LS-SVM Assisted Multi-rate INS UWB Integrated Indoor Quadrotor Localization Using Kalman Filter

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Abstract. This paper focuses on the problem of positioning accuracy degradation caused by inconsistent sampling frequencies of INS/UWB navigation system. In order to achieve the same sampling frequency of INS and UWB, this paper proposes a data fusion algorithm combining extended Kalman filter (EKF), locally weighted linear regression (LWLR), least squares support vector machine (LS-SVM). First, during the UWB data sampling interval, the UWB data are fitted by LWLR, and the fitted UWB data and INS data are fused by EKF. Then, estimation error of EKF is optimized by LS-SVM. At last, the simulation results indiciate data fusion algorithm restrains divergence problem in the UWB sampling interval. And the positioning accuracy of indoor quadrotor INS/UWB navigation system has been increased through the algorithm.

Keywords: INS/UWB · least squares support vector machine · extended Kalman filter

1 Introduction

As a commonly used positioning system, the inertial navigation system (INS) doesn't rely on the transmission and reception of signals. The linear motion, angular motion, magnetic field strength and direction of the carrier are measured by the inertial measurement unit (IMU), and the position, speed and attitude are calculated to realize the positioning of the carrier. It has the advantages of strong anti-interference, short-term high precision and good concealment. However, the positioning accuracy gets lower and lower with the time up [3]. Due to its obvious advantages in indoor positioning occasions, the ultra wide band (UWB) is widely used in indoor positioning. However, positioning accuracy of UWB is affected by non-line-of-sight (NLOS) error [1]. Besides, the environmental adaptability is not strong and the positioning performance is unstable. Due to the advantages and disadvantages of INS and UWB, the most common practice in the field of indoor positioning is to combine UWB and INS to build INS/UWB navigation system [5].

B. Wang et al. (Eds.): ICMTEL 2023, LNICST 534, pp. 11–18, 2024.
https://doi.org/10.1007/978-3-031-50577-5_2

In order to improve the positioning accuracy of integrated navigation system, some navigation strategies based on improved extreme learning machine and improved deep belief network are proposed [6]. Particle-based Kalman filter [10], complementary Kalman Filter [4], and cubature Kalman filter [2] are proposd to improve the robustness. Further, a data fusion method combining machine learning algorithms is proposed to improve the performance of UWB positioning system in NLOS situation [9]. To tune hyperparameter of the model faster and more effective, a PSO-guided Self-Tuning Convolution Neural Network is proposed [7]. To improve the speed and accuracy of distinguishing infected patients from healthy populations, a deep learning model (WE-SAJ) using wavelet entropy, two-layer FNNs and the adaptive Jaya algorithm is proposed [8]. The above papers only focus on how to improve the performance of machine learning algorithms. In fact, there exits difference in sampling frequency between INS and UWB, which leads to decrease in positioning accuracy of INS/UWB system within the UWB sampling interval.

To solve the problem, this paper presents a data fusion algorithm including extended Kalman filter (EKF), locally weighted linear regression (LWLR), and least squares support vector machine (LS-SVM). First, UWB data within the UWB data sampling interval is predicted by LWLR. Then, the fitted UWB data and INS data is fused by EKF. Finally, the bias of EKF is decreased by LS-SVM. The main contribution of this paper is that it proposes a new strategy for sampling frequency synchronization and data fusion error compensation using LWLR and LS-SVM.

The remainder of this paper is: EKF algorithm is introduced in Sect. 2. Section 3 is about the detailed introduction of the fusion algorithm. Section 4 shows the simulation results. The conclusion is given in Sect. 5.

2 EKF Algorithm

A discrete nonlinear system is usually modelled as

$$\begin{cases} x_{k+1} = f(x_k, w_k, k), w_k, k) \\ z_k = g(x_k, k) + h_k \end{cases} \tag{1}$$

in Eq. 1, w_k and h_k denote uncorrelated white noises, its variance are Q_k and R_k, x_k denotes an n×1 dimensional state vector,z_k denotes an m×1 dimensional measurement vector, f denote nonlinear state function, g denote measurement function. Similar to the traditional Kalman filter algorithm, EKF is also divided into one step prediction and measurement update two steps to complete a filter, one step prediction procedure is:

If the state estimation after measurement update at time k is $\hat{x}_k(+)$, let

$$F_k = \frac{\partial f}{\partial x}|_{x_k=\hat{x}_k(+)} \tag{2}$$

Then the one-step prediction equation is

$$\begin{cases} \hat{x}_{k+1}(-) = f[\hat{x}_k(+), k] \\ P_{k+1}(-) = F_k P_k(+) F_k^T + Q_k \end{cases} \tag{3}$$

where $\hat{x}_{k+1}(-)$ represents state estimation of measurement filter correction at time k+1, P(-) denotes estimation bias correlation matrix of one-step prediction, $\hat{P}_k(+)$represents estimation bias covariance matrix after measurement update at time k.

