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XGB ASSISTED SELF-LEARNING KALMAN FILTER FOR UWB LOCALIZATION

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ABSTRACT:

Recent years, more and more mobile robot has been used in many fields. In order to improve the service quality of mobile robot, how to improve the accuracy of robot position information has gradually become a research hotspot in this field. In this work, we will focus on the following situation: in an indoor environment, one mobile robot moves along one similar trajectory repeatedly. And the extreme gradient boosting (XGB) assisted self-learning Kalman filter (KF) will be derived in this work. To the method, the XGB is used to build the mapping between the distances from the ultra wide band (UWB) reference nodes (RNs) to the UWB blind node (BN) and the mobile robot's position. Then, the XGB is used to build the measurement of the Kalman filter by using the off-line and on-line mode, which is able to provide the accurate position information. The real test has bee done, and the results show that the proposed XGB assisted self-learning KF is able to improve the localization accuracy gradually.

1. INTRODUCTION

Recent years, as the key technologies for mobile robots to complete various tasks, the navigation and positioning of mobile robots in indoor complex environment has gradually become a research hotspot in this field (Xu et al., 2021a, Jaenal et al., 2021, Zhao and Huang, 2020).

In order to provide accurate positioning information, many approaches have been proposed (Cui et al., 2019, Zhao et al., 2016). For example, in (Han et al., 2007), one attempt using radio frequency identification (RFID) has been designed, and ultra wide band (UWB) localization technology has been proposed for indoor quadrotor localization (Xu et al., 2021b). It should be pointed out that although the UWB localization technology improves the localization accuracy, its positioning in the indoor environment is still facing challenges. When compared with the back propagation (BP) neural network, the extreme gradient boosting (XGB) algorithm has the advantages of high interpretability, high computational efficiency and less requirements for data (Chen and Guestrin, 2016).

A single learner has a small scope of application, low universality, and cannot show a good prediction effect in the face of complex and highly volatile data. Meanwhile, the model composed of a single learner is not conducive to parameter adjustment and segmentation of multiple features. With the development of The Times, there are more and more kinds of time series data, and algorithms need to adapt to more kinds of data as much as possible while ensuring accuracy. Therefore, the concept of integrated learning algorithm is proposed, which can be divided into Bagging, Boosting and Stacking according to different sampling and training methods (Shi et al., 2010, Zhang et al., 2021, Zhang et al., 2020).

To create training data, bagging employs a band-and-put sampling strategy. Using multiple rounds of return, the original training set is randomly sampled, and several training sets are generated in parallel, corresponding to the training of multiple basic learners (there is no strong dependence between them). Then, to create a strong learner, combine these fundamental learners. The method mainly focuses on the randomness of samples by adding different sampling methods to improve the fitting degree of the model.

The sample composition of the training set used in Boosting algorithm remains unchanged. The algorithm first develops a base learner through the original training group, and then adjusts the distribution of training samples according to the performance of the base learner, so that the training samples made wrong by the previous base learner get more attention in the follow-up, and then trains the next base learner based on the adjusted sample distribution. Finally, the trained base learners are weighted and summed to form the final strong classifier. Boosting algorithm mainly focuses on training models by giving different weights to different samples, in order to distinguish the importance of relevant features in prediction and ultimately improve the prediction accuracy of the model. XGBoost algorithm is one of the most representative algorithms in Boosting class, and it will be introduced in detail next (Chen and Guestrin, 2016). XGBoost algorithm is essentially a method based on Tree structure combined with ensemble learning, and its basic Tree structure is CART (Classification and Regression Tree).

The essence of CART is a binary tree, which continuously divides the sample space by input features. Each region is recursively divided into two sub-regions by setting thresholds for features, and the output values of each sub-region are determined. The criteria for dividing molecular regions depends on the type of tree.

In this work, we investigte the XGB assisted self-learning Kalman filter for UWB localization. In this mode, the XGB is used to build the mapping between the distances $\mathbf{d}^{(\mathrm{UWB})}$ between the UWB reference nodes (RNs) and the UWB blind node (BN) and the mobile robot's position $\mathbf{Po}$. Then, the XGB is used to build the measurement of the Kalman filter, which is able to provide the accurate position information. The rest of the paper is organized as follows. Section 2 presents the scheme of the

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XGB assisted self-learning Kalman filter. Section 3 shows the real test. Section 4 presents the conclusions.

