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Mobile Robot Localization and Acquisition Based on Extended Kalman Filtering

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Abstract

With the continuous development of the logistics and service industries in the country in recent years, mobile robots have begun to enter the public's field of vision and are widely welcomed by the industry due to their flexible operating capabilities and suitability for large-scale operations. Robots can also work in many fields that people cannot or find difficult to do well, which makes robots increasingly important in people's lives. Therefore, people are increasingly concerned about the positioning and activities of robots. This article uses extended Kalman filtering to locate and predict moving targets, as well as two path planning methods: the current shortest path method and the shortest path method after motion, to study the dynamic capture of mobile robots: (1)Localization of dynamic targets through extended Kalman filtering. Among them, the extended Kalman filtering method is studied for the localization of nonlinear motion, while the Kalman filtering method is applied for the localization of linear motion; (2)Calculate the shortest path during the capture process of mobile robots Combining the current shortest path planning method and the post motion shortest path planning method with the extended Kalman filtering method to achieve dynamic target acquisition for mobile robots.

Keywords

Mobile robots Extended Kalman filtering method Location Capture.

1. Background

With the continuous development of the logistics and service industries in the country in recent years, mobile robots have begun to enter the public's field of vision and are widely welcomed by the industry due to their flexible operating capabilities and suitability for large-scale operations. As a result, the robot market has been expanded, making its appearance more frequent in environments such as logistics transportation, shopping mall services, and airport handling. But with it comes high standards of market positioning, control, and tracking performance. So how to improve its performance has become an urgent demand in the market. In today's market, most mobile robots use the traditional Kalman filter to locate. However, due to its linear system, it requires a lot of data to accurately locate, and it cannot be used in complex nonlinear environments. The extended Kalman filtering method can meet market demand and improve the positioning, control, and tracking performance of mobile robots.

With the ravages of the global epidemic and the continuous intensification of aging in recent years, how to scientifically and efficiently improve production efficiency and better meet people's living needs before ensuring personal safety has become a focus of national and even global attention. Undoubtedly, for mobile robots that meet all the above conditions, it also makes them a focus of attention for countries. For the most important mobile robot, predictive positioning is particularly important. Especially how robots capture the position of moving targets in complex environments and predict their next position is an industry wide challenge.

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For traditional Kalman filter positioning algorithms, the main approach is to predict the position of mobile robots and observe the input and output data of the system, establish a linear equation of the system state, and thus achieve the so-called problem-solving. However, due to the linear equation it establishes, it cannot solve the vast majority of nonlinear and complex problems in real life. The extended Kalman filter positioning method is used to control the mobile robot, and the approximate linear system equation is solved by extending Taylor series to maintain the approximation of the low order derivative to the nonlinear. This ensures precise positioning during the movement process. This can solve the industry wide problem of being unable to lock the position of moving targets and predict their next position in complex nonlinear environments. Of course, it is not only to solve such problems, but also to meet the urgent market demand for high-performance mobile robots. It may also be another solution to the COVID-19, which will continue to be normalized in the future, and solve the problem of labor shortage caused by global aging.

2. Current research status at China and other countries

2.1. Development of Robots

The first generation of robot: teaching and reproducing robots.

In 1947, the Oak Ridge National Laboratory of the US developed the world's first remotely controlled robot to handle and process nuclear fuel.

In 1962, the United States successfully developed a PUMA universal teaching and playback robot. This type of robot controls a multi degree of freedom mechanism through a computer, stores programs and information through teaching, reads the information during operation, and then issues instructions. This way, the robot can repeatedly reproduce this action based on the results of human teaching at that time. For example, in the automotive spot welding robot, as long as it teaches the process of spot welding, it always repeats this kind of work.

Second generation robots: sensory robots.

Due to the lack of perception of the external environment by the teaching and reproducing robot, the magnitude of the operating force, the presence or absence of the workpiece, and the quality of the welding process, it is unknown and cannot report.

Therefore, in the late 1970s, people began to study second-generation robots, called sensory robots. These robots have senses similar to those of humans in certain functions, such as force, touch, sliding, vision, hearing, etc. They can sense and recognize the shape, size, and color of workpieces through sensation.

Third generation robots: intelligent robots.

This is a robot invented since the 1990s. This type of robot is equipped with multiple sensors and can perform complex logical reasoning, judgment, and decision-making, independently determining its own behavior in changing internal states and external environments.

