{\min}$. Finally, based on above two steps, a linear interpolation method is used to form the synthetic sample, which is added in $S_{o\min}$ to synthesize the sample of motion trajectory tracking prediction of fruit and vegetable picking robot.

The above discussion discusses the influence of motion trajectory data imbalance on the motion trajectory tracking prediction of fruit and vegetable picking robot. Due to the problem of sample training, the reason of imbalance of motion trajectory data class, which is still caused by the concept drift. After introducing the processing technology MWMO in RBF network, we embeds it in the tracking prediction method, and then use the semi-supervised learning algorithm as the frame and integrate the imbalance processing technology to realize the synthesis of motion trajectory tracking prediction sample of fruit and vegetable picking robot.

Optimization of prediction for motion trajectory track of fruit and vegetable picking robot based on RBF network

Based on the synthesis of tracking prediction samples of motion trajectory of fruit and vegetable picking robot, the motion trajectory of fruit and vegetable picking robot is tracked and predicted. Because the original motion trajectory τ of fruit and vegetable picking robot is a series of discrete points $\tau(<p_1,t_1>,\cdots,<p_i,t_i>,\cdots,<p_n,t_n>)$, in order to get further information, RBF network mapping and matching must be carried out, so as to obtain the specific motion trajectory information $\tau'(<p_1',e_1,t_1>,\cdots,<p_i',e_i,t_i>,\cdots,<p_n',e_n,t_n>)$.

For each motion trajectory point $<p_i,t_i>$, the candidate edge set is acquired. The candidate edge is defined as the edge e_i which is intersected with the circle that the center of circle is $<p_i,t_i>$ and the radius is r. The candidate point is defined as follows: if the projection point of motion trajectory point $<p_i,t_i>$ at the edge is between the two ends of the edge, the projection point is the candidate point. Otherwise, the end point which is close to the trajectory point $<p_i,t_i>$ is the candidate point. In the following Fig. 2, the candidate edges of p_i are e_i^1,e_i^2,e_i^3. Respectively, candidate points are c_i^1,c_i^2,c_i^3. The number of candidate points of p_i is a_i.

Then, a candidate map including a series of trajectory points is obtained by time-space analysis. Because the difference between the coordinate of measured user location point and the actual position conforms to Gauss distribution $N(\mu,\sigma^2)$, the probability that a candidate point c_i^j is really the projection point of point p_i is:

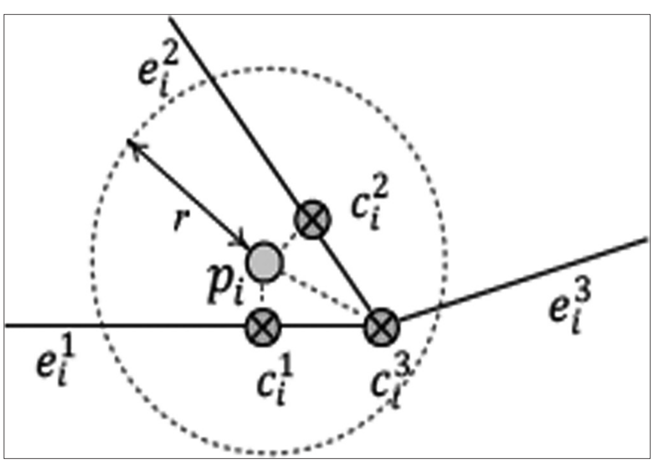


Fig 2. Candidate points.

$$N(c_i^j)=\frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(x_i^j-u)^2}{2\sigma^2}} \tag{10}$$

In the above formula, x_i^j denotes the Euler distance between c_i^j and p_i. e denotes the coefficient of Gaussian function. The spatial weight from the candidate point c_{j-1}^t to the candidate point c_j^s is defined as follows:

$$F_S(c_{j-1}^t\to c_j^s)=N(c_i^j)\times V(c_{j-1}^t\to c_j^s),2\le i\le n \tag{11}$$

In the above formula, $V(c_{j-1}^t\to c_j^s)$ denotes the transfer probability of $c_{j-1}^t\to c_j^s$:

$$V(c_{j-1}^t\to c_j^s)=\frac{d_{i-}}{w_{(i-1,t}} \tag{12}$$

In the above formula, $d_{i-1.i}$ denotes the Euler distance from p_{i-1} to $p_i\cdot w_{(i-1,t)\to(i,s)}$ denotes the shortest path from the candidate point c_{j-1}^t to c_j^s. There is a hypothesis that the fruit and vegetable picking robot often chooses the nearest path between two points, and it is restricted by the space of network, thus $|d_{i-1.i}|\le w_{(i-1,t)\to(i,s)}$. Then if the closer to $w_{(i-1,t)\to(i,s)}$ the value of $|d_{i-1.i}|$, the greater the probability that c_{j-1}^t transfers to c_j^s.

