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Kalman Filter Localization Algorithm Based on SDS-TWR Ranging

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Abstract

Node localization is the basic mechanism for wireless sensor networks. Which location data is indispensable information in the monitoring of events. In this paper, we proposed a new algortithm which is the Kalman filter localization algorithm based on SDS-TWR ranging method in order to solve the problem of node localization. Firstly, we use SDS-TWR algorithm to rang distance between the archor nodes and unknown node. Then, we sketchy calculate the unknown node coordinates using weighted maximum likelihood estimation (WMLE) method. Lastly, we use the Kalman filter algorithm to optimize the coordinates of the second step. The experimental results show that the algorithm can effectively improve the positioning accuracy of the system and achieve the desired objectives.

Keywords: *SDS-TWR, WMLE, Kalman filter*

1. Introduction

Node positioning in wireless sensor network, relys on the distribution of a limited number of anchor nodes [1]. Through some mechanism to determine the unknown node location information in wireless sensor networks. The sensor nodes are usually randomly deployed through self-organization to coordinate the work. The node localization problem is the most basic and most important part in the wireless sensor, because it is not perceived without the sensor nodes'location.

The node localization problem in sensor networks includes range-based localization and range-free localization [2]. The former relies on range (or distance) measurements between nodes that can be estimated by the received signal strength (RSS) method or the time-of-arrival (TOA) method [3], while the latter uses only connectivity information.Correspondingly, localization algorithms can be grouped into range-based localization algorithms and range-free localiza-tion algorithms. The range-based localization algorithms can provide higher localization accuracy than the range-free local-ization algorithms but the latter is cheaper and simpler since they do not require special hardware for ranging [4]. In terms of computational paradigm, the localization algorithms can also be divided into centralized algorithms and distributed algorithms. The centralized algorithms require transmission of all range measurements or connectivity information between nodes to a fusion center (e.g.,a sink node) for processing, resulting in large communication energy and bandwidth con-sumption and thereby shortening the lifetime of the whole network. The distributed algorithms are energy-efficient and scalable to the size of the networks, where the whole task of node localization is cooperatively carried out by all nodes with local information exchange between neighboring nodes. Hence, distributed localization algorithms are much more attractive for large-scale sensor networks [5]. We can directly see the wireless sensor node localization model from figure 1. We propose a localization algorithm which can be divided into three parts, as following:

1) Firstly, we use SDS-TWRalgorithm [6] [7] based on CSS (chirp spread spectrum) technology to range the distances between each anchor node and unknown node.
2) Secondly, according to the distance values obtained in step one, we propose WMLE algorithm based on MLE algorithm [8] [9] that can roughly calculated the unknown node's location information.
3) Lastly, we take the estimated location information as the observed values, considering kinds of interference noise present in the environment, we have established that the Kalman filter

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[10] [11] model to further improve the accuracy of the node's positioning, getting the optimal location information of the unknown node.

2. Ranging by SDS-TWR Algorithm with CSS Technology

SDS-TWR,is short for Symmetrical Double-Sided Two Way Ranging.SDS-TWR algorithm develops with the TWR algorithm.They are baed on clock synchronization mechanism. Figure 2, 3 shows the working procedure of the SDS-TWR algorithm.Tables and Figures are presented center, as shown below and cited in the manuscript.