2.2. Development of Kalman Filter

In the early 19th century, European astronomers were observing an asteroid when it suddenly disappeared. Gauss conducted research to determine the orbit of the planet and ultimately proposed the least squares estimation method.

In 1942, Wiener filtering theory was proposed to solve the problem of precision tracking in fire control systems. Wiener filtering theory is an organic combination of mathematical statistics theory and linear theory, which was the most effective theory for computing random signals at that time. With the emergence of frequency domain design methods and their application difficulties, people have begun to search for methods to directly design filters in the time domain.

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In 1960, Kalman published a paper titled "New Methods for Linearity and Prediction", and since then, Kalman filtering algorithms have emerged in people's vision

2.3. Research significance

In the manufacturing industry, industrial robots have even become indispensable core equipment, with nearly a million industrial robots fighting alongside workers on various fronts around the world. The emergence of robots is inevitable for social and economic development, and its rapid development has improved the production level of society and the quality of human life.

In daily life, service-oriented robots can provide medical care, cleaning, and security services for people; Underwater robots can help salvage sunken ships and lay cables; Engineering robots can climb mountains and dig holes to build roads; Agricultural robot can work, sow, fertilize and kill insects; Military robots can charge into battle, clear mines and dispose of bombs, and so on

In some special situations, some jobs can cause harm to the human body, such as painting, heavy object handling, etc; Some jobs require high quality and are difficult for people to perform for a long time, such as car welding, precision assembly, etc; Some staff members are unable to be present, such as volcanic exploration, deep-sea exploration, space exploration, etc; Some jobs are not suitable for people to do, such as harsh environments, monotonous repetitive work, etc. In this situation, areas that people cannot or are difficult to excel in make robots shine and shine in this field.

2.4. Future Development Forecast

In terms of software, most robots nowadays are very cumbersome and rely on programs to do whatever they are asked to do. They do not flexibly input programs that move left, and if they do not input programs that move right, they will not move right. And future robots do not rely on programming, they can independently execute requirements. And in the process of self-learning or responding to instructions, it takes less time to complete instructions and tasks more accurately.

In terms of hardware, that is, the body of the robot. Although there are relatively mature robots nowadays, such as robotic dogs and robotic cars, they are not well crafted in terms of humanoid machines and their operations are not flexible. At present, humanoid robots have rigid movements and occasionally make mistakes when executing actions, resulting in a high failure rate of completing actions. In the future, robots will not only be humanoid, but also simulation robots of animals such as spiders, fish, insects, birds, snakes, etc. will emerge one after another. At the same time, in the future, the size, weighing, flexibility, accuracy, perception ability, and reaction ability of robots will all become better and better.

3. Positioning of mobile robots

3.1. Localization Research of Extended Kalman Filter

The extended Kalman filtering method is suitable for the research of nonlinear motion localization, while the Kalman filtering method is suitable for the research of linear motion localization.

1) By means of Kalman filter model, Kalman increment, Cartesian coordinate system, normal distribution, Jacobian matrix and other tools, it is verified that Kalman filter can only be used for linear motion positioning.

2) The extended Kalman filter linearizes nonlinear motion through the Taylor formula, observes the observed values of the moving target with noise, and then predicts the position of the next step through the extended Kalman filter method. Moving the target one step, the

current noisy coordinates of the target body are obtained, and the current position of the moving target is compared with the predicted position to obtain an error. Verify that extended Kalman filtering can be used for predicting dynamic targets.

In order to compare with the extended Kalman filtering method, another mean approximation method was designed for comparative study of the impact of noise on the two methods and their error performance. The specific research is as follows:

1) Experiments are conducted under different noise conditions, and there may be different errors in the positions of predicted points and actual moving targets. A table of distance curves between predicted points and dynamic targets for EKF and MA under different noise conditions is established.

2) Analyze the impact of step fluctuations, motion velocity, and angular velocity errors on the position of actual moving targets under different noise conditions, and obtain the characteristics of the two methods.

3.2. Extended Kalman Filter Location Algorithm

The Kalman filter model assumes that the state of the system at time t evolves from a prior state at time t-1 according to the equation:

$$x_t = F_t x_{t-1} + B_t u_t + w_t \tag{3.1}$$

Xt is the state vector containing the system's terms of interest at time t (such as position, speed, heading), ut is the vector containing any control inputs (steering angle, thrust setting, braking force), and Ft is the state transition matrix, It measures the impact of each system state parameter at time t-1 on the system state at time t (for example, the position and velocity of t-1 will affect the position of time t), Bt is the control input matrix, and it measures the impact of each control input parameter in vector ut on the state vector (for example, the application of throttle settings on system speed and position), and wt is the vector containing the process noise term of each parameter in the state vector. It is assumed that the process noise comes from the zero mean multivariate normal distribution, and the covariance is represented by the covariance matrix Qt.