According to the candidate points obtained before, a matrix M can be established:

$$M=diag(M^{(2)},M^{(3)},\cdots,M^{(n)}) \tag{13}$$

In the above formula, $M^{(i)}=\left(m_{ts}^{(i)}\right)=F_S(c_{j-1}^t\to c_j^s)$.

The matrix M only reflects the local influence of adjacent two points. Due to the measured error, if we only consider adjacent two points, it is easy to fall into the local error (Zhang 2017, Lengyel et al., 2017). Meanwhile, this cannot reflect the whole relationship among n trajectory points. Therefore, a distance weight matrix W_i is established:

$$W_i=diag\{w_i^1,\cdots,w_i^{i-1},w_i^i,\cdots,w_i^n\} \tag{14}$$

Where, $w_i^j=f(dist(p_i,p_j))$, $f(\cdot)$ is a distance weight function, which is used to denote the influence of point p_j on point p_i.

$$f(dist(p_i,p_j))=2^{-dist(p_i,p_j)} \tag{15}$$

A weighted scoring matrix for each tracking prediction trajectory point can be obtained by W_i and M.

$$\Phi_i = W_i M = diag\{\Phi_i^2, \cdots, \Phi_i^n\} \tag{16}$$

Where, Φ_i^j denotes the weight score matrix of each prediction point.

After getting the weight score matrix Φ_i of each prediction point p_i, the best motion trajectory for p_i can be obtained, which satisfies.

$$Z = \min \sum_{j=2}^{n-1} \Phi_i^j \tag{17}$$

Finally, we vote for each candidate point in the best motion trajectory obtained by p_i. The candidate points should be selected from each best motion trajectory, and then vote is increased by 1. Corresponding to p_i, the candidate point c_i^k with the largest number of votes is chosen as the final mapping point. They are linked to get the required motion trajectory.

As mentioned above, to find the similar motion trajectory is a key to track and forecast the trajectory of fruit and vegetable picking robot. In order to find similar motion trajectories, we must quantify the specific definition of trajectory similarity. Considering that the trajectory mainly contains the factor of time and space, we use the two factors to define the similarity of trajectory.

At first, the spatial similarity of motion trajectory is considered. Because the motion trajectory of fruit and vegetable picking robot is actually composed of a series of edges, and each side can be regarded as a number, then the trajectory can be regarded as a character string. In character string processing algorithm, Levenshtein distance is a popular method to measure the similarity between two character strings. Based on the idea of Levenshtein distance, we propose a definition for spatial distance of motion trajectory.

The spatial distance of motion trajectory is the given trajectory τ_1' and τ_2', and their sub-trajectories $\tau_1'(1,i)$ and $\tau_2'(1,j)$ and the spatial distance $sd_{\tau_1',\tau_2'}(i,j)$ are defined as:

$$sd_{\tau_1',\tau_2'}(i,j) = \begin{cases} 0 & i = j = 0 \\ i & j = 0, i > 0 \\ j & i = 0, j > 0 \\ \min \begin{cases} sd_{\tau_1',\tau_2'}(i-1,j)+1 & i,j>0 \\ sd_{\tau_1',\tau_2'}(i-1,j-1)+1 & i,j>0, \tau_1'\cdot e_i \neq \tau_2'\cdot e_j \\ sd_{\tau_1',\tau_2'}(i-1,j-1) & i,j>0, \tau_1'\cdot e_i = \tau_2'\cdot e_j \end{cases} \end{cases} \tag{18}$$

The space distance between two motion trajectories is actually an edge sequence of motion trajectory. After deletion, insertion, and replacement operation, the minimum distance of another motion trajectory is obtained.

