High-accuracy ultrasonic positioning through optimization of the extended Kalman filter algorithm

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Abstract

The application of extended Kalman filter algorithm to ultrasonic positioning systems has difficulty in meeting the requirements of precision positioning because the algorithm produces a new calculation error when the system is linearized. Modal optimization of the extended Kalman filter algorithm is thus investigated. The received ultrasonic signal is first decomposed by empirical mode decomposition, the intrinsic mode functions that best represent the original signal are then selected to restructure the waveform, and the transition time is finally corrected. Meanwhile, the ultrasonic wave velocity can be corrected. Traditional ultrasonic positioning can also be improved by combining with a radio-frequency module. It is experimentally shown that the proposed method limits positioning error to within ±5 cm and within ±1 cm after multiple recursions.

Keywords: ultrasonic location, extended Kalman filter algorithm, modal optimization, intrinsic mode function, transition time

1 Introduction

With the development of the Internet of Things, information services based on the process of location (i.e., positioning) have become increasingly available [1]. Services such as intelligent parking lots, intelligent storage and other indoor services require positioning to be highly accurate. Furthermore, positioning using the Global Positioning System (GPS) is often affected by buildings shielding the satellite signal and is subject to error, making it particularly difficult to position accurately indoors[2-3]. Wireless local area network (WLAN) positioning is a mature indoor location technology but its positioning mode is strongly affected by the environment and its reliability is difficult to ensure. In addition, IEEE 802.11 specifications do not provide accurate measurement and control models of transmission power, making it difficult to make measurements with higher accuracy.

Compared with GPS and WLAN positioning, positioning with an ultrasonic wave has advantages in indoor locations, including its simple system structure, inexpensive hardware, high accuracy, and feasible algorithm [4]. However, because an ultrasonic wave can be disturbed by uncertain factors such as temperature, the shape of the detected object changes and noise and error perturbations are generated during positioning [5], which can reduce the accuracy and reliability of the positioning. As technologies and methods proposed in the literature [6, 7] are unable to control the error, the positioning accuracy reduces.

Adopting empirical mode decomposition (EMD) to optimize the extended Kalman filter algorithm, this paper effectively controls the error of transition time, thus realizing highly accurate indoor positioning [8]. This modal optimization method first decomposes the ultrasonic signal obtained from the receiving system of the ultrasonic wave by EMD and then removes a large proportion of the noise while retaining the original characteristics of the signal. The envelope of the signal is then obtained employing EMD again to obtain the time that the ultrasonic wave signal arrives accurately, and the Kalman filter algorithm finally corrects the transition time, thus providing highly accurate positioning results.

2 Shortcomings of the extended Kalman filter algorithm in eliminating error

2.1 ORIGIN AND ELIMINATION OF TRANSITION TIME ERROR

Ultrasonic positioning involves receiving ultrasonic waves launched at different fixed positions to estimate an object's position. Its principle is described in Figure 1, in which A and B are ultrasonic wave launchers at fixed positions, and C is an ultrasonic wave receiver installed on the detected object. A correlation model is adopted between the launcher and receiver.

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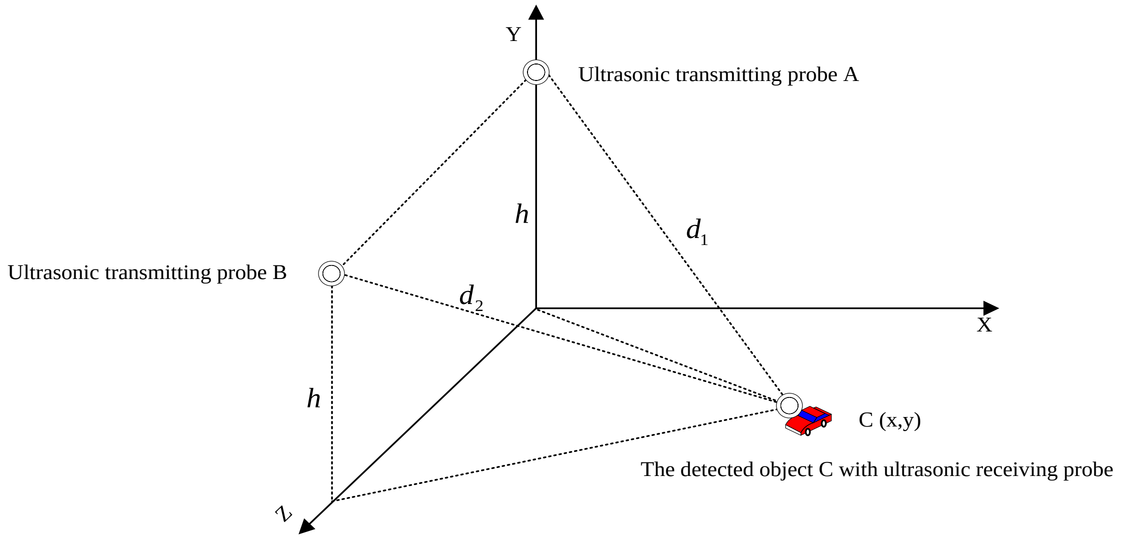