Zt is the measurement vector, Ht is the transformation matrix that maps the state vector parameters to the measurement domain, and yt is the error between the measurement vector and the observation vector:

$$y_t = H_t x_t - z_t \tag{3.2}$$

The Kalman filtering algorithm involves two stages: prediction and metric update. The standard Kalman filtering equation formula for the prediction stage is as follows:

$$x_{t|t-1} = F_t x_{t-1|t-1} + B_t u_t \tag{3.3}$$

$$P_{t|t-1} = F_t P_{t-1|t-1} F_t^T + Q_t \tag{3.4}$$

The measurement update formula is:

$$K_t = P_{t|t-1} H_t^T \left(H_t P_{t|t-1} H_t^T + R_t \right)^{-1} \tag{3.5}$$

$$\widehat{x_{t|t}} = \widehat{x_{t|t-1}} + K_t (y_t - H_t \widehat{x_{t|t-1}}) \tag{3.6}$$

$$P_{t|t} = P_{t|t-1} - K_t H_t P_{t|t-1} \tag{3.7}$$

The use of Kalman filter mainly utilizes the key characteristic of normal distribution: the product of two normal distribution generates another normal distribution.

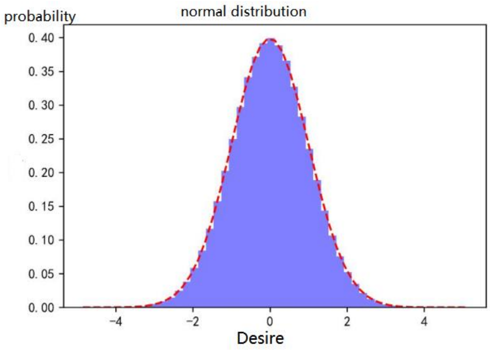


Fig. 2.2 Initial distribution

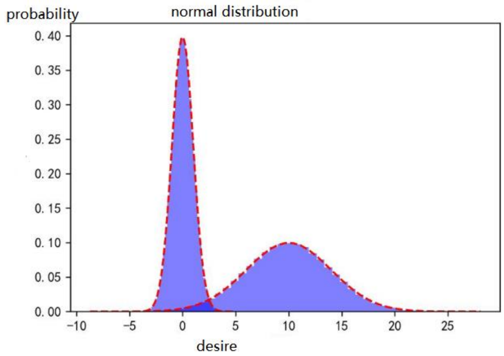
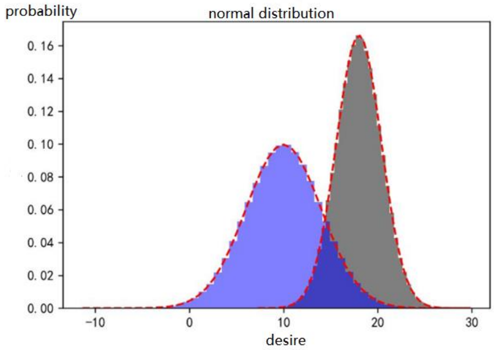


Fig. 2.3 Initial and predict distribution



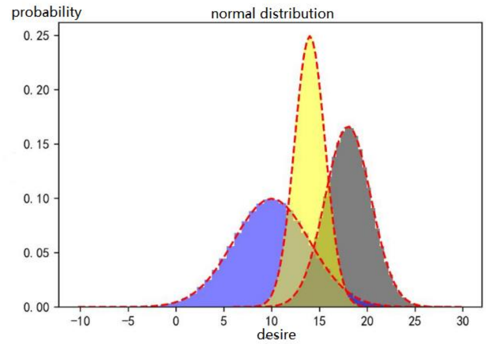


Fig. 2.4 Predict and observe distribution Fig. 2.5 Predict observe combine distribution