2. XGB ASSISTED SELF-LEARNING KALMAN FILTER

In this section, the XGB assisted self-learning Kalman filter will be designed. Firstly, the scheme of the XGB for the self-learning Kalman filter will be introduced. Secondly, the data fusion model for Kalman filter will be investigated.

2.1 The strategy of XGB assisting KF

The strategy of XGB assisting KF will be designed in this subsection. In this work, we will focus on the following situation: in an indoor environment, one mobile robot moves along one similar trajectory repeatedly. Meanwhile, the localization accuracy decreases since the signal of the localization will be affected by the indoor environment. The XGB assisted self-learning Kalman filter (KF) will be derived to improve the localization accuracy in this work.

In this mode, the XGB is used to build the mapping between the distances $\mathbf{d}^{(\mathrm{UWB})}$ from the UWB reference nodes (RNs) to the UWB blind node (BN) and the mobile robot's position $\mathbf{Po}$. Then, the XGB is used to build the measurement of the Kalman filter, which is able to provide the accurate position information. The XGB assisted self-learning Kalman filter needs the following steps:

- In the offline mode, we measure the $\mathbf{d}_{offline}^{(\mathrm{UWB})}$ on the fixed point's position $\mathbf{Po}_{offline}$. Then, both the XGB is used to build the mapping between the $\mathbf{d}_{offline}^{(\mathrm{UWB})}$ and the $\mathbf{Po}_{offline}$, which is shown in Fig. 1.
- In the online mode, when XGB is in estimation mode, the $\mathbf{d}_{t}^{(\mathrm{UWB})}$ input to the XGB, and then, the XGB outputs the $\mathbf{P\hat{o}}_{\mathrm{t}}$ by using the mapping between the $\mathbf{d}^{(\mathrm{UWB})}$ and the $\mathbf{Po}$, which is built in offline mode. The strategy of the online mode when the XGB is in estimation mode is shown in Fig. 2.
- When the XGB is training mode, the XGB builds the mapping between $\mathbf{d}_{offline}^{(\mathrm{UWB})} + \mathbf{d}_{1:t}^{(\mathrm{UWB})}$ and $\mathbf{Po}_{offline} + \mathbf{Po}_{1:t}$, which is used for the KF in the next time index. The strategy of the online mode when the XGB is in training mode is shown in Fig. 3.

2.2 The XGB method

The process of CART generation is actually a process of selecting features. Let's say we have a total of multiple features. The first step is to select a feature as the first node of the binary tree. Then select a segmentation point for the value of the feature. When the value of a sample feature is smaller than the segmentation point, it is divided into one category; if it is larger than the segmentation point, it is divided into another category. This builds one node of the CART tree and continues to generate other nodes through this method. Finally, after layer segmentation, the final node is given a certain value or category, that is, as the final prediction result. CART usually adopts the squared error minimization standard. The objective function generated by CART regression tree is:

$$\sum\nolimits_{x_i \in R_m} \left(y_i - f(x_i)\right)^2, \tag{1}$$

where $f(x_i)$ represents the fitted data, y_i represents the real data, and the function represents the sum of variances.

XGBoost model integrates the concept of integrated learning from the binary tree model, and XGBoost model is also a special GBDT. GBDT is an algorithm for data classification or regression by using an additive model (i.e. a linear combination of basis functions) and continuously reducing residuals generated during training. The XGBoost algorithm adds trees by adjusting the weight distribution of the sample, adding one tree at a time (essentially learning a new function) to fit the previously predicted residuals. XGBoost can define a set of objective functions, which can be converted into a unary quadratic function by Taylor expansion. The extreme point and the objective function of extreme XGBoost are as follows:

$$L(\phi) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k), \tag{2}$$

By adjusting the output of the base learner and the weight coefficients of each base learner, the fitting degree of the model is finally improved. The higher the accuracy of the model is, the lower the value of the objective function will be. On the contrary, if the objective function is high, the weight of the correlation learner will be adjusted by feedback.

In the objective function of XGBoost algorithm, $\sum\limits_k \Omega(f_k)$ represents the regularization term. When data is fitted by function, in fact, the real data is fitted by accumulative method through multiple influence factors (i.e. independent variables) with different weights. The formula is as follows:

$$f(x_i) = w_0 x_0 + w_1 x_1 + w_2 x_2 + \cdots + w_n x_n, \tag{3}$$

The independent variable x is the training feature in the data set. However, in the process of machine learning, many features have low weight in sample learning and can be discarded. Although over-fitting can make the algorithm train with high accuracy, the generality of the model will become poor, and its classification is only suitable for the current training data set. With the expansion of the data set, the more real samples need to be classified, and the practicability of the model will decrease. Therefore, it is always a major task to avoid the over-fitting of the model under the current data.