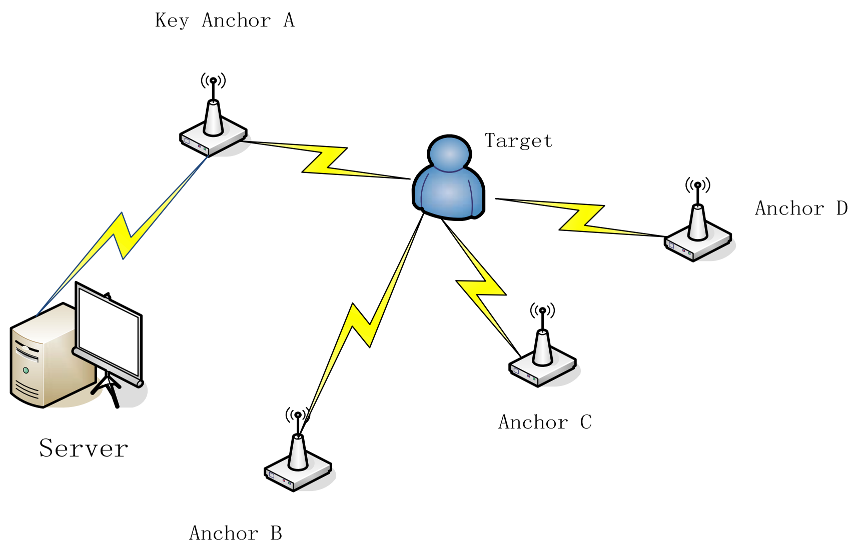

Figure 1. Wireless sensor node localization model

SDS-TWR algorithm works as following:

Firstly, the archor node A sends the ranging data to the un-known node B, node A starts a timer and begins timing, when node B recives the ranging data from node A, node B sends acknowledgment frame to node A.This time, records node B's response time is T_{replyB}. When node A recives the ACK (acknowledgment frame) which sends by the node of B, node A stops clock, and records the time of node A as T_{replyA}. Then, the node B sends the ranging data to the node A, node B starts a timer and begins timing, when node A recives the ranging data from node B, node A sends acknowledgment frame to node B. This time, records node B's response time is T_{replyB}. When node B recives the ACK (acknowledgment frame) which sends by the node of A, node B stops clock, and records the time of node B as t_{roundB}. We establish the propagation delay of the ranging signal in the air for t_p. According to the procedure of SDS-TWR, we can get the following formula:

$$T_{roundA} = 2T_p + T_{replyB} \tag{1}$$

$$T_{roundB} = 2T_p + T_{replyA} \tag{2}$$

According to the formula (1), (2), we can rapidly derive the value of as following formula:

$$T_p = \frac{1}{4} * (T_{roundA} - T_{replyB} + T_{roundB} - T_{replyA}) \tag{3}$$