FIGURE 1 Basic structure of the ultrasonic-wave ranging system

The sound velocity of the ultrasonic wave is denoted v, the transition time of the ultrasonic wave from A and B to C is denoted t, and the lengths d_1 and d_2 of AC and BC respectively can be determined using the formula $d = vt$. The coordinates of the detected object can then be obtained through triangulation. However, the formula $d = vt$ is inaccurate to some extent and should be presented as $d = (v + v')(t + t')$, where v' is the error in the sound velocity and t' is the error in transition time. Therefore, the premise of highly accurate positioning is to eliminate the errors in the sound velocity and transition time.

The main method of eliminating error in the sound velocity is temperature compensation. Sound velocity v of an ultrasonic wave depends on the pressure, density and other features of the propagation medium, but especially on temperature; changes in temperature are one of the main sources of error in ranging with ultrasonic waves. The relation between the propagation velocity of an ultrasonic wave and temperature is $V = v_0\sqrt{1+T/T_0}$, where v_0 is the sound velocity at normal temperature (v_0 = 331.45 m/s), T is the environmental temperature, and T_0 = 273.16 °C. The error in the sound velocity generated by a temperature change can be effectively eliminated by temperature compensation.

There are many processing methods of eliminating the error in transition time, such as amplification via automatic generation control to reduce the trigger error before the signal enters the control chip, and adjusting the threshold value for different measuring distances; using a dual comparator shaping circuit to determine the time that the forward edge of the echo arrives, and designing a circuit whose threshold voltage reduces with time; making multiple measurements and taking the average to eliminate the error in a single measurement; adopting an ill-conditioned mathematical method to match the relationship between the measured value and true value; and using a back-propagation neural network to carry out nonlinear correction. All the methods mentioned play a part in correcting the error in transition time, but the requirements of highly accurate positioning are difficult to meet owing to the characteristics of the digital circuit and the shortcomings of the above algorithms. This paper employs the extended Kalman filter algorithm for modal optimization, thus effectively eliminating the error in transition time.

2.2 EXTENDED KALMAN FILTER ALGORITHM

The extended Kalman filter algorithm is an improvement on the Kalman filter algorithm. The Kalman filter algorithm can only be applied to linear systems, and thus a linear approximation needs to be made for a nonlinear system and then the Kalman filter algorithm applied to the linearization model. The Kalman filter is an optimal recursive data processing algorithm that estimates the minimum variance of the signal to be processed using the system state equation and observed relation.

The ultrasonic location system can be described as hollows:

$$X_k = f(X_{k-1}, W_{k-1}), \quad (1)$$

$$Z_k = h(X_k, V_{k-1}), \quad (2)$$

where X_k is the system state variable and Z_k is the system observation variable, while W_{k-1} and V_{k-1} are the system noise and observation noise respectively. The system model is linearized using a Taylor expansion and the Kalman filter is then applied. The recursive process of the Kalman filter algorithm is shown in Fig. 2.