Then, after the measurement, the measurement is updated. The process is as follows:

$$G_{k+1} = \frac{\partial g}{\partial x} \tag{4}$$

The measurement update equation is:

$$\begin{cases} K_{k+1} = P_{k+1}(-)G_{k+1}^T[G_{k+1}P_{k+1}(-)G_{k+1}^T + R_{k+1}]^{-1} \\ \hat{x}_{k+1}(+) = \hat{x}_{k+1}(-) + K_{k+1}\{z_{k+1} - g[\hat{x}_{k+1}(-), k+1]\} \end{cases} \tag{5}$$

in (5), K represents gain array.

3 Proposed Fusion Strategy

3.1 LWLR Algorithm

An innegligible problem of linear regression is that the model may be under-fitting, because it seeks unbiased estimates with least mean square error. Obviously, if the model is under-fitting, it will not achieve the best prediction effect. So some methods allow the introduction of some bias in the estimation, thereby reducing the mean square error of prediction. LWLR is the most common method. The algorithm gives weights founded on gap between the predicted point and training point. The closer the distance is, the greater the weight is. Then weighted mean square error minimization model is solved. For most regression algorithms, when it completes learning process, parameters are settled. However, the situation is different in the LWLR algorithm, each prediction needs to update the regression coefficient parameters.

Therefore, LWLR is a real-time algorithm for global fitting through local fitting to achieve better generalization performance and prediction accuracy. For LWLR algorithm, kernel function is used to assign weights. The type can be freely selected, usually Gaussian kernel. As is shown in Eq. (6), the kernel used in this paper is Gaussian kernel.

$$w(i,i) = exp(\frac{|x^{(i)} - x|}{-2k^2}) \tag{6}$$

where x is the point to be predicted; $x^{(i)}$ is the sample point; k is a parameter specified by the user. The selection of k should be appropriate, otherwise it will cause underfitting or overfitting problems.

3.2 LS-SVM Algorithm

The LS-SVM algorithm is a useful tool to obtain the input and output fuzzy relations in the fields of classification, regression analysis and nonlinear estimation. Its mathematical model can be described by the next steps. First, given a training dataset $\{d_i, e_i\}, i = 1, 2, /cdots, m$. Then, goal function and constraints are determined as follows:

$$\min_{V,a,c} J_p(V,c) = \frac{1}{2}V^T V + \frac{r}{2}\sum_{i=1}^{m} c_i \tag{7}$$

$$s.t.e_i = V^T \varphi(d_i) + a + c_i \tag{8}$$

where V denotes the normal vector of the hyperplane, c denotes the square of prediction error, r represents the penalty factor of prediction error, a is a constant, $\varphi(d_i)$ denotes the kernel function.

After that, the cost function of LS-SVM founded on theory of structural risk minimization (SRM) is the following Lagrangian function:

$$L(V,a,c,b) = J_p(V,c) - \sum_{i=1}^{m} b_i[V^T \varphi(d_i) + a + c_i - e_i] \tag{9}$$

where b_i is Lagrange multiplier. The partial derivatives of V, a, c_i, b_i in (9) are calculated respectively and the derivative is set to be zero. The linear equations can be obtained as follows:

$$\begin{cases} \frac{\partial L}{\partial V} = 0 \\ \frac{\partial L}{\partial a} = 0 \\ \frac{\partial L}{\partial c_i} = 0 \\ \frac{\partial L}{\partial b_i} = 0 \end{cases} \tag{10}$$

The solution of (10) can be obtained:

$$e_i = \sum_{i=1}^{m} K(d, d_i) + a \tag{11}$$

where $K(d, d_i)$ represents the kernel function. Similar to the LWLR algorithm, the choice of kernel function needs to be careful, the kernel chosen in the paper is Gaussian kernel shown as follows:

$$K(d, d_i) = exp(-\frac{(d - d_i)^2}{-2\sigma^2}) \tag{12}$$

where σ represents kernel parameter. Gaussian kernel is very sensitive to σ, and the selection of σ will affect the accuracy and generalization performance of model. Therefore, the selection of σ should be appropriate, otherwise it will cause underfitting or overfitting problems.