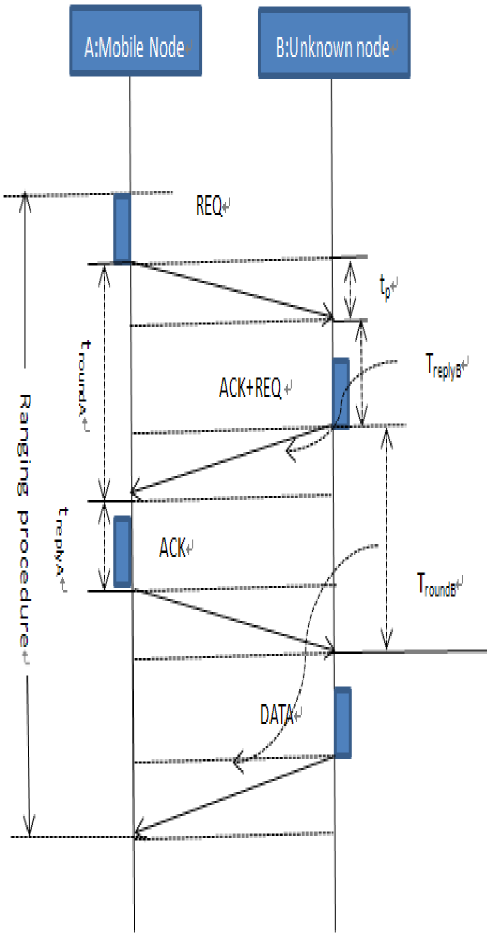

Figure 2. working procedure of SDS-TWR

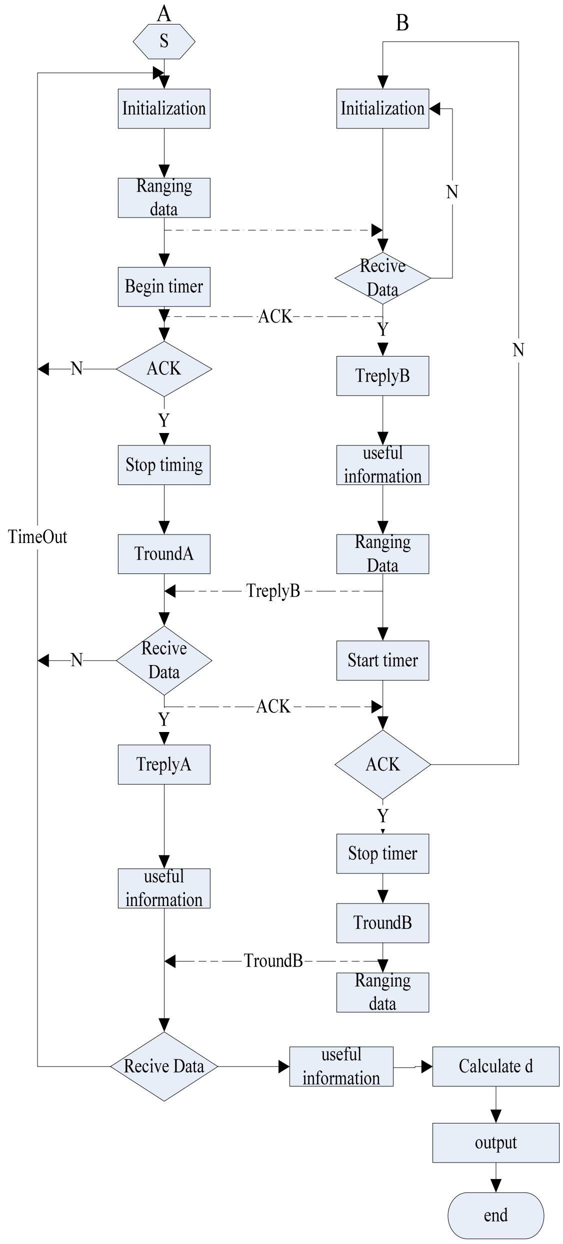

Figure 3. flowchart of SDS-TWR algorithm

Under normal circumstances, we believe that the ranging signal propagation speed is the same as in the air, according to the ranging signal derived in the air propagation delay T. we can obtain the distance between the anchor node and unknown nodes.

$$d = c * T_p = \frac{1}{4} * (T_{roundA} - T_{replyB} + T_{roundB} - T_{replyA}) * c \qquad (4)$$

The distance obtained by the algorithm is only an ideal.we have not take the Clock frequency of the node into consideration. Assume that node A and node B's clock frequency are, stands for the real propagation delay of the ranging signal in the air. Finally, we could derive easily as following formula:

$$\tilde{t}_p = \frac{1}{4}[(t_{roundA} - t_{replyA})(1+e_A) - (t_{roundB} - t_{replyB})(1+e_B)] \quad (5)$$

Then, the ranging error can be expressed as the difference between $\tilde{t}_p$ and T_p : $\Delta t_p = \tilde{t}_p - t_p \ = \frac{1}{4}[(t_{roundA} - t_{replyA})e_A) \ -(t_{roundB} - t_{replyB}) + e_B]$.

Substituting Tround Ai and Tround Bi of the above equation with formula (1) and (2) respectively, then we have the formula (6):

$$\Delta t_p = \tilde{t}_p - t_p = \frac{[(e_A - e_B)\cdot(t_{replyB} - t_{replyA}) - 2(e_A + e_B)\cdot t_p]}{4} \quad (6)$$

Here, since the propagation time between the two nodes is very small compared with the packet processing time at nodes, we can neglect the first term of formula (6).Then, it becomes: $\Delta t_p = \tilde{t}_p - t_p = (e_A - e_B)\cdot(t_{replyB} - t_{replyA})/4$.

Acorrding to the Δt_p ,we can calculate the distance error with SDS-TWR algorithm.

$$\Delta d = c * \Delta t_p = c*(\tilde{t}_p - t_p) = c*\frac{(e_A - e_B)\cdot(t_{replyB} - t_{replyA})}{4} \quad (7)$$

Through using SDS-TWR algorithm, we can calculate distance values between each anchor node and unknown node.Assuming such an environment, there are n anchor nodes and one unknown node.We can conveniently get a set of distance values with SDS-TWR algorithm. $d = \{d_1, d_2, d_3 ...di...d_n\}, i \in [1, n]$.

When we calculated the distance between the unknown node and anchor nodes, we can use many ways to find the unknown node coordinates information, such as trilateration, least squares method.In this paper, proposes weighted maximum likelihood estimation (WMLE) method to calculate the coordinates of the unknown node information.