The prediction accuracy of the algorithm model is jointly determined by the deviation and variance between the model and the actual data, that is, the prediction data should be as close to the actual data as possible to reduce the deviation, and the allowable data fluctuation range should be defined to reduce the variance between the model and the actual data. The objective function of XGBoost algorithm is composed of loss function and regularization term. The loss function represents the deviation of the model, and the regularization term represents the variance of the model. The algorithm will reduce the number of samples in the fitting function as much as possible (in the algorithm structure of XGBoost, each tree should not be too complicated for the improvement of accuracy). To prevent the occurrence of over-fitting conditions.

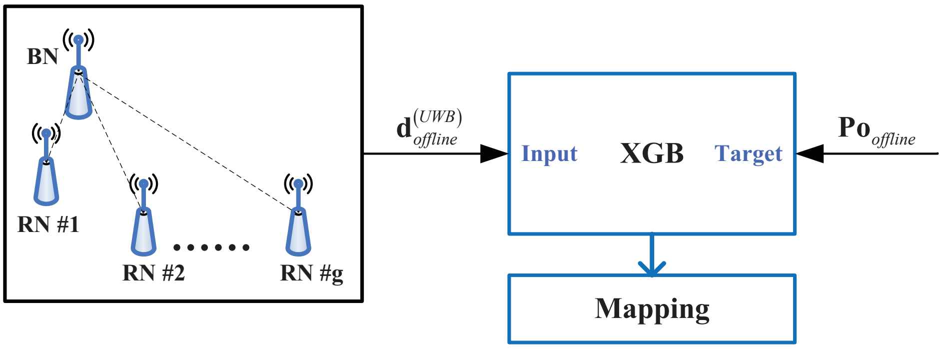

Figure 1. The strategy of the offline mode.

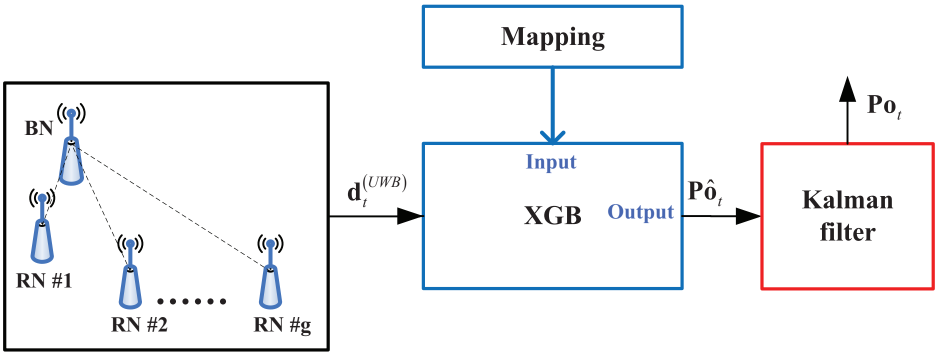

Figure 2. The strategy of the offline mode when the XGB is in estimation mode.

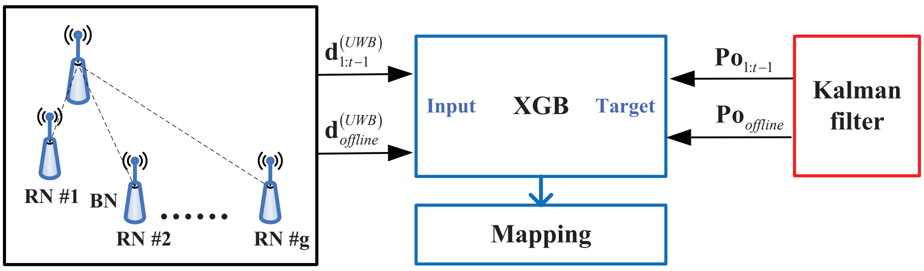

Figure 3. The strategy of the offline mode when the XGB is in training mode.