3.3 Fusion Algorithm

In order to realize the consistency of INS and UWB sampling frequency, we presents a new data fusion algorithm in this section. First of all, it predicts the UWB data within UWB sampling interval by LWLR. Then, INS data and fitted UWB data are fused by EKF. Finally, the bias of EKF algorithm is optimized by LS-SVM algorithm. The data fusion algorithm consists of training phase and prediction phase shown as Fig. 1 and Fig. 2. Detailed introduction of the algorithm is as follows.

1) Due to the different sampling frequency of UWB and INS, there is a moment when only INS data is available and UWB data is not.

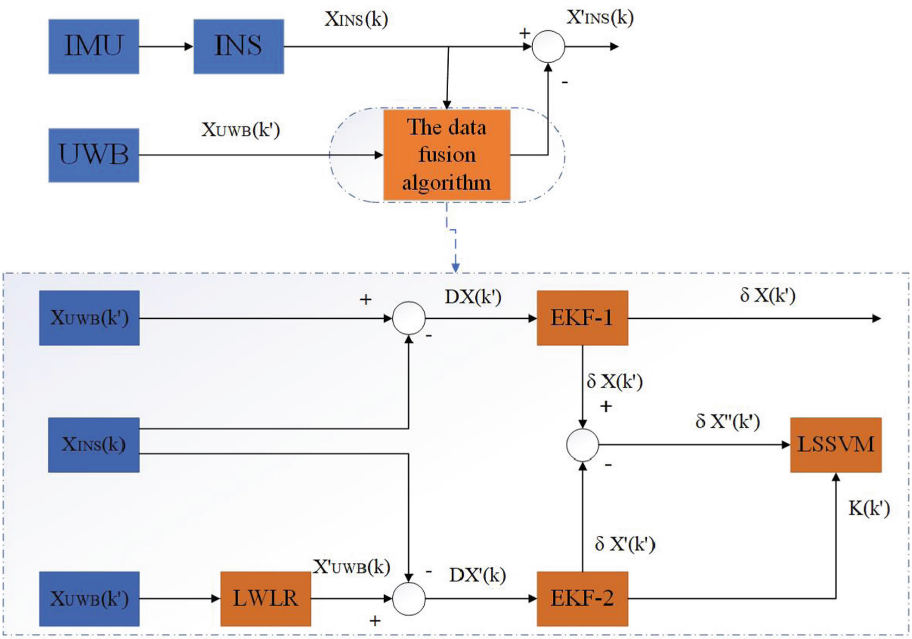

Fig. 1. The training phase

Therefore, INS data and UWB data can be represented as $X_{INS}(k)$ and $X_{UWB}(k')$ respectively, where k' denotes epochs, it satisfies $k = 1, 1 + n, \cdots$,(n=6 in this paper), $k = 1, 2, \cdots, k'$. Both EKF-1 and EKF-2 represent EKF. They have the same parameters and structure, including state covariance, process noise and measurement noise covariance, etc. The core of the training phase can be divided into two parts, LWLR training and LS-SVM training. For the LWLR training phase, we use LWLR to fit UWB data and then determine the linear regression parameters. For the LS-SVM training phase, it establishes

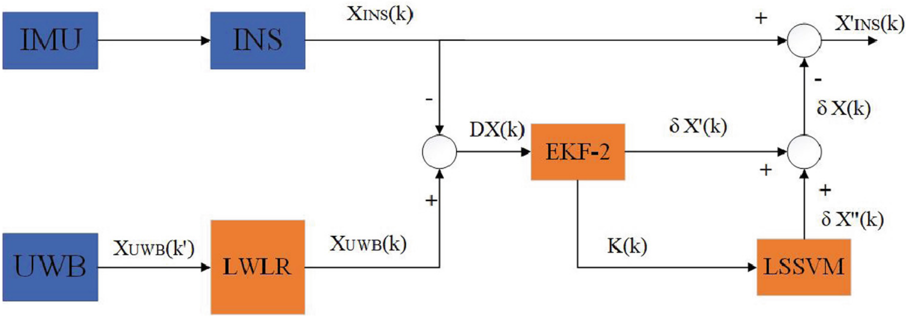

Fig. 2. The prediction phase

the fuzzy relationship between K(k') and $\delta X^{''}(k')$ through the training samples determined by Eqs. (13)–(15), where K denotes gain array of EKF-2, $\delta X^{''}(k')$ represents the estimation error of EKF-2 due to the use of UWB data predicted by LWLR.