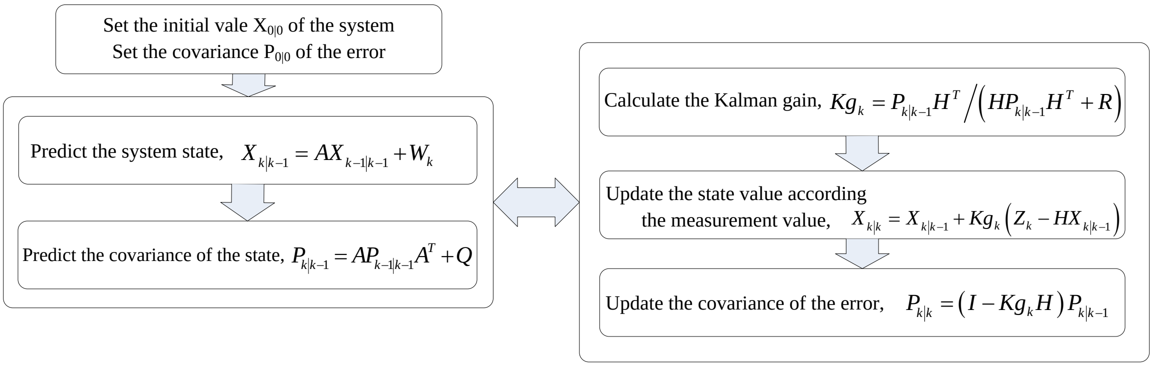


FIGURE 2 Recursive process of the Kalman filter algorithm

The extended Kalman filter algorithm can perfectly handle a dynamical system with noise, and it is widely used in ultrasonic positioning. Furthermore, the Kalman filter algorithm and extended Kalman filter algorithm were adopted in Ref. [9] and Ref. [10] to good effect. However, the two algorithms have some limitations: the Kalman filter algorithm can only be applied to a linear model while theextended Kalman filter algorithm uses a Taylor expansion in transforming a nonlinear model to a linear model and abandons all high-order components, leading to inestimable error [11]. The results obtained with the extended Kalman filter depend on the statistical characteristics of the state noise and observation noise, and if the evaluation of covariance matrices of the two types of noise is not sufficiently accurate, cumulative errors are generated. The existence of the Jacobian matrix and the complexity of the calculation are also factors of unreliability.

The evaluation of the transition time relies critically on the selection of the time that the ultrasonic wave arrives. As a result of the effect of noise and other factors, the waveform signal becomes complicated when the ultrasonic wave arrives at the receiver, which can impair the determination of the arrival time of the ultrasonic wave by the receiver detection circuit and prevent the measurement of the arrival time when the ultrasonic wave first arrives at the pulse edge. Therefore, directly applying the extended Kalman filter algorithm to the ultrasonic signal model from the receiving edge will cause inestimable error.

On the basis of the above discussion, modal optimization of the extended Kalman filter algorithm will be carried out. Replacing the Taylor expansion with EMD can effectively eliminate the problems discussed above.

3. Extended Kalman filter algorithm after modal optimization

3.1 PROCESS OF MODAL OPTIMIZATION

This paper applies modal optimization to the extended Kalman filter algorithm using the EMD algorithm, whose basic method is first to decompose the received ultrasonic signal x(t) by EMD to obtain intrinsic mode functions (IMFs) and then to obtain a pure ultrasonic signal with most noise filtered out through the screening and recombination of IMFs. The process of modal optimization is shown in Figure 3.

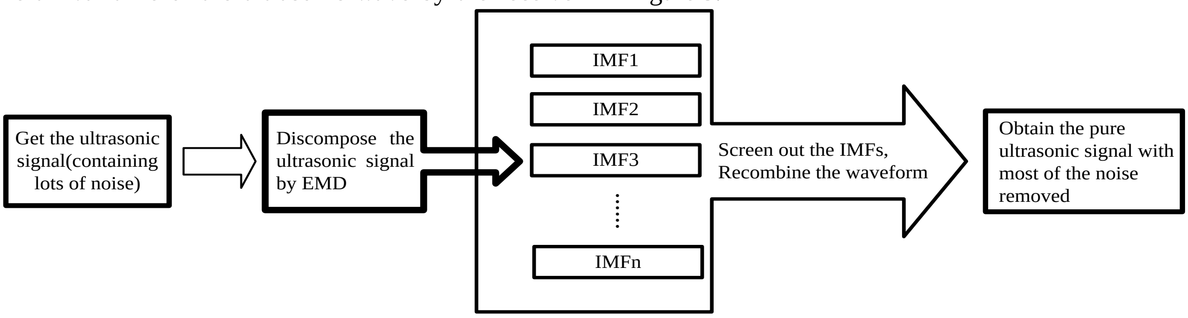


FIGURE 3 Process of modal optimization

According to the local characteristic time scale of the signal, the EMD method decomposes the signal into a finite number of IMFs whose frequencies range from high to low, and then obtains $x(t) = \sum_{i=1}^{n} c_i + r_n$, where c_i is an IMF and r_n is the residual term. A low-order IMF represents a high-frequency component of the signal and mainly contains sharp parts of the noise and signal, while a high-order IMF represents a low-frequency component of the signal and mainly contains the signal and little noise. There must therefore be a k th IMF component, either side of which the energy of the noise and signal suddenly change, meaning that the first k IMFs are oriented toward the noise while the remaining IMFs are guided by the signal. Therefore, the key to performing the modal optimization of the extended Kalman filter algorithm is to seek out the IMF for which there is a sudden change in energy. This paper employs the successive mean-square error method:

$$CMSE\left(\tilde{x}_k, \tilde{x}_{k+1}\right) = \frac{1}{N}\sum_{i=1}^{N}\left[IMF_k\left(t_i\right)\right]^2 \quad k+1\left(=1,\cdots,\mathrm{n}-1\right). \tag{3}$$

The k th IMF corresponding to a sudden energy change can then be found. The definition of k is

$$k = \underset{1\le k\le N}{\operatorname{argmin}}\left[CMSE\left(\tilde{x}_k, \tilde{x}_{k+1}\right)\right] + 1. \tag{4}$$

That is to say, the IMF whose energy is the global minimum is regarded as the boundary point of the abrupt change in energy. In the case of a low signal-to-noise ratio, the energy of an IMF dominated by certain signals is lower than that dominated by noise, and k corresponding to the global minimum is defined as

$$k = \underset{1 \le k \le N}{\text{argfirstlocalmin}} \left[CMSE\left(\tilde{x}_k, \tilde{x}_{k+1} \right) \right] + 1 . \quad (5)$$

After finding the k th IMF corresponding to the abrupt energy change employing this method, the signal is reconstructed from the $k+1$ th IMF to the final IMF, and the ultrasonic signal $\tilde{x}(t)$ with the vast majority of noise removed can then be obtained:

$$\tilde{x}(t) = \sum_{i=k+1}^{N} imf_i(t) . \quad (6)$$

The extended Kalman filter algorithm can thus be used to estimate the transition time.

3.2 OPTIMIZED EXTENDED KALMAN FILTER ALGORITHM

The optimized extended Kalman filter algorithm adopts EMD to replace the Taylor expansion, which is conducive to obtaining an ultrasonic signal with most noise removed and its enveloped empirical model. Employing this model, the arrival time of the ultrasonic wave can be obtained. The Kalman filter algorithm is then used to estimate the arrival time of the ultrasonic wave, and finally, the transition time of the ultrasonic wave is accurately obtained.

From the discussions in sections 2.2 and 3.1, the basic steps of the optimized extended Kalman filter algorithm can be summarized as follows.

Step 1: Decompose the ultrasonic signal obtained from the ultrasonic receiver by EMD, and then obtain the IMF components and residual term.

Step 2: Search for the energy breakpoint k according to the distribution of the IMF components, recombine the IMF components from the $k+1$ th component to the final component, and thus obtain the ultrasonic signal with most noise removed.

Step 3: Employ EMD to extract the upper envelope of the signal according to the result of step 2, and then output the envelop signal.

Step 4: Apply the envelop signal from step 3 to the rectification, and obtain the arrival time of the ultrasonic wave.

Step 5: Keep the position of the detected object obtained from multiple measurements, and process the arriving ultrasonic wave successively using steps 1–4, thus obtaining a set of results. Establish an array to store the data.

Step 6: Predict the next state of the array from step 5 as the state value of the system, and forecast the covariance of the state.

Step 7: Calculate the Kalman gain, update the state value in accordance with the measured value, and update the covariance of the error. Output the optimal estimated value.

Step 8: Put the obtained transition time and revised sound velocity into the locating calculation formula, and obtain the location coordinates of the detected object.

The process of the algorithm is shown in Figure 4.