3. Weighted Maxumum Likelihood Estimation

Assuming that n anchor nodes distribute randomly in wireless sensor networks. And the their coordinates of the information are known : . $(x_1, y_1, z_1), (x_2, y_2, z_2)...(x_n, y_n, z_n)$.

The coordinate of the target node (unknown node) is (x, y, z) . Having obtained the distance values between each anchor and target node with SDS-TWR algorithm. We can get the following formula:

$$\begin{aligned} &(x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2 = d_1{}^2 \\ &(x_2 - x)^2 + (y_2 - y)^2 + (z_2 - z)^2 = d_2{}^2 \\ &\qquad\qquad \cdots\cdots\cdots \\ &(x_n - x)^2 + (y_n - y)^2 + (z_n - z)^2 = d_n{}^2 \end{aligned} \quad (8)$$

Follows the deformation of the formula (8): acquires the sum of both sides of the equation, then average.

$$\frac{1}{n}\sum_{i=1}^{n}[(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2] = \frac{1}{n}\sum_{i=1}^{n} d_i{}^2 \quad (9)$$

Every formula in the formula (8) minus equation (9). Afterwards, we can obtain the n linear equations as formula (10) shows.

$$\begin{aligned}
&(x_1-\frac{1}{n}\sum_{i=1}^{n}x_i)x+(y_1-\frac{1}{n}\sum_{i=1}^{n}y_i)y+(z_1-\frac{1}{n}\sum_{i=1}^{n}z_i)z=\\
&\frac{1}{2}[x_1^2+y_1^2+z_1^2-d_1^2-\frac{1}{n}\sum_{i=1}^{n}(x_i^2+y_i^2+z_i^2-d_i^2)]\\
&(x_2-\frac{1}{n}\sum_{i=1}^{n}x_i)x+(y_2-\frac{1}{n}\sum_{i=1}^{n}y_i)y+(z_2-\frac{1}{n}\sum_{i=1}^{n}z_i)z=\\
&\frac{1}{2}[x_2^2+y_2^2+z_2^2-d_2^2-\frac{1}{n}\sum_{i=1}^{n}(x_i^2+y_i^2+z_i^2-d_i^2)]\\
&\qquad\qquad\qquad\cdots\cdots\cdots\\
&(x_n-\frac{1}{n}\sum_{i=1}^{n}x_i)x+(y_n-\frac{1}{n}\sum_{i=1}^{n}y_i)y+(z_n-\frac{1}{n}\sum_{i=1}^{n}z_i)z=\\
&\frac{1}{2}[x_n^2+y_n^2+z_n^2-d_n^2-\frac{1}{n}\sum_{i=1}^{n}(x_i^2+y_i^2+z_i^2-d_i^2)]
\end{aligned}\tag{10}$$

Formula (10) is the one containing the expression of n linear equations, it can be expressed as a matrix in the form AX = B. Of which, X stands for the target node's location information. Simultaneously, X is our goal. In this paper, we have unified the three-dimensional coordinate system. A, B are available on matrixs as formula (11), (12). And X can be expressed as $X=(x,y,z)^T$.

$$A=\begin{pmatrix} x_1-\frac{1}{n}\sum_{i=1}^{n}x_i & y_1-\frac{1}{n}\sum_{i=1}^{n}y_i & z_1-\frac{1}{n}\sum_{i=1}^{n}z_i \\ \ldots & \ddots & \ldots \\ x_n-\frac{1}{n}\sum_{i=1}^{n}x_i & y_n-\frac{1}{n}\sum_{i=1}^{n}y_i & z_n-\frac{1}{n}\sum_{i=1}^{n}z_i \end{pmatrix}\tag{11}$$

$$B=\begin{pmatrix} x_1^2+y_1^2+z_1^2-d_1^2-\frac{1}{n}\sum_{i=1}^{n}(x_i^2+y_i^2+z_i^2-d_i^2) \\ x_2^2+y_2^2+z_2^2-d_2^2-\frac{1}{n}\sum_{i=1}^{n}(x_i^2+y_i^2+z_i^2-d_i^2) \\ \cdots\cdots\cdots \\ x_n^2+y_n^2+z_n^2-d_n^2-\frac{1}{n}\sum_{i=1}^{n}(x_i^2+y_i^2+z_i^2-d_i^2) \end{pmatrix}\tag{12}$$

According to the above formula, we have no difficulty to calculate the coordinate of the target node. Scilicetly, we can get the value of the matrix X as $X=(A^TA)^{-1}\cdot A^T\cdot B$.

