A Robot Self-Positioning System based on Robust EKF Using Degree of Confidence

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Abstract. Self-positioning system is the key link of humanoid soccer robot, in which the robot needs to estimate its position and direction in the football field based on non-probing sensors. However, the modeling error of the robot system and the deviation of information acquisition bring the uncertain noise to the self-positioning system, which makes it difficult to carry out effective real-time positioning by using the traditional methods such as geometric measurement and track prediction. Existing filtering methods such as Kalman Filter and Monte Carlo Filter estimate the position and direction of the robot through observations, reducing the influence of uncertain factors. Although the accuracy of positioning is improved, the state estimation method relies on the accuracy of observations. The deviation in blurred image processing and camera ranging during the motion of the robot results in the deviation of the observations, which is more obvious in the case of multi-target observations. In this paper, a self-positioning method based on robust EKF using confidence is proposed to improve the accuracy of the robot's self-positioning by integrating observations.

1. Introduction
Humanoid soccer robot is a fully autonomous humanoid robot, which can make decisions to execute actions according to its position and direction in the football field. According to the rules of the game [1], robots are not allowed to use probing sensors to sense the environment, therefore, the input information of the self-positioning system comes from the strategic decisions of motion and the visual system. Due to the influence of motor rotation error and grass resistance, the robot cannot completely meet the requirements of the strategic decisions of motion, so it is necessary to use the information obtained by the visual system to correct the error of robot’s posture. Up to now, there are also many models applied in error correction of positioning system, mainly including Monte Carlo Filter model [2] and Kalman Filter model [3]. Early solutions based on Kalman Filter model have been widely used due to their advantages of small computation, strong convergence and small complexity. Later, many scholars made improvements on the residual errors caused by the omission of higher order terms in the Kalman Filter model, and proposed Extended Kalman Filter model [4], Robust Kalman Filter model [5], Ensemble Kalman Filter model [6], etc. However, these models all relied on the accuracy of observations.

The shaking of the robot in the process of movement will inevitably result in the deviation of information collection in the visual system, and there is a difference between the deviation of nearby markers and that of distant markers. In order to reduce the influence of this deviation on the robot's self-positioning system, this paper proposes a self-positioning method based on robust EKF using confidence. By integrating the obtained observations based on the confidence, the influence of the deviation of information collection on the robot's self-positioning system can be reduced.
2. The Self-Positioning System of Robot

The purpose of self-positioning is to obtain the robot's global attitude, that is, its position and direction in the football field, which provides an important basis for the subsequent decision-making system. The self-positioning system of robot is divided into two parts: preliminary estimation and deviation correction. As shown in figure 1, firstly, the motion model can preliminarily estimate the global attitude of the robot after the strategic decisions of motion are carried out. Because the motion model can’t be accurately modeled, there is a deviation in the initial estimation of the robot's global attitude, which needs to be corrected using the information obtained by the sensors. The process of correcting this deviation serves as the feedback link of the self-positioning system, thus forming a closed loop of the robot's self-positioning system.

2.1. Preliminary Estimation

The link of preliminary estimation is to preliminarily estimate the global attitude of the robot based on the moving amount \( \Delta = [\Delta x, \Delta y]^T \) and rotation \( \Delta r \), where \( \Delta x \) and \( \Delta y \) are respectively the robot's moving amount on X-axis and Y-axis in the global coordinate system [7]. The global coordinates and direction of the robot at time \( t \) are \( p_t = [x_t, y_t]^T \), and \( r_t \), where \( x_t \) and \( y_t \) are the coordinate of the robot on X-axis and Y-axis in the global coordinate system. Then the state of the robot in the global coordinate system at time \( t+\Delta t \) can be calculated by the motion model of the robot:

\[
p_T = p_t + R[−(r_t + r_T)/2] * \Delta
\]

Where,
\[
R(\theta) = \begin{bmatrix}
\cos \theta & \sin \theta \\
-\sin \theta & \cos \theta
\end{bmatrix}.
\]

2.2. Correction of Deviation

The process of correcting the deviation is to correct the deviation in the preliminary estimated state based on the information detected by the sensor. The visual system is used to collect the marker information in the upper system of the humanoid soccer robot, and then the collected information is converted into the observations of the process of correcting the deviation. In order to correct the deviation caused by errors in motion, image processing [8], or monocular camera ranging [9], extract the appropriate observations firstly, and then update the state of the robot according to the extracted observations.

2.2.1. Extraction of Observations

Landmarks in a football field that can be detected by the visual system include field lines and goal posts. As shown in figure 2, the information of landmarks in football field collected by the visual system includes the distance of the goal post, the angle between the goal post and the line of sight, and the angle between the direction of the field line and the line of sight.