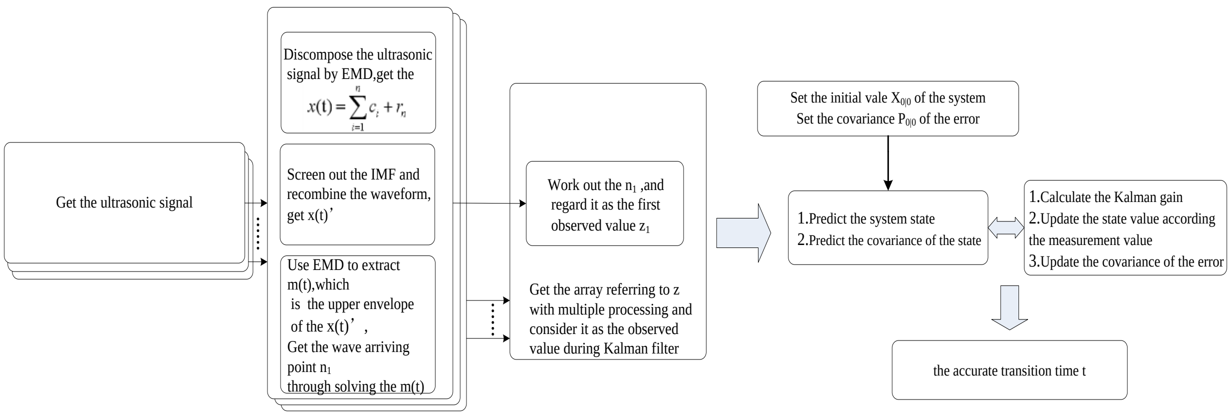


FIGURE **4** Process of the optimized extended Kalman filter algorithm

4 System design and experimental analysis

4.1 SYSTEM DESIGN

Positioning a target object on a plane requires a coordinate system to be established and the transmitting probe of the ultrasonic wave to be defined. To measure the planar coordinates, which are two unknown numbers, at least two relations referring to object coordinates are needed.

The deployment of the system is presented in Figure 5. Two probes transmitting ultrasonic waves are installed at fixed positions with known coordinates, and the receiver is mounted on the detected object, thus establishing a ranging system consisting of two satellites (i.e., the probes). The two satellites comprise three parts: the micro controller unit, ultrasonic ranging module and radio-frequency module. The two satellites transmit ultrasonic waves from different positions and measure the distance to the target object separately, and the coordinates of the object can thus be determined from the distance relationship between the target object and two ultrasonic launchers. If the detected object is R(x,y) and the ultrasonic receiver is installed on R, then the two satellites have a master–slave relationship, in which the primary component is $T_1(X_1,Y_1)$ while the subordinate component is $T_2(X_2,Y_2)$, and the positions of the two satellites are known. H denotes the terrain clearance and d_1 and d_2 denote the straight-line distances to R, respectively.

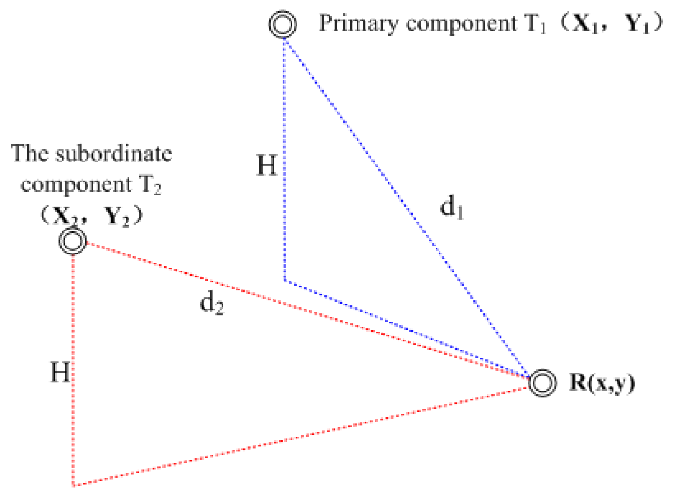
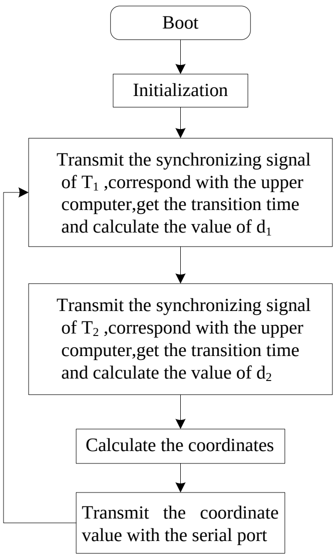
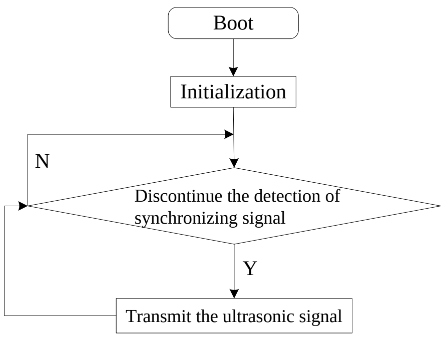