2.3 The data fusion model of the KF

The data fusion model used in this work will be introduced in this subsection. The state equation used by KF in this work is listed ib Eq. (4).

$$\underbrace{\begin{bmatrix} \mathrm{x}_t^- \\ \mathrm{Vx}_t^- \\ \mathrm{y}_t^- \\ \mathrm{Vy}_t^- \end{bmatrix}}_{\mathbf{x}_t^-} = \underbrace{\begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} \mathrm{x}_{t-1} \\ \mathrm{Vx}_{t-1} \\ \mathrm{y}_{t-1} \\ \mathrm{Vy}_{t-1} \end{bmatrix}}_{\mathbf{x}_{t-1}} + \mathbf{w}_t\,, \quad (4)$$

where the sampling interval is denoted as Δt; x_t and y_t are the robot's position in x and y direction in the time index t respectively; Vx_t and Vy_t are the robot's velocity in x and y direction in the time index t respectively; and $\mathbf{w}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_t)$ means the system noise.

The measurement equation used by KF in this work is listed ib Eq. (5).

$$\underbrace{\begin{bmatrix} \hat{x}_t \\ \hat{y}_t \end{bmatrix}}_{\mathbf{z}_t} = \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}}_{\mathbf{G}} \underbrace{\begin{bmatrix} x_t^- \\ y_t^- \end{bmatrix}}_{x_t^-} + \mathbf{v}_t\,, \quad (5)$$

where $\mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_t)$ means the measurement noise. The code of the KF filtering algorithm based on model (4) (5) is listed in Algorithm 1.

3. TEST

In this section, we will employ one real test to show the performance of the proposed method. Firstly, the parameters of the experimental equipment and the data fusion filter will be introduced. and then, the performance of the proposed method will be compared.

3.1 The setting of the test

In this subsection, the parameters of the experimental equipment and the data fusion filter will be introduced. In this work,

Algorithm 1: The KF filtering algorithm based on model (4) (5)

Data: $\mathbf{z}_t$, $\hat{\mathbf{x}}_0$, $\hat{\mathbf{P}}_0$, $\mathbf{Q}_t$, $\mathbf{R}_t$
Result: $\hat{\mathbf{x}}_k$
begin
  for $t = 1 : \infty$ **do**
    $\hat{\mathbf{x}}_t^- = \mathbf{F}\hat{\mathbf{x}}_{t-1}$
    $\hat{\mathbf{P}}_t^- = \mathbf{F}\hat{\mathbf{P}}_{t-1}\mathbf{F}^T + \mathbf{Q}_\mathbf{t}$
    $\mathbf{K}_t = \hat{\mathbf{P}}_t^- \mathbf{G}^T \left(\mathbf{G}_t \hat{\mathbf{P}}_t^- \mathbf{G}^T + \mathbf{R}_t\right)^{-1}$
    $\hat{\mathbf{x}}_t = \hat{\mathbf{x}}_t^- + \mathbf{K}_t \left[\mathbf{z}_t - \mathbf{G}\hat{\mathbf{x}}_t^-\right]$
    $\hat{\mathbf{P}}_t = (\mathbf{I} - \mathbf{K}_t\mathbf{G}_t)\,\hat{\mathbf{P}}_t^-$
  end for
end

one real test will be done in the No.2 teaching building of the University of Jinan, China. Fig. 4 displays the real test environment used in this work. In this work, we employ four UWB reference nodes (RNs) and one UWB blind node (BN). From the figure, we can see that four UWB RNs are fixed on the known position, and the UWB BN is fixed on the mobile robot, which is shown in Fig. 5. Moreover, in this work, in order to provide the reference path, we use the LiDAR, which is also fixed on the mobile robot. The architecture of experimental platform used in this work is shown in Fig. 6. In the test, the LiDAR used in this work can provide the reference path by using the environmental characteristics. The UWB localization system is used to provide the robot's position. In this test, two computers are used. The computer fixed on the mobile robot is used to collect the sensors's data, Meanwhile, the other computer is used to control the mobile robot. To the data fusion filter, we set $\Delta t = 0.2s$, $\mathbf{Q}_t = \mathbf{I}_{4\times4}$ and $\mathbf{R}_t = \mathbf{I}_{2\times2}$ in this work.