After getting the space distance between two trajectories, the similarity degree of two trajectories is defined. In fact, Levenshtein distance only considers the absolute factor such as those edges with difference of the two trajectories, but does not take into account the relative factor such as length of motion trajectory (Zhou et al., 2016, Wolz et al., 2018). For example, the space distance between two pairs of trajectories is 5, but one pair is 50 and the other pair is 20. Then for the first pair of track, they are very similar, but for the latter pair, they are very different. Thus, the formal definition of similar motion trajectory is given based on the length of motion trajectory.

The motion trajectories with spatial similarity: two trajectories τ_1' and τ_2' are considered to be similar. If they satisfy following conditions:

$$\frac{st_{\tau_1',\tau_2'}}{\tau_1'\cdot len} \geq \phi_1, \frac{st_{\tau_1',\tau_2'}}{\tau_2'\cdot len} \geq \phi_2, sRatio_{\tau_1',\tau_2'} \leq \phi_2 \tag{19}$$

Where, $sRatio_{\tau_1',\tau_2'} = \left| \frac{st_{\tau_1',\tau_2'} \times (\tau_1'\cdot len - \tau_2'\cdot len)}{\tau_1'\cdot len \times \tau_2'\cdot len} \right|$, $st_{\tau_1',\tau_2'} = \max\{\tau_1'\cdot len, \tau_2'\cdot len\} - sd_{\tau_1',\tau_2'}$, ϕ_1 and ϕ_2 denote the parameters of two trajectories.

Because $sd_{\tau_1',\tau_2'}$ is the space distance between two motion trajectories. In other words, it is the minimum operation times, if we use the length of longer motion trajectory sequence to subtract $sd_{\tau_1',\tau_2'}$, then we can get $st_{\tau_1',\tau_2'}$. In other words, it is the number that two trajectories pass same edges, namely the same sub trajectories. The motion trajectory is not necessarily continuous. For example, the edge sequence passed by two sub-trajectories is $\tau_1'(e_{11} \to e_{23} \to e_{28}), \tau_2'(e_{11} \to e_{18} \to e_{28} \to e_{35})$, and then their $sd_{\tau_1',\tau_2'}$ is 2, and $st_{\tau_1',\tau_2'}$ is 2. ϕ_1 and ϕ_2 are the specified parameters, which are set as 0.7 and 0.3. This definition shows that the two sub-trajectories with the same motion trajectory must be proportional to the length of two motion trajectories. Meanwhile, the difference of proportion cannot be too large.

The similarity degree with the historical motion trajectory: a motion trajectory $c\,\tau_i'$ moving in a social network and a historical motion trajectory $h\,\tau_j'$ are given. Their similarity degree is as follows:

When $c\tau_i'.e_i = h\tau_j'.e_k, c\tau_i'.\delta = h\tau_j'.\delta$, $c\,\tau_i'$ and $h\,\tau_j'$ are the space similar trajectory.

$$S_{ij} = w_1 \times c\tau'_i, h\tau'_j(1,k) + w_2 \times e^{c\tau'_i - h\tau'_j} \tag{20}$$

Otherwise, $S_{ij} = 0$.

Where, w_1 is the weight of spatial factor. w_2 is the weight of time data. The historical trajectory $h\,\tau'_j$ which is similar to the driving motion trajectory $c\,\tau'_i$ must also pass the edge $c\,\tau'_i.e_k$ in the same time period $c\,\tau'_i.\delta$. That is the last side of current user.

After finding all the similar historical trajectories $h\tau'_j$ of running trajectories $c\tau'_i$ of fruit and vegetable picking robot, and their similarity S_{ij}, the probability that $c\tau'_i$ appears on edge e_k at some future time $t+\delta t$ can be obtained:

$$P_i^{k,t+\delta t} = \frac{\sum_m S_{im}}{\sum_j S_{ij}} \tag{21}$$

Where, S_{im} are all the trajectories appearing on the edge e_k after time δt which are similar to $c\tau'_i$. The user density of a certain edge at some future time $t+\delta t$ is:

$$e_k \cdot \rho^{t+\delta t} = \sum_i P_i^{k,t \quad t} \tag{22}$$

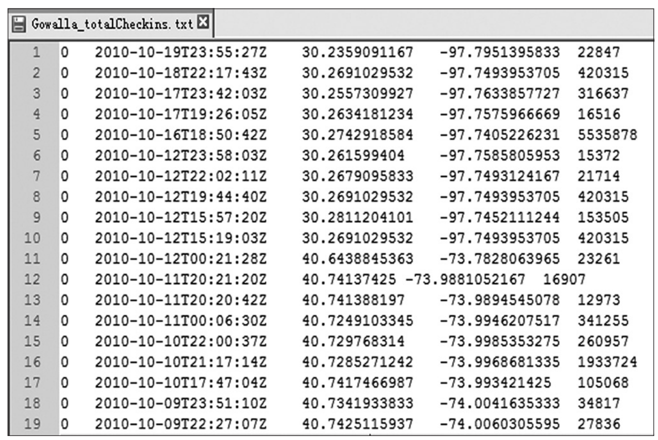
Through the above discussion, the optimization method of tracking and forecasting motion trajectory of fruit and vegetable picking robot was described in detail. By matching the trajectory of fruit and vegetable picking robot with the actual trajectory, the motion trajectory of fruit and vegetable picking robot could be tracked and predicted in real time. Therefore, we hoped to use similar historical trajectories for the tracing and prediction. The core was to design a matching principle of motion trajectory similarity that considered the space factor and time factor synthetically. Thus, the tracking and prediction the trajectory of fruit and vegetable picking robot could be realized.

RESULTS

In order to prove the effectiveness of research on motion trajectory optimization of fruit and vegetable picking robot based on RBF network, the proposed method is used to track and predict the motion trajectory of fruit and vegetable picking robot, and the experimental verification is carried out. This experiment uses the Gowallaregistration data set from famous American LBS website to track and predict the motion trajectory of fruit and vegetable picking robot. The experiment extracts the more than 30 thousand active trajectory data. Each motion trajectory data contains the Id of fruit and vegetable picking robot, the starting operation time, the latitude of operating trajectory point, the longitude of motion trajectory point and the longitude and latitude of end point of motion trajectory. The example is shown in Fig. 3 and the distribution of original motion trajectory points is shown in Fig. 4.

The initial clustering radius ε of motion trajectory is 10 km. The minimum number $MinPts$ in neighborhood is 1000. The initial clustering area of motion trajectory is shown in Fig. 5.

From Fig. 5, the clustering points of original motion trajectory are divided into five clustering regions (the black part is the noise point, which should be eliminated), and the radius of each region is relatively large, which does not conform to the actual application of motion trajectory judgment of fruit and vegetable picking robot. The traditional method is used to repeat the experiment. When the sign-in points are very dense, the smaller and more ideal cluster area cannot be obtained no matter how to adjust ε and $MinPts$. Nevertheless, RBF network can solve the problem well. If the initial cluster radius of a


Gowalla_totalCheckins.txt

0	2010-10-19T23:55:27Z	30.2359091167	-97.7951395833	22847
0	2010-10-18T22:17:43Z	30.2691029532	-97.7493953705	420315
0	2010-10-17T23:42:03Z	30.2557309927	-97.7633857727	316637
0	2010-10-17T19:26:05Z	30.2634181234	-97.7575966669	16516
0	2010-10-16T18:50:42Z	30.2742918584	-97.7405226231	5535878
0	2010-10-12T23:58:03Z	30.261599404	-97.7585805953	15372
0	2010-10-12T22:02:11Z	30.2679095833	-97.7493124167	21714
0	2010-10-12T19:44:40Z	30.2691029532	-97.7493953705	420315
0	2010-10-12T15:57:20Z	30.2811204101	-97.7452111244	153505
0	2010-10-12T15:19:03Z	30.2691029532	-97.7493953705	420315
0	2010-10-12T00:21:28Z	40.6438845363	-73.7828063965	23261
0	2010-10-11T20:21:20Z	40.74137425	-73.9881052167	16907
0	2010-10-11T20:20:42Z	40.741388197	-73.9894545078	12973
0	2010-10-11T00:06:30Z	40.7249103345	-73.9946207517	341255
0	2010-10-10T22:00:37Z	40.729768314	-73.9985353275	260957
0	2010-10-10T21:17:14Z	40.7285271242	-73.9968681335	1933724
0	2010-10-10T17:47:04Z	40.7417466987	-73.993421425	105068
0	2010-10-09T23:51:10Z	40.7341933833	-74.0041635333	34817
0	2010-10-09T22:27:07Z	40.7425115937	-74.0060305595	27836

Fig 3. Registration example.

