

Localization by DKF Multi Sensor Fusion in the Uncertain Environments for Mobile Robot

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Abstract—This paper presents an optimized algorithm for robot localization which increases the correctness and accuracy of the estimating position of mobile robot to more than 150% of the past methods [1] in the uncertain and noisy environment. In this method the odometry and vision sensors are combined by an adapted well-known discrete kalman filter [2]. This technique also decreased the computation process of the algorithm by DKF simple implementation. The experimental trial of the algorithm is performed on the robocup middle size soccer robot; the system can be used in more general environments.

Keywords—Discrete Kalman filter, odometry sensor, omnidirectional vision sensor, Robot Localization.

I. INTRODUCTION

ONE of the most challenging issues in mobile robot navigation is the localization problem. Many different methods have been suggested for self-localization such as vision-based self localization, laser range finders, ultrasonic sensors, and gyroscope, also many new algorithm like, Monte Carlo localization, SLAM, Markov [3], etc. each one is appropriate for special applications.

The middle size league is an appropriate environment to develop such localization system, because of the standard play field, the robot has pre-knowledge of the environment by using the flags in the for corner points. Also recently by extension of the soccer field to its two times, the localization of the robots in the field of play is getting too complex. So, in this project which is implemented on MRL middle size soccer robot team, an omni directional mirror is used as vision sensor, for each soccer robot in order to use vision based localization.

Also, there are three shaft encoders as odometry sensors to measure the displacements and changing in orientation of the robot at each time steps.

But the odometry data are just reliable in two or three meter moving because the errors of the encoders are accumulative and the wheels slippage and the fields surface, influence on its measured values.

In the stand alone sensor localization such as vision, odometry or etc, the localization confidence level became too low because of the mentioned reasons, so adding another sensor and using multi sensor data fusion is a suitable method for precision enhancement.

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Fig. 1 shows the mechanical structure and the location of the odometry sensors underneath of the robot platform.

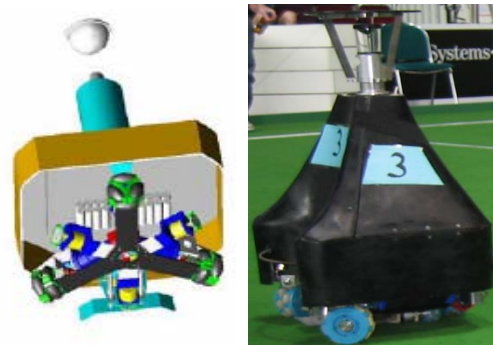


Fig. 1 MRL robots mechanical structure

II. THE PROPOSED LOCALIZATION ALGORITHM PROCEDURE FOR PAPER SUBMISSION

The structure of our localization system, shown in Fig. 2, is directly proceeds from the DKF equations.

The advantages of proposed algorithm are, if the robot couldn't see any of the corner flags by vision sensor, it can trusted to the prior position which is obtained from the past time-steps and use its new odometry data, this enables the robot to estimate the best current position in the environment.

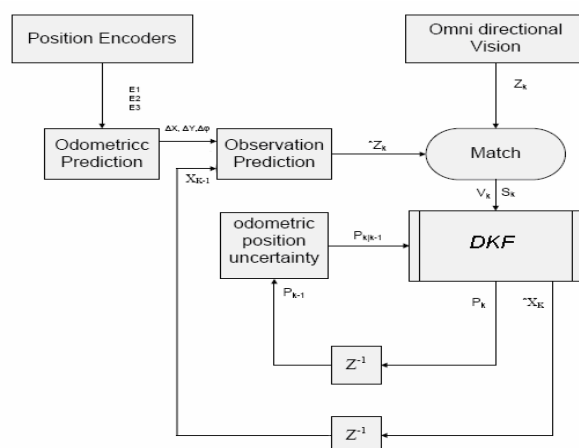


Fig. 2 The structure of our localization system

The other advantage is using the Discrete Kalman filter algorithm, which is used for noise reduction of two sensors fusing. Kalman filter is used in this application because; in the spite of the computational and probabilistic origin it also has experimental origin [4]. For example, each sensor should has its own affectivity_ which is measured under the standard experiments before utilizing_ in the algorithm according to the environmental conditions.

At the k-th step, the sensory system provides from odometric sensors like encoders (E1, E2, and E3) as well as vision (Zk) measures. Next, the transformation function (h) converts the robot displacement in the movement to the global map. Then it is feed to the DKF for fusion and noise reduction.

The implementation of the algorithm is described step by step:

A. Odometric Prediction

This part is composed of three odometric sensors which are connected in the three wheel omnidirectional model to the robot platform [5].