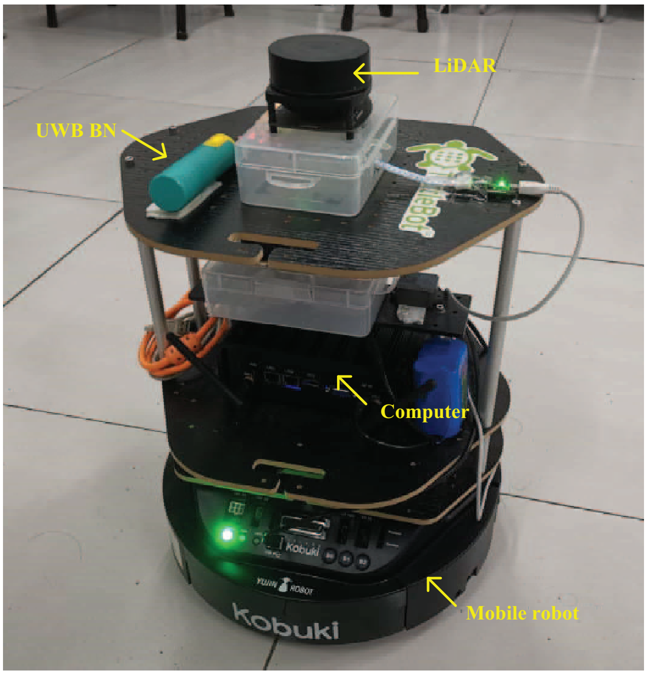

Figure 5. The mobile robot used in this work.

3.2 The localization error

In this section, the localization error of the proposed method will be investigated. In the test, firstly, we collect some distances between the UWB RNs and the UWB BN. It should be pointed out that the UWB BN's position used for the off-line training is static points, the static points' positions for the off-line training of the XGB method used in this work are shown in the Fig.7.

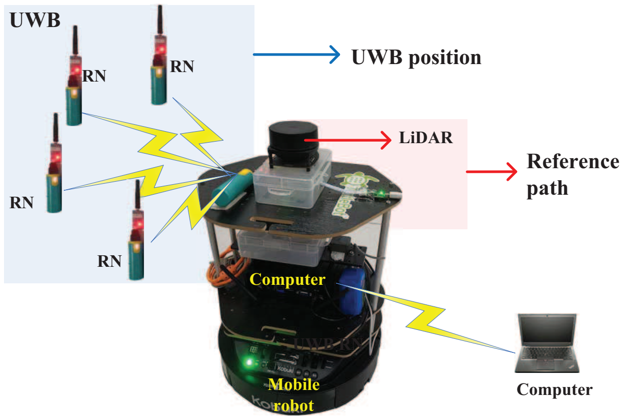

Figure 6. The architecture of experimental platform used in this work.

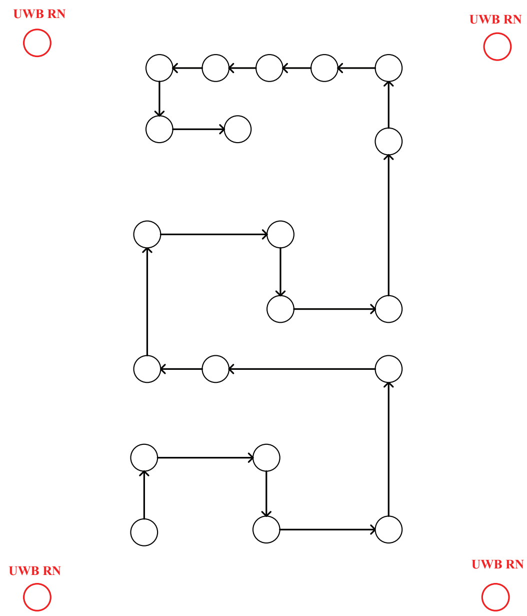

Figure 7. The static points' positions for the off-line training of the XGB method used in this work.

In this test, we firstly measure the $\mathbf{d}_{offline}^{(\mathrm{UWB})}$ on the fixed point's position $\mathbf{Po}_{offline}$. Then, both the XGB is used to build the mapping between the $\mathbf{d}_{offline}^{(\mathrm{UWB})}$ and the $\mathbf{Po}_{offline}$, which is shown in Fig. 1. Secondly, we require the robot to run follow a similar trajectory three times. The positions of the XGB and XGB+KF in X and Y directions of the first time are shown in Figs. 8 and 9. Figs. 10 and 11 display the positions of the

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Figure 4. The real test environment.

