LS-SVM/Federated EKF Based on the Distributed INS/UWB Integrated 2D Localization

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Abstract. In this paper, a novel distributed integrated 2D localization scheme for fusing the fusing the ultra wide band (UWB)- and inertial navigation system (INS)-derived ranges using least squares-support vector machines (LS-SVM)/federated extended Kalman filter (FEKF) integrated approach is presented. In the proposed scheme, the local filter is capable of fusing UWB- and INS-derived distances, and then, the main filter is employed to fuse the local data fusion filter's outputs and compensate the INS position error. Moreover, for overcoming the outage of the UWB, the LS-SVM is used to assist the FEKF, which can compensate the missing UWB measurement. The test demonstrates that the proposed LS-SVM/FEKF can effectively improve the position accuracy compared with the traditional FEKF.

Keywords: INS/UWB-integrated positioning · Seamless navigation · LS-SVM · Federated EKF

1 Introduction

Nowadays, how to obtain continuous and accurate location information has played an important role on the location based service (LBS) in indoor environment [1,2].

The global positioning system (GPS) positioning accuracy drops rapidly in indoor environment. For avoiding the above problem, many LBS-based localization attempts have been investigated. For instance, radio frequency identification (RFID) based the algorithm of indoor positioning has been considered in [3]. An magnetic field/WiFi integrated indoor localization has been presented in [4]. Moreover, for improving the positioning accuracy of indoor positioning, ultra wide band (UWB)-based methods have been proposed [5]. Meanwhile, the inertial navigation system (INS) has been used to get rid of dependence on additional

W. Fu et al. (Eds.): ICMTEL 2021, LNICST 387, pp. 502–509, 2021.
https://doi.org/10.1007/978-3-030-82562-1_49

equipment [6,7]. However, the INS-based approach is poor in long-term working owing to the cumulative error. As a consequence, the integrated localization strategy has been used in the indoor navigation. For instance, an integrated human tracking fusing INS and UWB measurement has been proposed in [8,9], a weighted least squares-based INS/WiFi system about indoor positioning has been considered in [10]. At the same time, many filtering algorithms have also been considered in [11,12]. In harsh indoor environment, the LBS-based measurement is relatively easy to be outage, which should be also considered in INS-based integrated schemes. Therefore, tightly-coupled integrated model with missing data is not considered.

A novel distributed integrated 2D localization scheme for fusing the UWB's ranges and INS's ranges using LS-SVM/FEKF integrated approach will be considered in this paper. In the remainder of the paper, LS-SVM/FEKF is designed in Sect. 2, a verification is implemented in Sect. 3, and the Sect. 4 presents conclusions.

2 Design of LS-SVM Assisted Federated EKF Filter

At the first place, the distributed tightly-coupled integrated scheme using federated EKF filter will be briefly reviewed.

2.1 The Distributed Integrated Scheme Using the LS-SVM Assisted Federated EKF Filter

The distributed integrated scheme is used in our previous work [2]. Thus, in this subsection, the distributed integrated scheme will be briefly reviewed. Figure 1 demonstrates the distributed integrated scheme. In this model, the UWB reference nodes (RNs) are pre-positioned on known coordinates, inertial measurement unit (IMU) and the UWB blind node (BN) are fixed to a person. Then, the UWB-derived distance between the BN and the RNs $\left(d^{(i)U}, i = 1, 2, \ldots, m\right)$ m is the RNs' number, and INS position $\mathbf{Po}^{I}$ are employed to input to the LS-SVM assisted federated EKF filter, which will be presented in the next section. Finally, the outputs of the data fusion filter are employed to compensate the INS position error.

2.2 Design of the Federated EKF

In this subsection, the federated EKF filter's state and observation equations based on the distributed integrated scheme will be addressed. The federated EKF includes the local EKF and main EKF, in this model, the local EKF filter is used to estimate the local state of the INS position error, and then, the main EKF integrate the local EKFs' estimations to output the final INS position error estimation of the data fusion filter.

The *ith* local EKF state equation is listed in Eq. (1)–(3).