Formula (3.8) gives the predicted values of blue normal distribution and the observed values of gray normal distribution in Figure 2.4:

$$y_1\left(\gamma;\mu_1;\sigma_1\right)=\frac{1}{\sqrt{2\pi\sigma_1^2}}e^{\frac{\left(\gamma-\mu_1\right)^2}{2\sigma_1^2}}$$

$$y_1\left(\gamma;\mu_2;\sigma_2\right)=\frac{1}{\sqrt{2\pi\sigma_2^2}}e^{\frac{\left(\gamma-\mu_2\right)^2}{2\sigma_2^2}} \tag{3.8}$$

The information provided by two normal distribution is fused by multiplying them. The best current estimate of the system is given by the product of these two normal distribution in Formula (3.9):

$$y_r\left(\gamma;\mu_1;\sigma_1;\mu_2;\sigma_2\right)=\frac{1}{\sqrt{2\pi\sigma_1^2}}e^{-\frac{\left(\gamma-\mu_1\right)^2}{2\sigma_1^2}}*\frac{1}{\sqrt{2\pi\sigma_1^2}}e^{-\frac{\left(\gamma-\mu_2\right)^2}{2\sigma_2^2}}$$

$$=\frac{1}{2\pi\sqrt{\sigma_1^2\sigma_2^2}}e^{-\left(\frac{(\gamma-\mu_1)^2}{2\sigma_1^2}+\frac{(\gamma-\mu_2)^2}{2\sigma_2^2}\right)} \tag{3.9}$$

The quadratic term in this new function can be extended, μγ yes μ1 and μ Weighted average of 2, σγ yes σ1 and σ The whole expression is rewritten in the form of normal distribution:

$$k = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}$$
$$\mu' = \mu_1 + k\left(\mu_2 - \mu_1\right)$$
$$\sigma'^2 = \sigma_0^2 - k\sigma_0^2 \qquad (3.10)$$

Formula (3.10) can be converted into high-dimensional matrix expressions, where Σ Is the covariance matrix of normal distribution, μ For the average value of each dimension, substituting the relevant data into formula (3.10) can obtain formula (3.11), where K is the Kalman gain:

$$K = \sum_1 (\sum_1 + \sum_2)^{-1}$$
$$\overrightarrow{\mu'} = \overrightarrow{\mu_1} + K\left(\overrightarrow{\mu_2} - \overrightarrow{\mu_1}\right)$$
$$\Sigma' = \Sigma_1 - K\Sigma_1 \qquad (3.11)$$

There are currently two distributions, and the predicted distribution is $(\mu_1, \Sigma_1) = (H_k x_k, H_k P_k H_k^T)$, the distribution of the observed values of the sensor is$(\mu_2, \Sigma_2) = (z_k, R_k)$, now bring these two distributions into formula (3.12) to obtain the simplified formula (3.13) as follows:

$$x'_k = x_k + K'(z_k - H_k x_k)$$
$$P'_k = P_k - K' H_k P_k \qquad (3.12)$$
$$K' = P_k H_k^T (H_k P_k H_k^T + R_k)^{-1} \qquad (3.13)$$

Next, let's take a look at two formulas for extended Kalman filtering:

$$S = HP'H^T + R$$
$$K = P'H^T S^{-1} \qquad (3.14)$$

According to the observation, z is the column vector of 5*1 containing the coordinate position x, y, and the state vector x 'is the column vector of 5*1 containing the angular velocity information of position and velocity. According to the formula y=z-Hx', the dimension of measurement matrix H is two rows and five columns, namely:

$$h(x) = \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} H_{00} & H_{01} & H_{02} & H_{03} & H_{04} \\ H_{10} & H_{11} & H_{12} & H_{13} & H_{14} \end{bmatrix} \times \begin{bmatrix} x' \\ y' \\ v' \\ \theta' \\ w' \end{bmatrix} = H \times x' \qquad (3.15)$$

It is easy to see from formula (3.15) that the transformation on both sides of the equation is nonlinear and there is no constant matrix H, which can make both sides of the equation hold. Nonlinear functions can be approximated using Taylor's formula:

$$h(x) = h\left(x_0\right) + \frac{\dot{h}\left(x_0\right)}{1!}\left(x - x_0\right) + \frac{\ddot{h}\left(x_0\right)}{2!}\left(x - x_0\right)^2 \dots\dots\dots \qquad (3.16)$$

Ignoring higher order terms above the second order, we can get an approximate linearized equation, which is used to replace the nonlinear function h (x), and expand the nonlinear function to multiple dimensions, that is, to find the partial derivative of each variable, that is:

$$h(x) \approx h\left(x_0\right) + \frac{\partial h\left(x_0\right)}{\partial x}(x - x_0) \quad (3.17)$$