$$\text{Training Dataset}$$

$$[K(k'), \delta X^{''}(k')] \tag{13}$$

$$\delta X^{''}(k') = \delta X(k') - \delta X'(k') \tag{14}$$

$$\begin{cases} EKF-1 \rightarrow \delta X(k') \\ EKF-2 \rightarrow \delta X'(k') \end{cases} \tag{15}$$

2) After introducing the training phase of the data fusion algorithm, the prediction phase should be introduced. In prediction phase, the UWB data is predicted by trained LWLR model, so that EKF can be used to fuse INS data and fitted UWB data. For LS-SVM algorithm, the EKF-2 gain matrix K is used as the input of the trained LS-SVM model to predict bias of EKF-2 within the UWB sampling interval, and then the INS data is corrected by the estimation error. The above steps are determined by equations (16)–(18).

$$\begin{cases} In : [K(k)] \\ Out : [\delta X^{''}(k)] \end{cases} \tag{16}$$

$$\delta X^{''}(k) = \delta X(k) - \delta X'(k) \tag{17}$$

$$X^{'}_{INS}(k) = X_{INS}(k) - \delta X(k) \tag{18}$$

Notably, in the LS-SVM used in the paper, the kernel parameter and regularization parameter are set to 0.001.

4 Experiment and Analysis

This section verifies and analyzes the effect of the algorithm through simulation experiments. The experimental results are shown as Fig. 3.

From Fig. 3, it can be seen that the position error of INS data modified by the algorithm is significantly reduced. However, the bias suddenly becomes larger at some epochs. This is because the position error of the UWB data suddenly become larger in that moment, which leads to large deviations in UWB data predicted by LWLR.

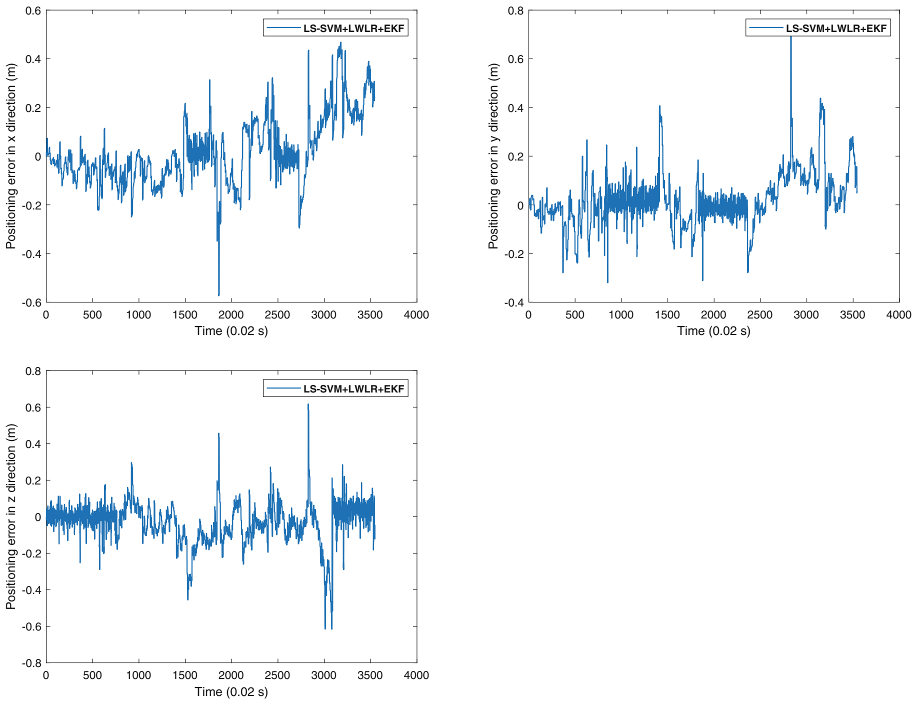

Fig. 3. Position error

5 Conclusion

Combining LWLR, EKF and LS-SVM, this paper presents a data fusion algorithm for indoor quadrotor INS/UWB navigation system. The LWLR algorithm achieves good results in predicting the UWB data of the sampling period interval, which solves the problem of inconsistent sampling frequency between INS and UWB, and achieves the same sampling frequency between INS and UWB. And the EKF algorithm suppresses accumulative errors of INS data and improves the positioning accuracy. Besides, the positioning error is further reduced by predicting the EKF error of the sampling period by the LSSVM algorithm. Simulation results prove that the above method eliminates accumulative errors of INS data and further increases the positioning accuracy of indoor quadrotor INS/UWB navigation system.

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