FIGURE **5** Ultrasonic ranging system

The primary component T_1 and subordinate component T_2 are transmitters, and the detected objected R is the receiver. The workflows of the transmitter and receiver are shown in Figure 6.



a) Workflow of the receiver



b) Workflow of the transmitters

FIGURE **6** Workflows of the receiver and transmitters

The receiver initiates the positioning event. The receiver first transmits a radio-frequency signal to the transmitters that it is ready to receive ultrasonic waves. Upon receiving the radio-frequency signal, T_1 and T_2 immediately transmit ultrasonic waves; the delay time is approximately 1 ms. The receiver takes turns in synchronizing with T_1 and T_2, while each transmitter receives an interrupted synchronizing signal.

The design of the system not only reduces the processing load but also reduces the receiver's reaction delay and system delay. The receiver transfers the received ultrasonic signal to the upper computer, which uses the optimized extended Kalman filter algorithm for processing and returns the calculated transition time to the receiver. The receiver determines the propagation distances of ultrasonic waves d_1 and d_2 according to the transition times. From the coordinate relationships among T_1, T_2 and R, it follows that:

$$\left(x-X_1\right)^2+\left(y-Y_1\right)^2+H^2=d_1^{\,2}\,, \tag{7}$$

$$\left(x-X_2\right)^2+\left(y-Y_2\right)^2+H^2=d_2^{\,2}\,. \tag{8}$$

Thus, $x=\sqrt{d_1^{\,2}-H^2-(Y^2-y)^2}$ and the coordinates of the detected object can be determined. This system can also be applied to simultaneously locate multiple detected objects.

4.2 EXPERIMENTAL ANALYSIS

To study the performance of the optimized extended Kalman filter algorithm in the estimation of the transition time, an experiment was conducted for a ranging system comprising a primary component T_1 and detected object R as shown in Figure 5. The experiment involves measuring the distance between T_1 and R. The distance d_1 between the primary component T_1 and the detected object R is a fixed value of 4 m, which will contrast with experimental data presented later.

Because the recursion of the algorithm is reasonably rapid, 80 measurements of d_1 were made using T_1 to get sufficient measurement data for calculation. The operation of the extended Kalman Filter algorithm requires an initial value of state of d_1 to be inputted; this value is randomly set as $X_{0|0}$ = 3.8 m. After the initial value is inputted, the extended Kalman filter algorithm and T_1 begin to work cooperatively, and data analysis is carried out after 80 calculations.

Two sets of measurements were made to highlight the effect of modal optimization. The first set of measurements directly applies the extended Kalman filter to the received ultrasonic signal instead of modal optimization; the obtained distance data are shown in Figure 7. The second set of measurements applies the extended Kalman filter algorithm with modal optimization; the obtained distance data are shown in Figure 8. Figure 9 shows the convergence tendency of the error.