The extended Kalman filter linearizes nonlinear motion through the Taylor formula, discarding high-order derivatives. As long as the low-order derivatives are present, curve motion can be approximated as linear motion.

$$X' = A \times X_{t-1} + u$$
$$P = F \times P \times F^T$$
$$Z = [x_t, y_t]$$
$$y = Z^T - \left(H \times X'\right)$$
$$S = H \times P \times H^T + R$$
$$K = P \times H^T \times S^{-1}$$
$$X_t = X' + (K \times y)$$
$$P = (I - (K \times H) \times P) \quad (3.18)$$

The observed values of the moving target (x_t, y_t) are known, and although there is noise, the velocity vt can be calculated using the current observed values and previous observed values (x_{t-1}, y_{t-1}). The specific formula is as follows:

$$v_t = \frac{\sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}}{dt} \quad (3.19)$$

This way, the speed of each step of the moving target can be obtained, while facing the direction θ T can also be calculated using x_t, y_t, x_{t-1}, y_{t-1}:

$$\theta_t = \arctan\left(x_t - x_{t-1}, y_t - y_{t-1}\right) \quad (3.20)$$

For the specific application of the extended Kalman filter positioning method, the first step is to observe a noisy (x, y) coordinate. Then, the extended Kalman filtering method is used to predict the position of the next step, and the moving target moves one step to obtain the current noisy coordinates of the target body. The current position of the moving target is compared with the predicted position to obtain an error. When the error is less than 0.02v (v is the speed of the moving target), it is determined that the predicted position matches the position of the moving target.

4. Movement of mobile robots

4.1. Capture of dynamic targets for mobile robots

The dynamic target acquisition of mobile robots requires not only dynamic target localization, but also path planning after localization. Combining the current shortest path planning method and the post motion shortest path planning method with the extended Kalman filtering method to achieve dynamic target acquisition for mobile robots. This section will conduct the following research:

1) Research comparing the current shortest path method with the shortest path method after motion, which path planning method is most efficient in the current task environment.

2) Study the capture of single moving targets using EKF and MA. The distance between the current shortest path and the shortest path after motion is the same for the capture of a single moving target. Analyze which of the two localization methods, EKF and MA, is more advantageous for capturing a single moving target based on the current shortest path planning.

3) Studying the capture of multiple moving targets in EKF and MA, the capture of a single moving target and the capture of two moving targets cannot determine which method, the

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current shortest path method or the post motion shortest path method, has fewer steps for capturing multiple dynamic targets in the case of extended Kalman filtering localization. The experiment designed the capture of three dynamic targets under the extended Kalman filter localization, and studied which method had the best efficiency.

4.2. Motion Path of Dynamic Targets for Mobile Robots

Path planning can make mobile robots most efficient in the current task environment. For dynamic target acquisition, this paper studies a current shortest path method. As shown in Figure 4.1, the red circle represents the mobile robot replaced by hunter, and the blue circle represents the moving target replaced by robot1 and robot2. From the graph, it can be seen that there is only one hunter and two robots, so at this point, the hunter needs to make a decision when planning the path, which robot to pursue first and then which robot to pursue can minimize the total number of steps in the end. Hunter's coordinates are the coordinates of the current mobile robot, while robot1 and robot2 are the coordinates predicted by the extended Kalman filtering method for moving targets. By using the distance formula, calculate the distance distance1 between robot1 and hunter, as well as the distance distance2 between hunter and robot2. By comparing the two distances, the mobile robot turns to the dynamic target with a smaller distance. Then Hunter first captures the robot with a short distance, and then captures another robot.

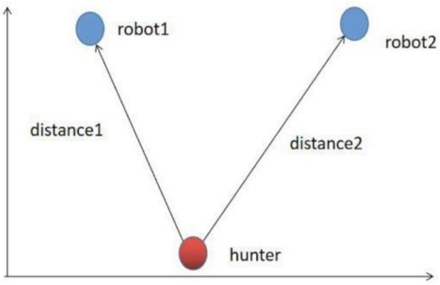

Fig.4.1 Current shortest path

As shown in Figure 4.1, the blue curve represents the mobile robot hunter, and the two circular movements are all moving target robots. Set the circle on the left as robot1, the circle on the right as robot2, and the Hunter starting point is located slightly lower than the right point between the two robots. It can be seen that the distance between Hunter and Robot2 is smaller, so the blue curve directly advances towards Robot2 from the beginning. When the mobile robot captures Robot2, it immediately turns to move towards Robot1. As the positioning of Robot1 is determined, the mobile robot captures Robot1 and ultimately completes the capture of two dynamic targets. Two dynamic targets are more difficult to capture than one moving target, and one dynamic target can be directly captured based on the predicted position of the robot. Two moving targets require Hunter to perform extended Kalman filter prediction localization based on the current noisy coordinates of the two dynamic targets, select the closest moving target to capture the current mobile robot position, and then capture the other moving target.

