The Application of Particle Filtering in Dynamic Locating and Tracking of Intelligent Wheelchair

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Abstract. In order to reduce dynamic positioning errors of intelligent wheelchair efficiently, this paper discusses the application of particle filter. At first, a localization algorithm of an intelligent wheelchair by using CSS ranging is proposed. Then the principle of standard particle filter was introduced and a corresponding filtering model of dynamic positioning was set up in this paper. The filtering algorithm was programmed on the intelligent wheelchair prototype which based on ARM chip as hardware platform, the experimental results showed that the filtering algorithm applied for dynamic positioning of intelligent wheelchair overcame the problem that kalman filter and extended kalman filter is weak for nonlinear state, reducing dynamic positioning error by 27.8% compared to trilateration.

Introduction

To implement the function of autonomous navigation, the intelligent wheelchair has to determine its position in the process of movement at first. With the continuous development of wireless communication technology, as one of the absolute positioning methods, positioning with wireless sensor network (WSN) gets widely used. Wireless sensors usually include ultrasonic sensors, Bluetooth sensors, Zigbee sensors, RFID, UWB and CSS ranging chips, commonly using ranging method like the signal attenuation law (RSSI), time of arrival (TOA), arrival time difference method (TDOA) and arrival Angle (AOA) method [1], etc.

In practice, however, when a wireless network node moves with the intelligent wheelchair in the indoor environment, reflection and refraction of the wireless signal will increase, resulting in serious multipath interference phenomenon and that lead to the dynamic positioning accuracy of the intelligent wheelchair falls sharply. As a result of the unsteady movement of the intelligent wheelchair, the variance of the position comes bigger and the positioning performance and stability of the wheelchair will be seriously affected [2].

Kinematics model of the intelligent wheelchair system is established and positioning system is taken as a state estimation space in this paper. By comparing the particle filter with kalman filter and extended kalman filtering applied in dynamic positioning tracking, which are programmed on the intelligent wheelchair prototype, this paper discuss how to improve the dynamic positioning precision of intelligent wheelchair.

Localization Using CSS Signal Ranging

Chirp-spread-spectrum (CSS) is defined in the standard IEEE 802.15.4a which is applied in pulse compression radar at first. CSS is able to measure the distance between a pair of CSS nodes and has low cost, low power consumption and high environmental applicability [3]. This paper presents a localization algorithm for intelligent wheelchair that uses CSS ranging. The structure of positioning system is shown in Fig. 1.

In this positioning system, there are 4 known nodes in permanent position and 1 unknown node that put on the intelligent wheelchair. CSS ranging is based on the time of flight (TOF) of radiofrequency signals which is based on the method of symmetric double-sided two-way ranging (SDS-TWR) [4]. With SDS-TWR, CSS ranging does not require time synchronization between node pairs and decreases the measurement errors caused by clock drift. The unknown node measure the distance between known nodes and itself, then sends the observed values to upper embedded chip through UART for calculating the position of the intelligent wheelchair.

The distance d_i from unknown node to known node *i* at time *k* is given by

$$d_i = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2} \quad (1)$$

Trilateration is widely used for ranging-based localization. Due to the distance measurement error, three circles which take fixed nodes as the origin and ranging distance as the radius can't intersect to one point but a triangle region, so we take the centroid of the triangle area as position of the wheelchair, as is shown in Fig. 2. Four distances between the wheelchair and reference CSS node can be measured which means four positions can be calculated each time. Assume that four positions of wheelchair are(x_1, y_1), (x_2, y_2), (x_3, y_3) and(x_4, y_4), then the position of wheelchair (x, y) can be calculated by weighted trilateration. The function can be defined as follows:

$$x = (x_1 + x_2 + x_3 + x_4)/4, \quad y = (y_1 + y_2 + y_3 + y_4)/4 \quad (2)$$

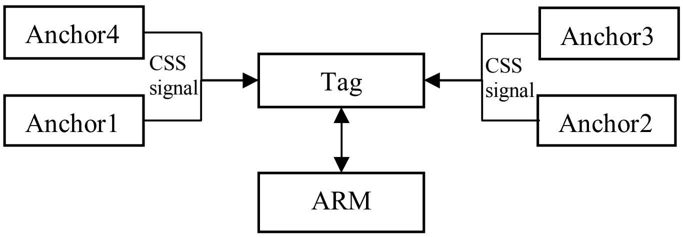

Fig. 1 Structure of positioning system

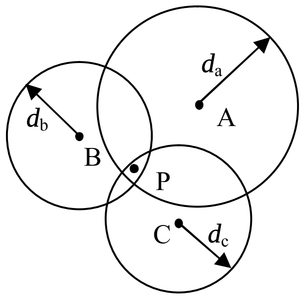

Fig. 2 Trilateration

Standard Particle Filter Module

The particle filtering (PF) is usually the solution in a lot of nonlinear and/or non Gaussian problems. It approximates the posterior distribution using particles (system state samples). To develop a state-space equation model, we define the vector of the CSS node on the wheelchair as follows:

$$X_k = [x(k) \quad y(k) \quad q(k)]^{\mathrm{T}} \quad (3)$$

Where $x(k)$ and $y(k)$ are the 2-D coordinates of the wheelchair at time *k*, $q(k)$ is the angle from the moving direction of the wheelchair to *x* axis.

Suppose that the wheelchair is moving according to a known dynamic model:

$$X_k = F(X_{k-1}, W_k), \; Z_k = H(X_k, V_k) \quad (4)$$

where X_k and X_{k-1} are the state vectors, Z_k is the measurement vector from CSS ranging, W_k and V_k are process noise and the measurement noise vector, the state vector at time *k* is determined by the matrix function *F* and The nonlinear measurement matrix function *H* represents the relationship among X_k, V_k and Z_k.

The basic function of the particle filter is to approximate the posterior density of the target state by a set of points and corresponding weights called particles [5, 6]. To estimate the state of intelligent wheelchair $\hat{X}_k$, each particle x_k^i and its weight w_k^i is calculated and the prior probability density P_k is also updated, which can be expressed as

$$\hat{X}_k = \sum_{i=1}^{N} w_k^i x_k^i, \quad P_k = \sum_{i=1}^{N} w_k^i \left(x_k^i - \hat{X}_k\right)\left(x_k^i - \hat{X}_k\right)^{\mathrm{T}} \quad (5)$$

Experiment and Analysis

Set the initial position of the intelligent wheelchair at the point A (1, 1), the initial speed 0.2 m/s and sampling period of positioning module 0.25s. Control the intelligent wheelchair move along a closed rectangular guide line which consist of the point A (1, 1) and B (1, 4), C (4, 4) and D (4, 1) at the initial speed. The coordinates of output positions and error at direction of x axis and direction of y axis are depicted in Figs. 5 and 6 respectively. To show the performance of particle filtering, the data of the wheelchair using trilateration without any processing while moving is also shown in Figs. 3 and 4.