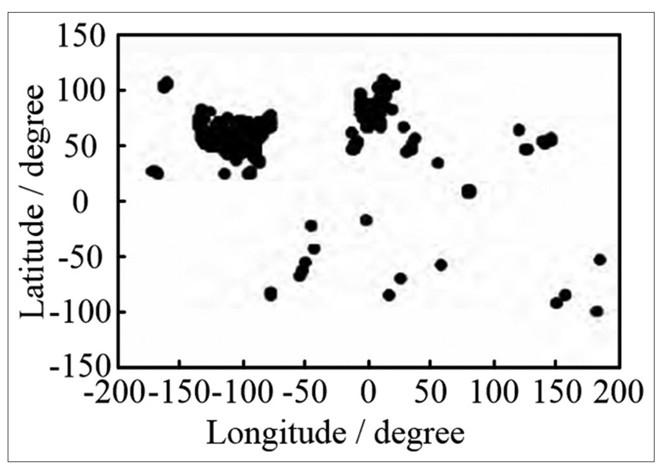


Fig 4. Distribution of original motion trajectory points.

motion trajectory is too large, it will adjust ε and $MinPts$ adaptively, and then divides clustering areaagainuntil it meets the requirement.

Base on the proposed method, the distribution contrast between the motion trajectory of tracking prediction and the actual motion trajectory (the circle denotes the motion trajectory of tracking prediction, and the triangle denotes the actual motion track),which is shown as shown in Fig. 6.

From the above Fig., the proposed method can accurately track and predict the motion trajectory of fruit and vegetable picking robot. Because the proposed method analyzes the unbalance of motion trajectory data class in the process of tracking and prediction, and then reduces the interference of noise, the tracking accuracy is high and the tracking effect is good.

The effectiveness of motion trajectory optimization method of fruit and vegetable picking robot based on RBF network is proved through the collected trajectory data of fruit and vegetable picking robot. Because the model only tracks and predicts the future motion trajectory of fruit and vegetable picking robot, it does not consider the retention of robot in the picking operation, we need to filter out the redundant trajectory data collected by robot at a certain point, and then abstract the motion trajectory data of fruit and vegetable picking robot based on the similarity of trajectory space. Table 1 shows the total amount of trajectory points collected by the acquisition program, the number of motion trajectory points after the abstraction, and the number of motion trajectory points in active regions after the abstraction.

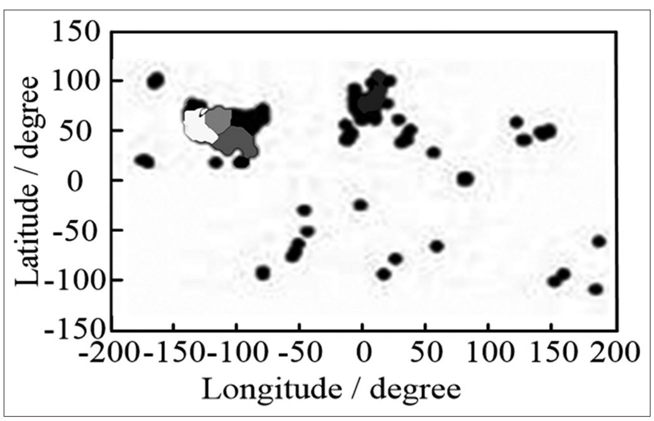


Fig 5. Initial clustering area distribution of motion trajectory.

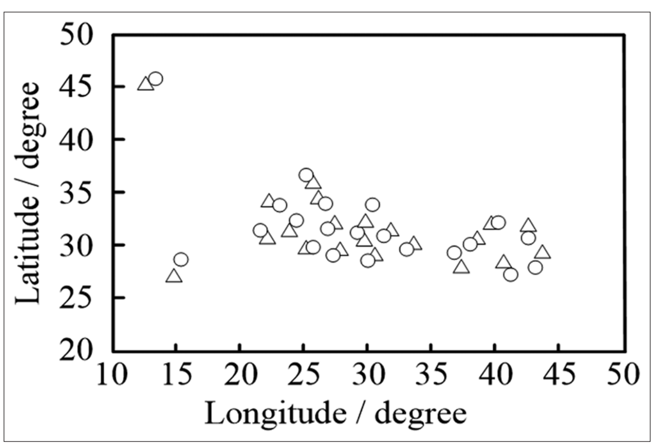


Fig 6. Distribution contrast between tracking predicted motion trajectory and actual motion trajectory.

The total number of trajectories of a fruit and vegetable robot is processed and the total number of trajectories is active.