Through maximum likelihood estimation method, we can cursory derive the target node's coordinate information. Due to errors in the ranging process, in this paper, we propose a weighted maximum likelihood estimation. It is a good solution to the error accumulated.

In order to resolve the problem of the error accumulated, in the paper,we propose the weighted maximum likelihood estimation method, according to the accuracy of the location of each anchor node in the maximum likelihood estimates by using different weighting factor to the position calculation to improve positioning accuracy. Generally speaking, weighted maximum likelihood estimates has the following equation: $\widehat{X}=(A^T\cdot W\cdot A)^{-1}\cdot A^T\cdot W\cdot B$.

Where W is the weighting matrixand the inverse matrix of ranging error equation matrix.

Frontly, we have analyzed the SDS-TWR algorithm's ranging error. Generally. We can see from the formula (7).

We record that   is the variance of the ranging error:

$$S_i = \frac{1}{n-1}\sum_{i=1}^{n}\sqrt{(\Delta d_i - \sum_{i=1}^{n}\Delta d_i)^2} \tag{13}$$

$$W = \begin{pmatrix} S_1 & 0 & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & s_n \end{pmatrix} \tag{14}$$

With weighted maximum likelihood estimation method, we expect to improve the accuracy. Later, through experiments simulation, we will have a concrete analysis of this idea.

4. Kalman Filter

Rudolf Emil Kalman who is mathematician of United States proposed Kalman filter.The Kalman filter was extracted from the signals measured through the observation method to estimate the required signal and can handle one-dimensional or non-stationary or multi-dimensional random process. The data storage capacity of kalman filter is also small. Because of the advantages of Kalman filter, the theory has been applied in many engineering fields after it was proposed. The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm which uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those that would be based on a single measurement alone. More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. The filter is named for Rudolf (Rudy) E. Kálmán, one of the primary developers of its theory. The Kalman filter has numerous applications in technology. A common application is for guidance, navigation and control of vehicles, particularly aircraft and spacecraft. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics. The algorithm works in a two-step process: in the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. Because of the algorithm's recursive nature, it can run in real time using only the present input measurements and the previously calculated state; no additional past information is required. From a theoretical standpoint, the main assumption of the Kalman filter is that the underlying system is a linear dynamical system and that all error terms and measurements have a Gaussian distribution (often a multivariate Gaussian distribution). Extensions and generalizations to the method have also been developed, such as the Extended Kalman Filter and the Unscented Kalman filter which work on nonlinear systems. The underlying model is a Bayesian model similar to a hidden Markov model but where the state space of the latent variables is continuous and where all latent and observed variables have Gaussian distributions.

Using SDS-TWR to range is vulnerable to the impact of the environment, it will produce white noise. We need to eliminate the white noise by using the Kalman filter, in order to improve the positioning accuracy of the system.

In order to simulate the performance of the location estimation system, we formulate the location estimation as a filtering problem in state-space. The mathematical model for the target motion and the measurement vector on the target are denoted by following formula:

$$X_k = f(X_{k-1}, W_{k-1}), W_k \in N(0, Q_k) \tag{15}$$

$$y_k = h(x_k, v_k), v_k \in N(0, R_k) \tag{16}$$

Among the two formula, all of the parameters' description shown in Table 1 .

Table 1. Parameters' Description

Parameters	Description
x_k	State vector
$f(\bullet)$	state transition matrix
w_k	target model noise
Q_k	target model noise covariance matrix
y_k	actual measurement equation
$h(\bullet)$	measurement matrix
v_k	measurement noise
R_k	measurement noise covariance matrix

Let $x(k) = [x_k, y_k, z_k, v_k{}^x, v_k{}^y, v_k{}^z]^T$, x_k, y_k, z_k , $v_k{}^x$, $v_k{}^y, v_k{}^z$,respectively stand for target node in three directions of the displacement and speed estimated value in the coordinate system in k moment.