XGB and XGB+KF in X and Y directions of the second time. And the Figs. 12 and 13 display the positions of the XGB and XGB+KF in X and Y directions of the third time. From the figures, we can see that all the methods can provide the accurate position information. When compared with the performance of the first time, the positions estimated in the third time are more closer to the reference path. The position errors of the cumulative distribution function (CDF) are shown in Fig. 14. And its enlarged view near 0.9 is shown in the Fig. 15. From the figure, we can see that the proposed method is able to improve the localization accuracy gradually.

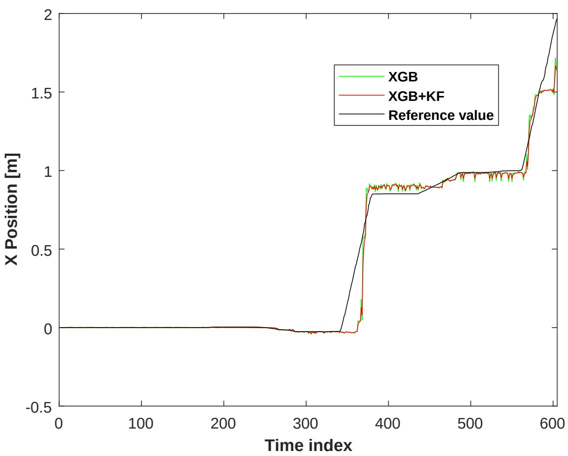

Figure 8. The position of the XGB and XGB+KF in X directions of the first time.

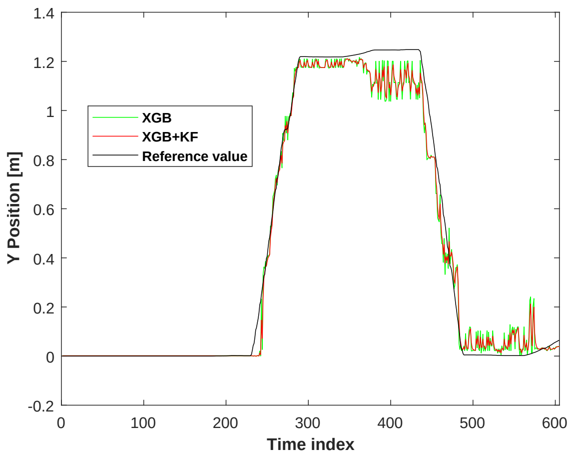

Figure 9. The position of the XGB and XGB+KF in Y directions of the first time.

4. CONCLUSIONS

In this work, we will focus on the following situation: in an indoor environment, one mobile robot moves along one similar trajectory repeatedly. And the extreme gradient boosting (XGB) assisted self-learning Kalman filter (KF) has been derived in this work. To the method, the XGB has been used to build the mapping between the distances from the UWB reference nodes (RNs) to the UWB blind node (BN) and the mobile robot's position. Then, the XGB has been used to build the measurement of the Kalman filter by using the off-line and on-line mode, which is able to provide the accurate position information. The real test has bee done, and the results show that the proposed XGB assisted self-learning KF is able to improve the localization accuracy gradually.

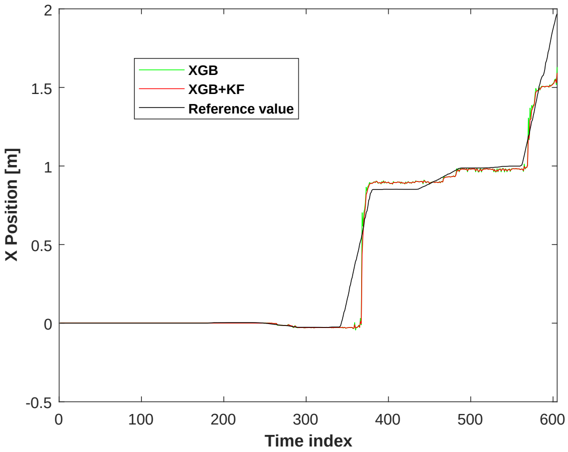

Figure 10. The position of the XGB and XGB+KF in X directions of the second time.