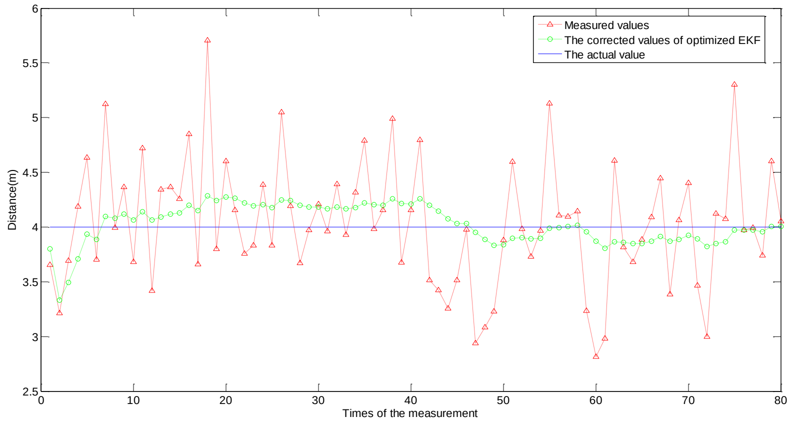


FIGURE 7 Distance data for the first set of measurements

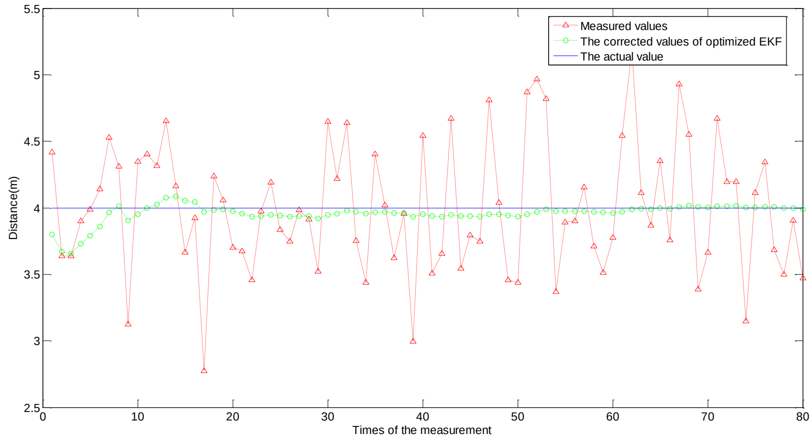


FIGURE 8 Distance data for the second set of measurements

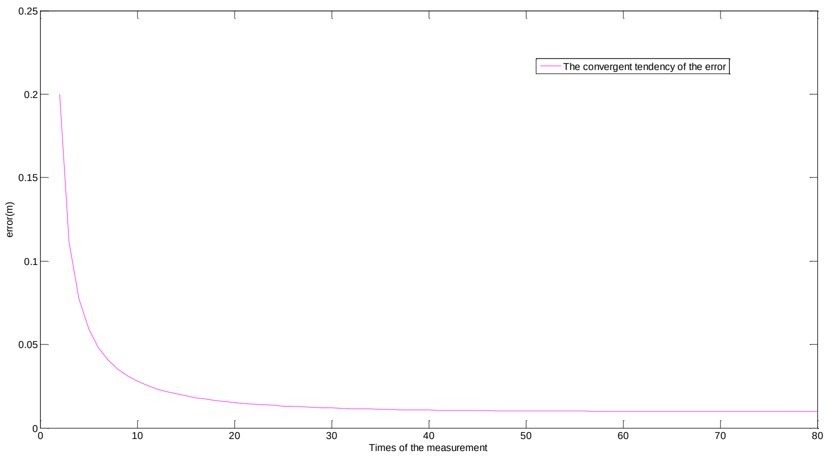


FIGURE 9 Convergence of the error in the second set of measurements

In Figure 7, the red line represents the measurement of d_1 by the positioning system, the green line represents the value amended by the extended Kalman filter algorithm, and the blue line is the actual value. It is clear that the error greatly decreases and the correction value is much closer to the actual value when using extended Kalman filter algorithm. However, much error remains, with more than 70% of the data points having errors exceeding ±5 cm and 50% of the data points having errors in excess of ±15 cm.

In Figure 8, the green line shows the results optimized and processed by the extended Kalman filter algorithm with modal optimization, the red line shows the measured values, and the blue line shows the actual values. The revised value after modal optimization is seen to closely approach the actual value. After the first 10 recursions, the error is basically controlled within ±5 cm, and the effect of optimization is thus clear. Figure 9 shows the convergence of the error in the second set of measurements; after 50 recursions, the error remains within ±1 cm. Modal optimization of the extended Kalman filter algorithm thus improves the measurement accuracy, with the error effectively controlled within ±5 cm, or even ±1 cm after many recursive calculations, which meets the requirements of highly accurate positioning indoors.

5 Summary

Ranging systems are established by adopting advanced modules, yet the requirements of high accuracy measurements have not been met. There are many factors resulting in ranging error, including changes in the characteristics of ultrasonic media, environmental noise and the limits of hardware circuits. This paper greatly avoided error due to the limits of hardware through improvement of the workflow of the location system, temperature compensation in accurately obtaining the ultrasonic sound velocity, and improvement of the extended Kalman filter algorithm using EMD in accurately obtaining the transition time. The positioning error was thus limited within ±1 cm and meets the required accuracy of millimeter-level positioning. However, significant positioning error remains. Although this paper improved the performance of system hardware and improved waveform restructuring by introducing EMD, how to select the IMFs that best represent the original waveform by eliminating the most noise remains as future work.

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