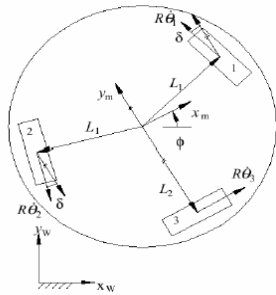


Fig. 3 Kinematics diagram of three wheel robot

The equation of such model robot kinematics is shown in the Fig. 3.

$$\begin{bmatrix} \theta'_1 \\ \theta'_2 \\ \theta'_3 \end{bmatrix} = \frac{1}{r} \begin{bmatrix} -\sin(\delta) & -\cos(\delta) & L_1 \\ -\sin(\delta) & \cos(\delta) & L_1 \\ 1 & 0 & L_2 \end{bmatrix} + \begin{bmatrix} \dot{x}_m \\ \dot{y}_m \\ \dot{\psi}_m \end{bmatrix} \quad (1)$$

Also the inverse kinematics matrix is implemented to control the movements, by calculating the inputs from odometry sensors.

$$\hat{X}_k^- = \begin{bmatrix} X(k+1) \\ Y(k+1) \\ \Phi(k+1) \\ e1 \\ e2 \\ e3 \end{bmatrix} = S * \begin{bmatrix} X(k) \\ Y(k) \\ \Phi(k) \\ \Delta e1 \\ \Delta e2 \\ \Delta e3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \sigma e \\ \sigma e \\ \sigma e \end{bmatrix} \quad (2)$$

Here X (k+1), Y (k+1) and Phi (k+1) are the robot position at the k+1th step and e1, e2, e3 are the robot displacement from previous position. sigma_e is the odometry sensor measurement

error variance which would be discussed about later.

S is the inverse equation of the kinematics and the state equation of the system.

$$A = S = \begin{bmatrix} 1 & 0 & 0 & (L2*\cos(Fe)+L3*\sin(A2))*\delta & a_{13} & a_{14} \\ 0 & 1 & 0 & -(L3*\cos(A2)+L2*\sin(Fe))*\delta & a_{23} & a_{24} \\ 0 & 0 & 1 & \delta & \delta & a_{34} \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

$$\begin{aligned} A_{13} &= -(L1 * \cos(\theta) + L3 * \sin(A1)) * \delta \\ A_{14} &= (-L1 * \sin(A2) + L2 * \sin(A1)) * \delta \\ A_{23} &= (-L3 * \cos(A1) + L1 * \sin(\theta)) * \delta \\ A_{24} &= (L1 * \cos(A2) + L2 * \cos(A1)) * \delta \\ A_{34} &= 2 * \sin A * \delta \end{aligned}$$

$$pos = \begin{bmatrix} X_r \\ Y_r \\ \Phi_r \end{bmatrix} = \begin{bmatrix} X(k+1) \\ Y(k+1) \\ \Phi(k+1) \end{bmatrix} \quad (4)$$

B. Observation Prediction

The observation prediction is the next stage, at this stage the position which is caught by the odometry sensor is matched by the real world environment. This matching is done by the conversion equation which name is h. H is an equation with one input; “robot position” and then it convert it with its map to the unique point in the environment. Here the map is the standard middle size soccer robot play field. At the end of this section, Z-hat(k+1) is obtained, which is one of the vital inputs for fusion process. In fact Z-hat(k+1) is the result of observation prediction stage which is the predicted global map of the environment by odometry instrument.

$$\hat{Z}(k+1) = h(pos, M) = \begin{bmatrix} \hat{\alpha}_1 \\ \hat{\alpha}_2 \\ \hat{\alpha}_3 \\ \hat{\alpha}_4 \end{bmatrix} = \begin{bmatrix} atan((w/2) - Y_r / (l/2) - X_r) - \Phi_1 \\ atan((w/2) - Y_r / (l/2) - X_r) - \Phi_2 \\ atan((w/2) - Y_r / (l/2) - X_r) - \Phi_3 \\ atan((w/2) - Y_r / (l/2) - X_r) - \Phi_4 \end{bmatrix} + \begin{bmatrix} \sigma_{od} \\ \sigma_{od} \\ \sigma_{od} \\ \sigma_{od} \end{bmatrix} \quad (5)$$

C. Measurement Prediction

It is the result of the vision based self localization algorithm which is used as the other feature of DKF.

$$Z(k+1) = CX(k) + V(k) \tag{6}$$

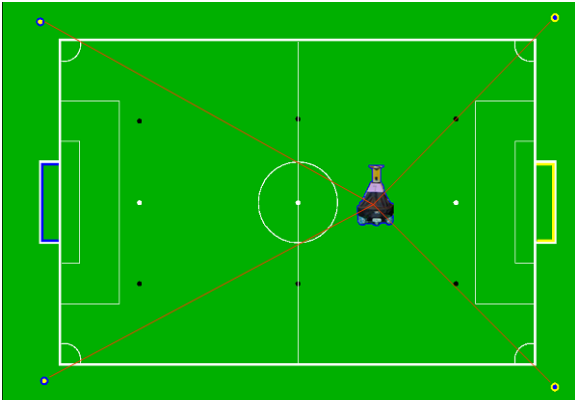


Fig. 4 Global localization with flags

Where $Z(k+1)$ is the measurement result_ the measured global map of the environment_ C is the conversion matrix, $X(k)$ is the measurement and V

(k) is the omni directional vision sensor noise matrix.

$$Z(k+1) = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} + \begin{bmatrix} \sigma_{ob} \\ \sigma_{ob} \\ \sigma_{ob} \\ \sigma_{ob} \end{bmatrix} \tag{7}$$

D. Landmarks Radial Detection by Vision Sensor

The advantages of ray scanning [Fig. 5] are first, the small fraction of the image data is accessed, and second the direction is given also. For instance field line could be detected very simply_ like, a transition from white to green [Fig. 5].