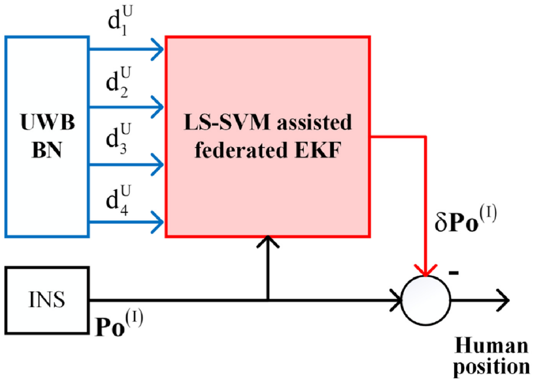

Fig. 1. The distributed integrated scheme.

$$\underbrace{\begin{bmatrix} \phi_{t|t-1} \\ \delta\mathbf{V}^n_{t|t-1} \\ \delta\mathbf{P}^n_{t|t-1} \\ \nabla^b_{t|t-1} \\ \varepsilon^b_{t|t-1} \end{bmatrix}}_{\mathbf{X}^{(i)}_{t|t-1}} = \underbrace{\begin{bmatrix} \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & -\mathbf{I}_{3\times3}\mathbf{C}^n_b \varDelta T \\ S\left(\mathbf{f}^n_t\right)\varDelta T & \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3}\mathbf{C}^n_b \varDelta T & \mathbf{0}_{3\times3} \\ \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3}\varDelta T & \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} \\ \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} \\ \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{0}_{3\times3} & \mathbf{I}_{3\times3} \end{bmatrix}}_{\mathbf{A}^{(i)}_t} \underbrace{\begin{bmatrix} \phi_{t-1} \\ \delta\mathbf{V}^n_{t-1} \\ \delta\mathbf{P}^n_{t-1} \\ \nabla^b_{t-1} \\ \varepsilon^b_{t-1} \end{bmatrix}}_{\mathbf{X}^{(i)}_{t-1}} + \mathbf{w}^{(i)}_{t-1}, \tag{1}$$

$$\mathbf{C}^n_b = \begin{bmatrix} \cos\gamma & 0 & -\sin\gamma \\ 0 & 1 & 0 \\ \sin\gamma & 0 & \cos\gamma \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & \sin\theta \\ 0 & -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{2}$$

$$S\left(\mathbf{f}^n_t\right) = \begin{bmatrix} 0 & f^n_{Ut} & -f^n_{Nt} \\ -f^n_{Ut} & 0 & f^n_{Et} \\ f^n_{Nt} & -f^n_{Et} & 0 \end{bmatrix}. \tag{3}$$

where the local filter's number is denoted as (i), where the time index t, ϕ_t, $\delta\mathbf{V}^n_t$, and $\delta\mathbf{P}^n_t$ are denoted as the INS's attitude, velocity, and position errors vector respectively, the accelerometer bias and gyroscope drift vectors employ $\left(\nabla^b_t, \varepsilon^b_t\right)$, $\varDelta T$ represents the sample time, $\omega_t \sim N\left(0, \mathbf{Q}\right)$ is the system noise, $\mathbf{C}^n_b$ is rotation matrix, θ, γ, ψ represent around the X, Y, Z axis of rotation angle, $(f^n_{Ut}, f^n_{Et}, f^n_{Nt})$ is the acceleration up, east and north in the coordinate system.

The ith local EKF's observation equation can be given as Eq. 4.

$$\underbrace{\left[\delta\left(d_t^{(i)}\right)^2\right]}_{\mathbf{Y}_t^{(i)}} = \left[\left(d_t^{I(i)}\right)^2 - \left(d_t^{U(i)}\right)^2\right] = \underbrace{\begin{matrix} 2\left(x_t^I - x_t^{(i)}\right)\delta x_t^{(i)} + 2\left(y_t^I - y_t^{(i)}\right)\delta y_t^{(i)} \\ -\left(\left(\delta x_t^{(i)}\right)^2 + \left(\delta y_t^{(i)}\right)^2\right) \end{matrix}}_{g\left(\mathbf{X}_{\mathrm{t|t-1}}^{(i)}\right)} + \underbrace{\left[\nu_{d_t^{(i)}}\right]}_{\nu_t^{(i)}} \tag{4}$$