Firstly, we establish the state equation and discretizate according to the displacement and velocity of the system above location information.Positioning system status equation as following:

$$X(k+1) = \Gamma X(k) + W(k) \tag{17}$$

$$O(k) = \Psi X(k) + V(k) \tag{18}$$

In formula (17), (18). $X(k)$ is a state vector which is the target node's location information needs to be optimized. $x(k) = [x_k, y_k, z_k, v_k{}^x, v_k{}^y, v_k{}^z]^T$; Γ is a system matrix; $O(k)$ is a observation vector which observe the target node's location information. $O(k)$ can be formulated as following: $O(k) = (o_k{}^x, o_k{}^y, o_k{}^z)^T$.

$o_k{}^x, o_k{}^y, o_k{}^z$ respectively stands for observed displacement values in the coordinate system in three directions. Ψ is a matrix of output. $W(k)$ and $V(k)$ respectively representative the state noise and observation noise. And satisfy the following equation:

$$E[W(k)] = E[V(k)] = 0 \tag{19}$$

$$E[W(k)W(k)^T] = Q \tag{20}$$

$$E[V(k)V(k)^T] = R \tag{21}$$

Equations (19), (20), (21) aboved represent that $W(k)$ and $V(k)$ are independently zero mean white noise sequence.

The statistical properties of the initial value of the state vector X (0) is defined as: $E[X(0)] = u_0$, $E\{[X(0) - u_0][X(0) - u_0]^T\} = p_0$.

Kalman filter is divided into two main parts, namely, the forecasting process and correction process. There are two main equations as following in the forecasting process.

State equation:

$$\widehat{X}(k\,|\,k-1)=\Gamma\widehat{X}(k-1\,|\,k-1) \tag{22}$$

Prediction equation:

$$p(k\,|\,k-1)=\Gamma p(k-1\,|\,k-1)\Gamma^{T}+Q \tag{23}$$

There are three main equations as following in the correction process.

The Kalman gain equation:

$$K(k)=[\,p(k\,|\,k-1)\Psi^{T}\,][\Psi p(k\,|\,k-1)\Psi^{T}+R]^{-1} \tag{24}$$

The optimal estimate of expression on the present state:

$$\widehat{X}(k\,|\,k)=X(k-1\,|\,k-1)+K_{k}[O(k)-\Psi\widehat{X}(k\,|\,k-1)] \tag{25}$$

State update equation:

$$p(k\,|\,k)=[E-K(k)\Psi]P(k\,|\,k-1) \tag{26}$$

E stands for the unit matrix.

The following formula is the three - dimensional model of the object movement:

$$\begin{pmatrix} x_k \\ y_k \\ z_k \\ v_k{}^{x} \\ v_k{}^{y} \\ v_k{}^{z} \end{pmatrix}=\begin{pmatrix} 1 & 0 & 0 & \Delta T & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta T & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta T \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \end{pmatrix}\begin{pmatrix} x_{k-1} \\ y_{k-1} \\ z_{k-1} \\ v^{x}{}_{k-1} \\ v^{y}{}_{k-1} \\ v^{z}{}_{k-1} \end{pmatrix}+\begin{pmatrix} \frac{\Delta T^{2}}{2} & 0 & 0 \\ 0 & \frac{\Delta T^{2}}{2} & 0 \\ 0 & 0 & \frac{\Delta T^{2}}{2} \\ \Delta T & 0 & 0 \\ 0 & \Delta T & 0 \\ 0 & 0 & \Delta T \end{pmatrix}\begin{pmatrix} w^{x}{}_{k-1} \\ w^{y}{}_{k-1} \\ w^{z}{}_{k-1} \\ w^{V_x}{}_{k-1} \\ w^{V_y}{}_{k-1} \\ w^{V_z}{}_{k-1} \end{pmatrix} \tag{27}$$

$$\begin{pmatrix} o_k{}^{x} \\ o_k{}^{y} \\ o_k{}^{z} \end{pmatrix}=\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix}\begin{pmatrix} x_k \\ y_k \\ z_k \\ v_k{}^{x} \\ v_k{}^{y} \\ v_k{}^{z} \end{pmatrix}+\begin{pmatrix} v_k{}^{x} \\ v_k{}^{y} \\ v_k{}^{z} \end{pmatrix} \tag{28}$$