From the above table, the total number of motion trajectory points of fruit and vegetable picking robot processed by proposed method is obviously reduced. Using the proposed method to determine the similar motion trajectory, we can remove the prediction point with large error and improve the accuracy of tracking prediction. Therefore, the effect of abstraction processing is good and the accuracy of prediction results can be ensured.

Finally, compared with different methods, the complexity of implementation of proposed optimization method is determined through the analysis of calculation time. In order to ensure the accuracy of analysis results, the method of reference (Yang et al., 2016) and the method of reference (Artaud, et al., 2016) method are introduced. Three methods are compared by the experiment. The contrast results of three methods are shown in Table 2.

From the above table, when method of reference (Artaud, et al., 2016) is used to track and predict the motion trajectory of fruit and vegetable picking robot, the average calculation time is 5.7s. When the number of experiments is ten times, the calculation time is 5.8S. When the experiment reaches 50 times, the calculation time is 5.5s. When method of reference (Yang et al., 2016) is used to track and predict the motion trajectory of fruit and vegetable picking robot, the average calculation time is 4.6s. When the number of experiments is 10 times, the calculation time is shortest and it is only 3.9s. When the number of experiments is 40, the calculation time is 5.0s which is the longest. When propose method is used to track and predict the motion trajectory of fruit and vegetable picking robot, the average calculation time is 2.0S. When the number of experiments is 10 times and 50 times, the calculation time is the longest, which is 2.3S.The calculation time is the shortest which is 1.9s when the fortieth experiment is carried out. Compared with the proposed method proposed with the method in reference (Yang et al., 2016) and (Artaud, et al., 2016), the average calculation time of proposed optimization

Table 1: Motion trajectory data statistics of fruit and vegetable picking robot in experiment

Serial number of fruit and vegetable robot	Total of motion trajectory point	Total of motion trajectory point after treatment	Amount of motion trajectory point in active area
1	341252	86421	152
2	153463	56447	101
3	120452	45122	94
4	245487	64513	164
5	141786	30654	75
6	31785	7941	31
7	124464	43815	158

Table 2: Computing time of trajectory tracking prediction of fruit and vegetable picking robot by different methods

Experiment times/times	Proposed method/s	Method of reference[8]/s	Method of reference [9]/s
10	2.3	3.9	5.8
20	2.1	4.6	5.7
30	2.0	4.8	5.8
40	1.9	5.0	5.6
50	2.3	4.2	5.5
60	2.2	4.7	5.6

method is far less than that of method in reference (Yang et al., 2016) and (Artaud, et al., 2016), and it is close to the half of average calculation time of method in reference (Artaud, et al., 2016). This fully proved that the proposed optimization method has the shortest calculation time and the calculation time is more uniform. Meanwhile, the proposed method can rack and predict the trajectory of the fruit and vegetable picking robot smoothly and quickly (Anuar, M.S., 2018)

DISCUSSIONS

For the tracking and prediction of motion trajectory of robot, this article puts forward a research on motion trajectory optimization of fruit and vegetable picking robot based on RBF network, that is to say, an optimization method based on the RBF network. This method has the following contributions:

The proposed method studied has a sufficient analysis on reasons for the imbalance of motion trajectory data class. Based on the imbalance of trajectory data class caused by the concept drift, MWMO technique is used to insert it into the tracking and prediction method, and a semi-supervised learning algorithm is introduced to integrate the motion trajectory data and form the trajectory tracking prediction sample (M.M. 2018).

The way matching the motion trajectory of fruit and vegetable picking robot with the actual trajectory is used to track and predict the motion trajectory, and then we find out the similar historical motion trajectory. Moreover, we design the matching principle of similarity of motion trajectory of space factor and time factor, so as to complete the tracking and prediction of motion trajectory of fruit and vegetable picking robot, namely the optimization of motion trajectory of fruit and vegetable picking robot based on RBF network is realized.

CONCLUSION

To track and predict the motion trajectory of fruit and vegetable picking robot can improve the accuracy of running and moving and the operation efficiency of fruit and vegetable picking robot. Due to low tracking prediction accuracy and long time-consuming prediction, a method to track and predict the motion trajectory of fruit and vegetable picking robot based on RBF network is proposed. Experimental results prove that the proposed method can accurately track and predict the motion trajectory of fruit and vegetable picking robot. Meanwhile, the prediction accuracy is higher and the effect is better.

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