where $\left(\delta x_t^{(i)}, \delta y_t^{(i)}\right)$ is the ith local filter's estimation of the 2D INS position errors at time index t, $\left(\delta V x_t^{(i)}, \delta V y_t^{(i)}\right)$ is the ith local filter's estimation of the 2D INS velocity errors at time index t, $\left(x_t^I, y_t^I\right)$ is the 2D INS position at the time index t, $\left(x_t^{(i)}, y_t^{(i)}\right)$ is the 2D position of the ith RN, $\nu_t^{(i)} \sim N\left(0, R^{(i)}\right)$ is the ith local EKF filter's measurement noise at time index t, $\left(d_t^I, d_t^U\right)$ is the distance obtained by INS and UWB respectively. Noted that we employ the data fusion model directly and one can find the detailed deducing in [13].

Nowadays, the centralized filter has been widely used, however, it is poor at the fault detection. The state and observation equations listed in Eqs. (1) and (4) are proposed for the local EKF filter, when the local data fusion filter can provide the local estimation, then the main EKF filter integrates local EKFs' estimations by the following equations ($\mathbf{P}_t$ is the covariance matrix, $\mathbf{X}_\mathrm{t}$ is the state vector):

$$\mathbf{P}_t = \left(\left(\mathbf{P}_t^{(1)}\right)^{-1} + \left(\mathbf{P}_t^{(2)}\right)^{-1} + \left(\mathbf{P}_t^{(3)}\right)^{-1} + \ldots + \left(\mathbf{P}_t^{(m)}\right)^{-1}\right)^{-1}, \tag{5}$$

$$\mathbf{X}_\mathrm{t} = \mathbf{P}_t \begin{pmatrix} \left(\mathbf{P}_t^{(1)}\right)^{-1}\mathbf{X}_t^{(1)} + \left(\mathbf{P}_t^{(2)}\right)^{-1}\mathbf{X}_t^{(2)} \\ + \left(\mathbf{P}_t^{(3)}\right)^{-1}\mathbf{X}_t^{(3)} + \ldots + \left(\mathbf{P}_t^{(m)}\right)^{-1}\mathbf{X}_t^{(m)} \end{pmatrix}. \tag{6}$$

2.3 Design of the LS-SVM Assisted Federated EKF Filter

In Subsects. 2.1 and 2.2, the distributed integrated scheme using the federated EKF filter (FKF) is investigated. However, it should be emphasized that the distributed integrated scheme's missing data has seldom been considered. In this subsection, we will improve the federated EKF filter by considering the missing the observation vector, which is the main contribution of this work. From the Eq. 4, it can be seen that the observation vector has the following relationship with the 2D INS position error.

$$\begin{aligned}\mathbf{Y}_t^{(i)} &= 2\left(x_t^I - x_t^{(i)}\right)\delta x_t^{(i)} + 2\left(y_t^I - y_t^{(i)}\right)\delta y_t^{(i)} - \left(\left(\delta x_t^{(i)}\right)^2 + \left(\delta y_t^{(i)}\right)^2\right) \\ &= f\left(\delta x_t^{(i)}, \delta y_t^{(i)}\right)\end{aligned} \tag{7}$$

In the INS/UWB-integrated scheme, when the UWB's ranges are not able to be updated, the observation vector is also not be used by the data fusion filter. Aim to overcome this problem, LS-SVM is used to estimate the missing observation vector in this work. It should be pointed out that the proposed seamless schemes are based on the loosely-coupled integrated scheme. This work focuses on the estimation of the missing data based on the distributed tightly-coupled integrated scheme. When the UWB measurement is available, the LS-SVM is applied to build the mapping including the INS position and its error. Once the UWB's range is unavailable, the data fusion filter is unable to continue to work because of the lack of the observation vector. At this time, the proposed LS-SVM/FEKF can work using the predicted missing observation vector of the local EKF provide by the LS-SVM.

Fig. 2. The real test environment.

3 Verification

The performance of the proposed LS-SVM assisted FKF will be investigated in this section, which includes the setting of the real test and the performance comparison of the LS-SVM assisted FKF and FKF.