Initial value selection: $X(0)=0$;

$$P(0|0)=\begin{pmatrix}16&0&0&0&0&0\\0&16&0&0&0&0\\0&0&16&0&0&0\\0&0&0&16&0&0\\0&0&0&0&16&0\\0&0&0&0&0&16\end{pmatrix} \quad (29)$$

5. Experimental Results and Analysis

In our experiment, we use the Wellnode Company's WD5032N module chip with 72MHz high-speed ARM and the PAN5375 measurement module. Its communication distance can reach as far as 800 meters. It uses the Nanotron unique chirp spread spectrum (CSS) communication technology, highly integrated mixed-signal chip, and works in the 2.4GHz band. The chip provides high wireless communication performance, but also provides accurate ranging function. It can be used to develop the ranging system in wireless sensor networks with location-aware functionality. WD5032N module chip as shown in Figure 4, 5.

Because of constraints, we are hardly carry out the algorithm that use n anchor nodes to distribute randomly in sensor network. In a specific lab environment, we use four anchor nodes to monitor and position the object real-time. For the distribution of nodes, in order to simplify the calculation, these nodes placed in the same height in the experimental scene. Then establish the three-dimensional coordinate system, the z coordinates of each node is zero, so all nodes are in the three-dimensional coordinate system xoy plane.

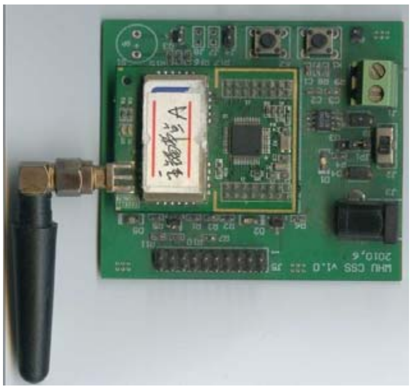

Figure 4. Anchor Node A

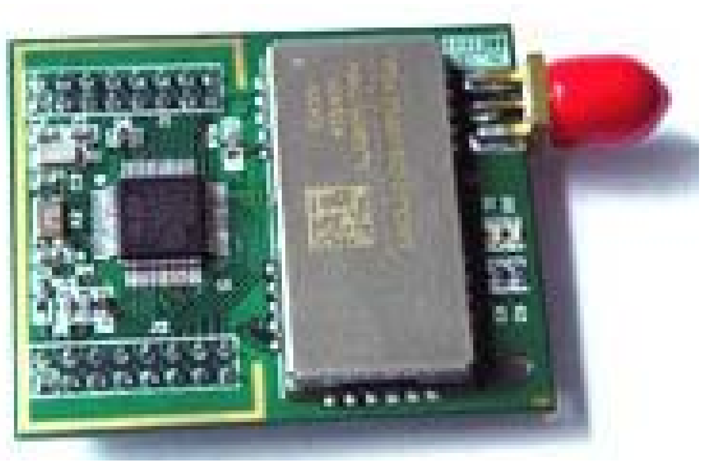

Figure 5. WD5032N Module Chip

The experiment is divided into three parts.The first part of the experiment is burning the SDS-TWR algorithm into the chip. Through using SDS-TWR algorithm, we can measure the distance between the target node and anchor nodes.The second part of is using the approach of weighted maximum likelihood estimate to obtain the coordinate information of the target node. Finally, we adopt the Kalman filter algorithm to optimize the results of the coordinate information. In order to achieve the purpose of real-time tracking and locating, the CSS module chip send ba set of positioning data to obtain location information of the target node interval 0.1 second, then host computer recives these data and process them.

In the experiment environment, we fixed the coordinates of the archor nodes included A, B, C, D. Then we establish the three-dimensional coordinates that take the main archor node (archor node A) as the orgin. A tap is used to measure the distances each archor nodes. In that case, we can determine the archor nodes' (A,B,C,D) coordinate information in the relative coordinate system by using space geometry.We connect the main archor node A with the PC via the serial line. The software in the PC can real-time upload and display the measurement results. Tables 2 and 3 have respectively given the distance information and the relative coordinate system calculated by the coordinate information of the tape measure for each anchor node (for experimental convenience, the experiment during all the nodes provided in the same plane, take the Z coordinates of all nodes as zero, then the three-dimensional coordinate system converts to a two-dimensional coordinate system for simplifying).