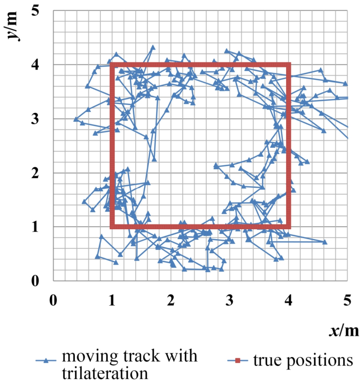

Fig. 3 Positions of the wheelchair using trilateration

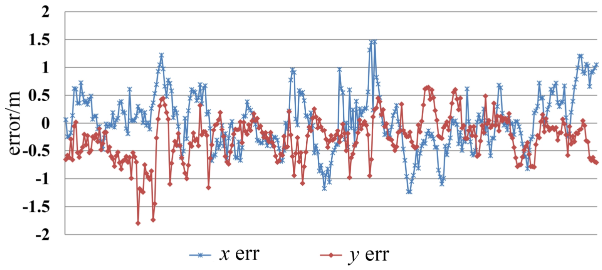

Fig. 4 Positions errors using trilateration

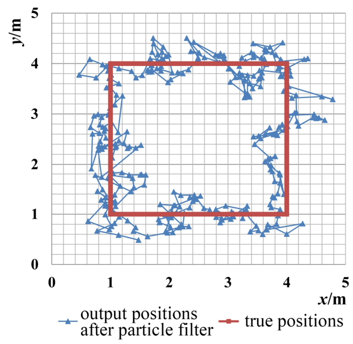

Fig. 5 Positions of the wheelchair using particle filtering

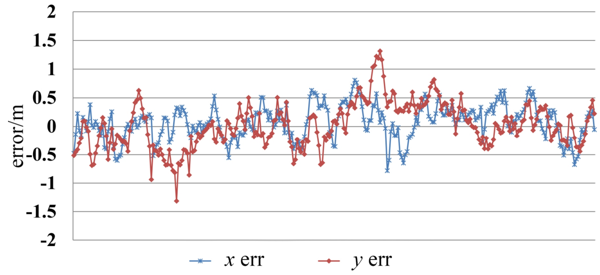

Fig. 6 Positions errors using particle filtering

In order to evaluate the performance of particle filter algorithm, we also executed the trilateration, KF (kalman filter) and EKF (extended kalman filter) estimated the coordinates of the wheelchair over time. The reliability of the four estimations was calculated by means of the root mean square error (RMSE) between the location and estimation [7]:

$$\mathrm{RMSE} = \sqrt{E\left[(x-\hat{x})^2 + (y-\hat{y})^2\right]} \tag{6}$$

As can be seen from Fig. 7, the RMSE of particle filter is less than the other three estimations. It proves that the proposed algorithm is feasible and efficient.

Define Δd_i as the bias degree of dynamic positioning of the intelligent wheelchair, statistics of which in different interval is shown in Table 1.

$$\Delta d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2} \; (i = 1 \ldots N) \tag{7}$$

Across all demographic groups, dynamic positioning using particle filter overcomes the nonlinear problem of standards and extended kalman filter, dynamic positioning error of the intelligent wheelchair within 1 m can reach 97.5% of all positions, which shows that positioning using particle filter has effectively improved the dynamic positioning accuracy of the intelligent wheelchair.

Conclusions

In this paper, a localization algorithm of an intelligent wheelchair by using CSS ranging is proposed firstly, then a model written as state-space equation is established trying to reduce the dynamic positioning error caused by multipath interference phenomenon of CSS signal. The particle filter algorithm is introduced and developed, through experimental results, it can be verified that the particle filter algorithm is acceptable for localization reducing dynamic positioning error by 27.8% compared to trilateration and the RMSE of particle filter is less than KF and EKF.

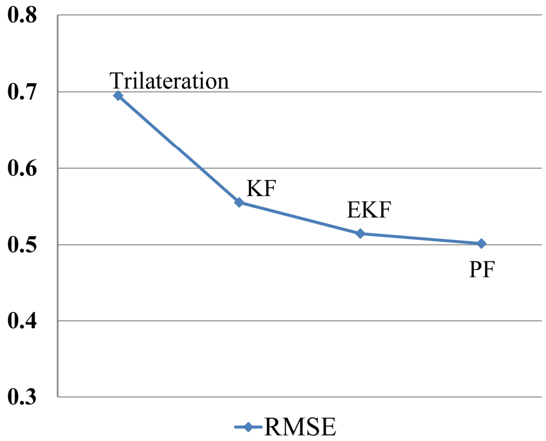

Fig. 7 RMSE of four estimations

Table 1. Error range of different estimates

Filter	Error Range			
	<0.5[m]	**0.5[m]-1.0[m]**	**1.0[m]-1.5[m]**	**>1.5[m]**
Trilateration	39.1%	48.9%	10.4%	1.6%
KF	51.2%	45.8%	3.0%	0
EKF	66.0%	29.5%	3.0%	1.5%
PF	63.4%	34.1%	2.4%	0

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