3.1 Real Test Setup

In this subsection, parameters of the real test will be sketched. The real test scene is shown in Fig. 2. In the test, the INS and UWB measure the target's position in parallel. Here, RoboMaster UWB localization system is employed as the UWB localization system. It includes two kinds of nodes: UWB reference nodes (UWB RNs) and UWB blind node (UWB BN). There are four UWB RNs and one UWB BN. The former is pre-positioned on known coordinates, and the latter is pre-positioned on target. The target is located by the change of the distance between the UWB BN and multiple UWB RNs. By placing the INS on the target carrier, information such as acceleration, direction and attitude can be obtained, and speed and position can be obtained through continuous integration of time. And the reference value is provided by a reference system, which includes the encoder and the compass. The reference velocity is provided by the encoder, and the reference orientation is provided by the compass. The sensors' data is collected by the computer. In the test, we set $\Delta T = 0.02s$.

Comparing with the INS, the UWB's trajectory is stable. The root mean square error (RMSE) of INS in east and north are 19.72 and 9.82 respectively. And the RMSE of UWB in east and north are 0.23 and 0.18. One can note that the UWB's localization approaches to the reference path than INS's localization.

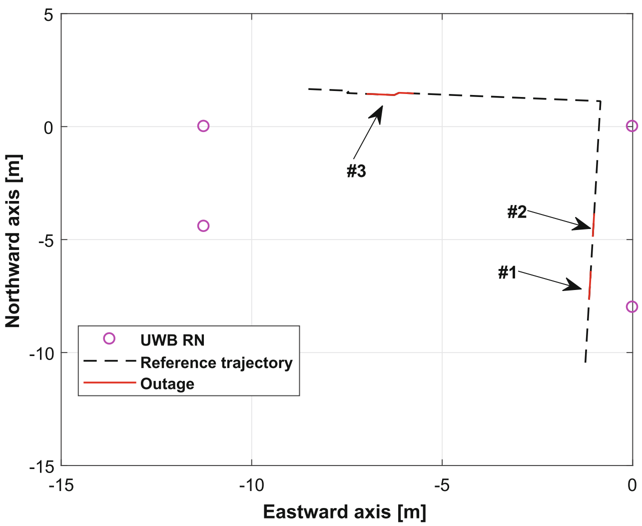

Fig. 3. The simulated outage area (red line). (Color figure online)

3.2 The LS-SVM Assisted FEKF and the FEKF

In this subsection, the performance of the proposed LS-SVM/FEKF will be investigated. In the test, we have created three simulated outage areas, which are shown in Fig. 3. Here, each simulated outage area includes about 50 sample numbers. In these simulated outage area, at least one UWB measurement will be set to be non-updated. If the UWB measurement is unavailable, its logical value is 1, otherwise, its value is 0. It should be emphasized that we do not consider that all the UWB measurements are unavailable in this paper. Once the target in the simulated outage area, the UWB measurement is unable to be updated, the UWB position will be constant. And thus, the measurement error of the data fusion filter will increase.

The RMSEs of the position, in m, produced by the FEKF and LS-SVM/FEKF in #1, #2, and #3 outage area are sketched in Table 1. From the table, we can see that the position RMSEs of the LS-SVM/FEKF are smaller than the position RMSEs of the FEKF. Then we can conclude that, the proposed LS-SVM/FEKF can effectively reduce position error.

Table 1. The RMSEs of position, in m, produced by the FEKF and LS-SVM/FEKF in #1, #2, and #3 outage area.

Method	#1		#2		#3	
	East	North	East	North	East	North
FEKF	0.18	0.71	0.12	0.25	0.36	0.16
LS-SVM/FEKF	0.05	0.13	0.09	0.22	0.29	0.04

4 Conclusion

In this paper, a novel LS-SVM/FEKF for the distributed INS/UWB integrated 2D localization scheme have been investigated to obtain accurate position information. In the proposed scheme, the local data fusion filter is used to fuse the UWB- and INS-derived distances between the UWB RN and the target, and then, the main filter is employed to fuse the local data fusion filter's outputs and compensate the INS position error. Moreover, face the outage of the UWB, the LS-SVM is used to assist FEKF, which can compensate the missing UWB's range. The test results exhibit that the proposed LS-SVM/FEKF can effectively maintain the performance when UWB's range is missing.

Acknowledgment. This work was supported in part by the National Natural Science Foundation of China under Grant 61803175, in part by the Shandong Key R&D Program under Grant 2019GGX104026, Shandong Provincial Natural Science Foundation ZR2020KF027.

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