The observed information obtained by the goal post includes distance and angle, and its transition matrix with the robot state is nonlinear. The EKF filtering algorithm selected in this paper is suitable for nonlinear systems with approximate linearity, so the observed information needs to be approximately linearized into the observations, that is, the distance information needs to be converted into the observations defined as \( Z_x \) and \( Z_y \), the value of \( Z_x \) and \( Z_y \) can be acquired from the following equations:

\[
Z_x = dx = \text{post.} x - \text{robot.} x
\]
The direction information of the goal post and the field line can be directly used as the observation quantity of the robot's direction state. In order to facilitate integration, the observations of the robot's direction state defined as $Z_{rot}$ is unified into:

$$Z_{rot} = \text{robot}. \text{rot}$$

(4)

So the observations of this system can be made of $Z_x, Z_y, Z_{rot}: Z = [Z_x, Z_y, Z_{rot}]^T$, and the predicted value of the observations corresponding to the goal post and field line are respectively:

$$\hat{Z}_{\text{post}} = \begin{bmatrix} \text{dis} \ast \cos(\text{robot}. \text{rot} + \alpha) \\ \text{dis} \ast \sin(\text{robot}. \text{rot} + \alpha) \\ \arctan \left( \frac{\text{post} \cdot \text{y} - \text{robot} \cdot \text{y}}{\text{post} \cdot \text{x} - \text{robot} \cdot \text{x}} \right) - \alpha \end{bmatrix}$$

(5)

$$\hat{Z}_{\text{line}} = \begin{bmatrix} 0 \\ 0 \\ \text{line}. \text{dir} - \beta \end{bmatrix}$$

(6)
As shown in figure 4, there are 11 field lines and 4 goal posts in the football field, before the calculation of observations have to identify the positions of markers correspond to the map. It is necessary to calculate the predicted value of observation for all goal posts and the field lines, and then select the landmarks whose predicted value of observation is the closest to the actual value of observation as observed markers.

Next, the observations in the update phase acquired by the integration of the observations of landmarks in the field of vision. Because the landmarks obtained in the images are different, so the integration of observations can only be done in the form of the difference between the actual observation and the predicted observation.

2.2.2. Filter by Observation
The observation quantity is extracted to correct the deviation of robot’s attitude in the preliminary estimation stage. In this system, robot’s attitude is defined as $X = [\text{robot. x}, \text{robot. y}, \text{robot. rot}]^T$, and the corresponding state and observation at time $k$ can be obtained by the following formula:

$$
X_k = f(X_{k-1}, u_k) + w_k \tag{7}
$$

$$
Z_k = h(X_k) + v_k \tag{8}
$$

Where, $f(\ast)$ is a function for state estimation in the preliminary estimation stage, which is used to predict the state at time $k$ according to the state at time $k-1$. $h(\ast)$ is the function to extract the observation, which is used to extract the observation observed by the robot according to the current state of the robot. $w_k$ and $v_k$ are the errors of the system for estimating states and the system for extracting observation respectively.

The estimate of the state of robot have been introduced in the preliminary estimation stage, and the main purpose of the second stage is to solve the value of $w_k$, then reduce the gap between the estimated value of the state and the actual value of the state.

3. Filtering Model

3.1. Extended Kalman Filter model
Extended Kalman Filter (EKF) is an extended form of standard Kalman Filter that can be applied to nonlinear situations. The Kalman Filter expands the system by Taylor, and $f(\ast)$ and $h(\ast)$ will be replaced by its Jacobian matrix $F$ and $H$. Assuming that the transformation matrix between the error and the observation at time $k$ is $G_k$, then the relationship between the state error and the observation is as follows:

$$
w_k = G_k(Z_k - \hat{Z}_k) \tag{9}
$$

The state transition matrix $w_k$ can be solved indirectly from the noise. The covariance matrix of the estimation of state at time $k-1$ is $P_{k-1}$, and the covariance matrix of the estimation of state at time $k$ can be deduced from formula (7) as follows:

$$
\bar{P}_k = FP_{k-1}F^T + Q \tag{10}
$$

The sensor's covariance matrix is $R$, which represents the uncertainty of the measured value. Then it can be inferred from formula (8) that the covariance of the corresponding observation is $HPH^T + R$, which can be substituted into formula (9) to obtain $G_k$:

$$
G_k = \bar{P}_k H^T / (HP\bar{P}_k H^T + R) \tag{11}
$$

Thus, the state and covariance matrix of the robot can be updated:

$$
X_k = \hat{X}_k + G_k(Z_k - \hat{Z}_k) \tag{12}
$$

$$
P_k = (I - G_k H)\bar{P}_k \tag{13}
$$
The iterative updating of robot state and covariance matrix can reduce the influence of noise in the system and reduce the error of estimated robot state.