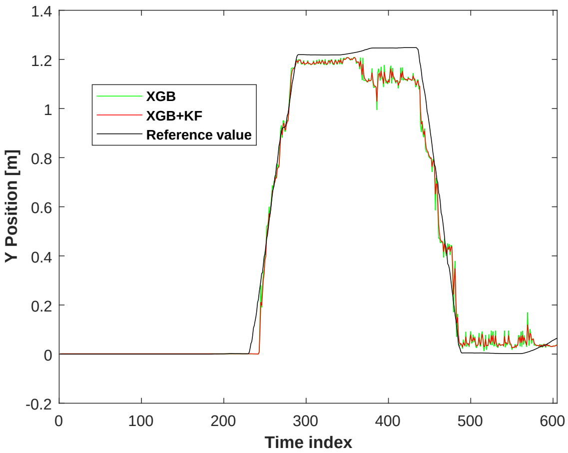

Figure 11. The position of the XGB and XGB+KF in Y directions of the second time.

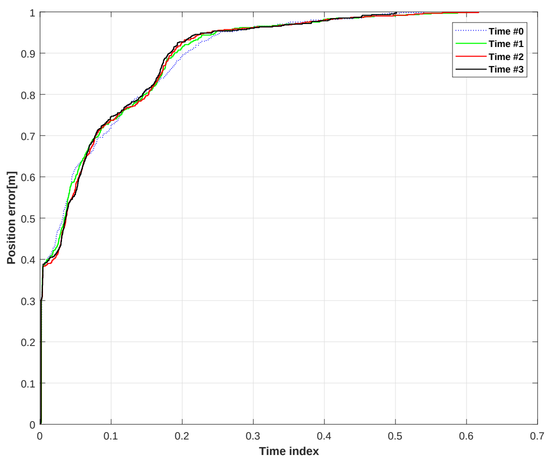

Figure 12. The position of the XGB and XGB+KF in X directions of the third time.

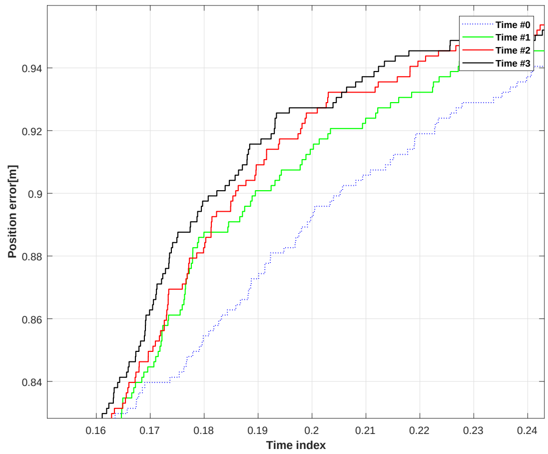

Figure 13. The position of the XGB and XGB+KF in Y directions of the third time.

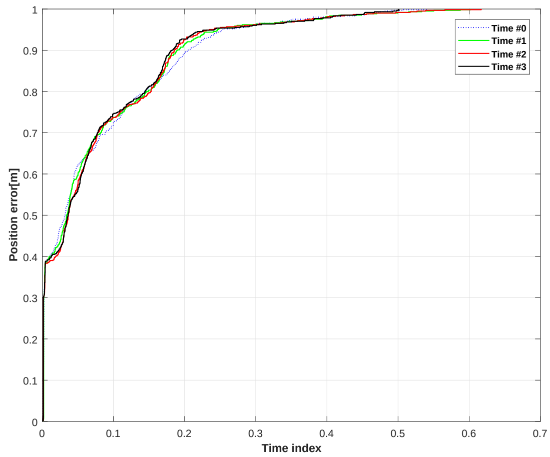

Figure 14. The position errors of the CDF.

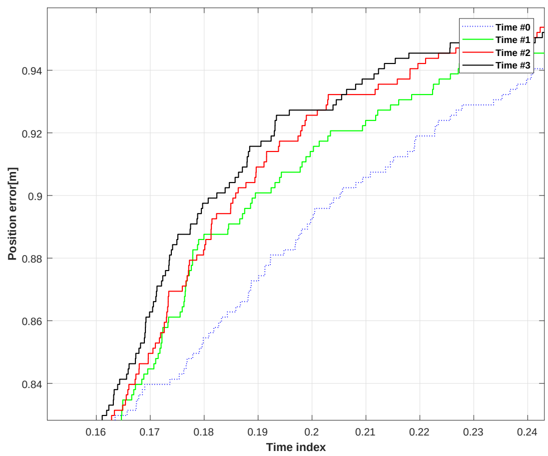

Figure 15. The position errors of the CDF at 0.9.

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