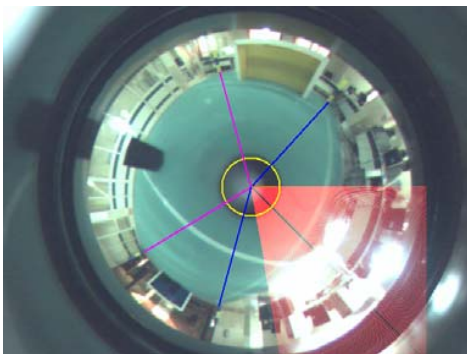


Fig. 5 Radial image scanning

This method is also implemented to recognize the playing field corner flags to calculate the exact global position of the robot by vision algorithm. This is done in 4 separate modes with specific confidence levels according to the number of the detected flags in each step.

If there was a transition from yellow to blue and then to yellow, or from blue-yellow-blue, a corner flag might be found. By continuing the obtained result the probability of detection increases. This is how to detect the corner flags in an omni image which is obtained from vision sensor.

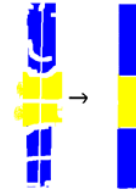


Fig. 6 Flags radial scan in an omni image

E. Matching

Matching is designed to combine the multi sensor data. It is implemented as the below equation:

$$V_k = Z_k - \hat{Z}_k \tag{8}$$

The result of matching is the input of the DKF block.

F. Discrete Kalman Filter (DKF)

At this stage, the Discrete Kalman Filter is used to correct the position estimation on the basis of validated observations and predictions. In particular, the final position estimate is obtained as:

$$\hat{x}_k = \hat{x}_k^- + K_k(V_k) \tag{9}$$

K_k is the Kalman gain which is obtained from:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{10}$$

Then, the covariance matrix associated with the final position estimate X_k is given by:

$$P_k = (I - K_k H)P_k^- \tag{11}$$

Finally, As with the basic discrete Kalman filter, the time update equations project the state and covariance estimates from the previous time step $K-1$ to the current time step K

$$\hat{x}_k^- = A\hat{x}_{k-1} + u_k \tag{12}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{13}$$

III. EXPERIMENTAL RESULTS

The experimental results show the efficiency of this method in the real environment, which is the Middle size league play field. The result of the proposed localization system is shown also in the Fig. 8.

Here, the red diagram is measurement sensor result, the Blue diagram is the prediction observation and the green one is the truth value which is obtained from the DKF algorithm.

In this experiment the robot is moved a square path in the field and the sampling is done simultaneously.

Most localization methods make use of a constant matrix R. However, the measurement noise depends on the interaction between the sensor and the environment. Also Q is in variant according to the testing environment.

In practice, the process noise covariance Q and measurement noise covariance matrices R might change with each time step or measurement, however here we assume they are constant.

The random variables W_k and V_k represent the process and measurement noise (respectively). They are assumed to be independent (of each other), white, and with normal probability distributions.

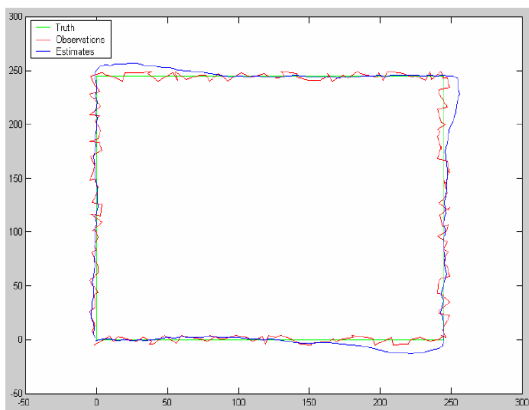


Fig. 7 Experimental result of the DKF localization

$$\begin{aligned} P(w) &\approx N(0, Q) \\ P(v) &\approx N(0, R) \end{aligned} \quad (14,15)$$

These parameters are obtained from some standard experimental tests, from the omnidirectional mirror sensor and the odometry shaft encoder sensors. The values obtained for our system are $Q=0.01$ (the omni vision sensor is very accurate in the orientations of the detected landmarks) and $R=0.5$.

IV. CONCLUSION

According to the experimental results the self localization system became more reliable in compare with the previous localization and stand alone sensor self localization; because of the DKF noise reduction algorithm the robot stability and

precision increases, and these are vital for any soccer robot to have a good performance in the playing field to do the playing strategies carefully.

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