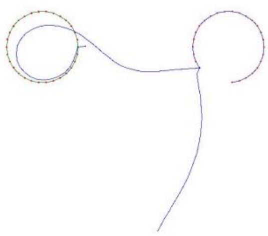

Fig .4.2 Capture two motion targets in currentshortest path

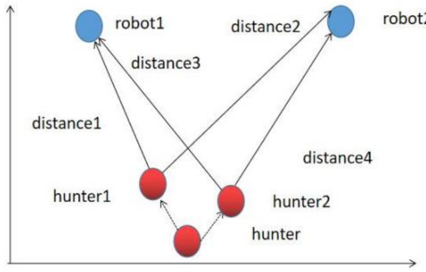

Fig.4.3 After motion shortest path

As shown in Figure 4.3, it is the same as Figure 4.1. The blue curve represents the mobile robot hunter, and the two circular movements are all moving target robots. Set the left circle as robot1 and the right circle as robot2. The Hunter starting point is located slightly to the right below the middle of the two robots, but their blue curve paths are completely different. The blue curve initially moves directly towards robot 2, but after a few steps of movement, according to the shortest path method after movement, it is found that it moves towards robot 1. After one step of movement, the total path distance is the smallest, so it moves towards robot 1 again. As the moving target and Hunter move, after a period of movement, Hunter discovers that the shortest path to robot 2 is the smallest, and Hunter moves towards robot 2 again. Until robot2 is captured, move forward towards the moving target of robot1 to complete the capture, and finally complete the capture of two dynamic targets. According to Figure 4.4, it is found that the curve of the shortest path method after motion is different from that of the current shortest path method in 4.2. The shortest path method after motion will adjust its capture target at any time based on the motion prediction coordinates of the hunter and robot.

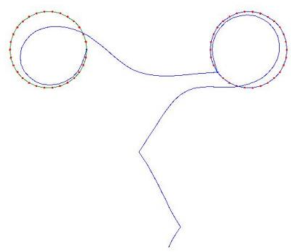

Fig.4.4 Capture two targets shortest path after one step motion

In order to compare which method is better for capturing multiple moving targets between the two methods, the current shortest path steps are processed and plotted based on the first, second, and third moving target capture steps, rather than simply comparing the moving robots 1, 2, and 3. The specific data is shown in Figure 4.5.

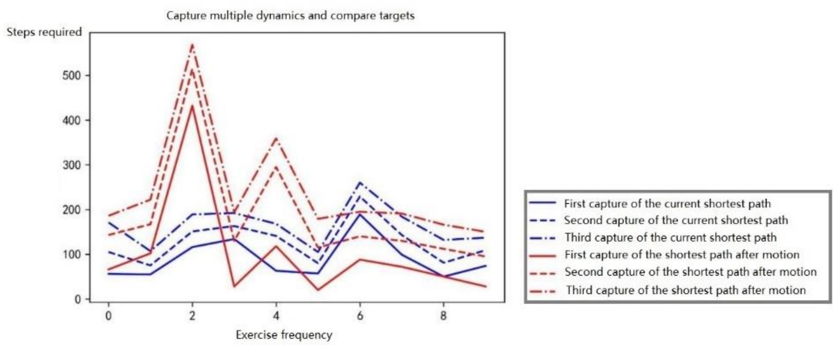

Fig.4.5 EKF capture 3 motion targets step compare

From Figure 4.5, it can be seen that the two methods have an advantage in capturing the first moving target by simply comparing the number of steps and capturing the shortest path after

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movement. The experimental results show that the total number of steps taken to capture all three moving targets, and the current shortest path method usually has fewer steps than the shortest path after motion. Since 10 experiments excluded contingency, it can be concluded that the current shortest path method has fewer total steps to capture three moving targets when positioning based on extended Kalman filter when three moving targets move at a uniform speed in a circle.

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