3.2. Robust Kalman Filter Model
In EKF model, it is assumed that both system noise and observation noise are white noise with a mean value of 0, and the coarse error caused by inaccurate camera ranging will interfere with the state of the model. The equation of the observation with coarse error can be expressed as:

\[ Z_k = h(X_k) + K_k \Delta_k + v_k \]  (14)

Where, \( K_k \) is the interference matrix of coarse error and \( \Delta_k \) is the vector of coarse error. Substituting formula (14) into formula (12), and the following results are obtained:

\[ X_k = \tilde{X}_k + G_k (K_k \Delta_k + v_k) \]  (15)

Reduce the influence of gross error by adjusting the transformation matrix \( G_k \):

\[
\bar{G}_{ij} = \begin{cases} 
G_{ij}, & s_j \leq k_0 \\
\frac{k_0}{s_j} \frac{[\xi_{i} - k_0]}{[k_1 - k_0]^2}, & k_0 < s_j \leq k_1 \\
0, & s_j > k_1 
\end{cases}
\]  (16)

Where \( k_0, k_1 \) are the upper and lower limit parameters of the regulation, and \( s_j \) = \[ v_{k,j} \]/\[ \sigma_j \], where \( \sigma_j \) is the standard deviation of the measurement of observation.

3.3. Improved Robust Kalman Filter Model
In the information acquisition stage of the robot vision system, the shaking in the robot movement process has a great influence on the information acquired by the distant markers, while has a small influence on the information acquired by the nearby markers. According to the confidence of the markers obtained in the image, the difference between the actual observation and the predicted observation can be obtained by the following formula:

\[ \Delta Z = \sum_{i=1}^{n} \frac{\lambda_i}{\sum_{j} \lambda_j} \cdot (Z_i - \tilde{Z}_i) \]  (17)

Where \( \lambda_i \) is the confidence corresponding to the observation of the ith marker, and the significance of the existence of \( \lambda_i \) is to reduce the influence of the error in the process of image processing or camera ranging on the value of final observation. In this paper, \( \lambda_i \) is defined as:

\[
\lambda_i = \begin{cases} 
1, & \xi_i \leq k_0 \\
\frac{k_0}{\xi_i} \frac{[\xi_{i} - k_0]}{[k_1 - k_0]^2}, & k_0 < \xi_i \leq k_1 \\
0, & \xi_i > k_1 
\end{cases}
\]  (18)

Where \( k_0, k_1 \) are the upper and lower limit parameters of the confidence, and \( \xi_i = \sum_{j=1}^{3} \eta_j \cdot |Z_{i,j} - \tilde{Z}_{i,j}| / \sqrt{\sigma_j} \), where \( \sigma_j \) is the standard deviation of the measurement of observation, and \( \eta_j \) is the error coefficient of observation.

4. Results and Discussion
By using the program to simulate the robot's self-positioning, the markers within the robot's field of vision are drawn and the effect of various models to update the robot's attitude is shown. As shown in figure 5, the robot’s attitude shown in yellow describes the actual attitude of the robot, and the sector range represents its field of vision, and the field lines and goal posts in red represent the markers detected by the robot vision system. The robot’s attitude shown in white describes the robot posture after preliminary estimation but without deviation correction, and the robot’s attitude shown in red, blue and black respectively describes the robot’s attitude after the deviation correction of Extended
Kalman Filter model, Robust Kalman Filter model and Robust Kalman Filter model using degree of confidence.

Figure 4. Simulation diagram of robot self-positioning

As shown in figure 4 (a), the robot has just detected a single goal post. As the distance is far, there is a deviation in the information of the goal posts, which corresponds to approximately the time of 60 in figure 6. In the Extended Kalman Filter model, a strong disturbance signal is generated due to this deviation; in the Robust Kalman Filter model, the disturbance caused by this deviation is weakened; in the Robust Kalman Filter model using degree of confidence proposed in this paper, the disturbance caused by this deviation is weaker than that in the Robust Kalman Filter model.

As shown in figure 4 (a), the robot has just detected two goalposts, corresponding to approximately the time of 80 in figure 5, the increase in the number of markers that can describe the distance detected results in deviation signals in the system. In the Extended Kalman Filter model and the Robust Kalman Filter model, a disturbance signal is generated due to this deviation. However, the Robust Kalman Filter model using degree of confidence proposed in this paper corrects this deviation effectively.

Figure 5. Effect diagrams of deviation correction model

5. Conclusions
This paper proposes a method to correct the deviation of robot’s attitude using degree of confidence, which weakens the influence of the deviation generated when information is collected in the robot's vision system on the robot’s attitude. However, the higher order terms of the Taylor series expansion
of the model are ignored in Extended Kalman Filter model, and the markers in the self-positioning system of the robot are not fixed, so the observation function in the extraction of the observation is linearized. Next, the nonlinear observation model can be constructed [10], and the distance and direction information obtained by the visual system can be directly taken as observation.

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