Table 2. The distances of each archor nodes

Number	AB	BC	AC	BD	AD	CD
Distance/m	3.2	2.8	4.65	3.9	4.85	2.1

Table 3. The coordinate of each archor node

A	B	C	D
(0.0000,0.0000)	(3.2000,0.0000)	(3.7535,2.7447)	(2.8988,3.4563)

Table 4. Experiment results with SDS-TWR

Number		t_p /ns		Distance/m	
		Measureme	t_p	Real distance	Error(Δ T)
1	TA	3.4500	11.507672	2.86	0.59
	TB	1.8600	6.204141	1.12	0.74
	TC	2.0400	6.804532	1.41	0.73
	TD	1.5800	5.287818	2.65	1.07
2	TA	2.9800	9.973226	1.86	1.12
	TB	2.2400	7.496653	1.58	0.66
	TC	2.5600	8.567604	2.04	0.52
	TD	3.0800	11.030789	2.54	0.56
3	TA	4.0500	13.554238	3.23	0.82
	TB	1.8600	6.224391	1.28	0.58
	TC	2.2400	7.496042	1.39	0.85
	TD	1.2500	4.183066	1.85	0.60
4	TA	3.2700	10.942951	2.86	0.41
	TB	2.2800	7.629908	1.48	0.80
	TC	1.2300	4.11613	2.46	1.23
	TD	1.8900	6.32478	1.27	0.62
5	TA	2.4600	8.23226	2.04	0.42
	TB	1.8700	6.25785	1.23	0.64
	TC	2.5600	8.56691	2.98	0.44
	TD	2.9800	9.97241	1.89	1.09
6	TA	1.9800	6.62596	1.28	0.70
	TB	2.1400	7.16139	2.87	0.73
	TC	2.8600	9.57084	3.52	0.66
	TD	3.2500	10.87591	4.06	0.81
7	TA	3.2700	10.9429	3.59	0.32
	TB	2.5300	8.46651	1.98	0.45
	TC	1.6200	5.42124	1.45	0.17
	TD	2.8200	9.43698	2.05	0.77
8	TA	1.5800	5.28738	2.34	0.76
	TB	2.2400	7.49604	1.98	0.26
	TC	3.4200	11.4448	2.88	0.54
	TD	4.0500	13.5531	3.15	0.90
9	TA	3.6500	12.2145	2.86	0.79
	TB	2.4600	8.23226	2.97	0.51
	TC	2.1800	7.29525	3.27	1.09
	TD	1.9800	6.62596	2.87	0.89
10	TA	2.9500	9.87202	2.42	0.53
	TB	3.2400	10.8425	2.76	0.48
	TC	2.6700	8.93501	1.86	0.81
	TD	3.0800	10.3071	2.28	0.80

We collect 10 sets of data in the ranging experiment by the chip with using SDS-TWR, each data was derived from 200 sample data averaged by the host computer in order to reduce the interference by the non-line-of-sight and singal. Among, TA, TB, TC, TD respectively stand for the distance between target node and archor nodes as A, B, C, D.

By using SDS-TWR ranging algorithm to measure the distance between the unknown node and each anchor node, we will use the maximum likelihood estimation, the weighted maximum likelihood estimation, and based on the weighted maximum likelihood estimation Kalman filter to get the unknown node's coordinate information, and table 4 shows the comparison of information using these three algorithm obtained coordinate information and the real coordinate information.

Table 5 gives the simulation analysis in Matlab platform, estimated (MLE), weighted maximum likelihood estimation (WMLE), based on the weighted maximum likelihood estimation Kalman filter (the KF & WMLE), these three algorithms respectively determined coordinates of the unknown node, and were compared with the coordinate information measured in the real environment of the unknown node. Table 6 shows the percentage of use of the positioning error of the three algorithms.

Table 5. Three algorithm positioning error

Number	three algorithm positioning error(%)		
	MLE	WMLE	WMLE&KF
1	39.34%	10.12%	7.94%
2	29.64%	20.07%	5.68%
3	15.65%	16.27%	7.17%
4	21.39%	20.10%	5.67%
5	13.07%	17.76%	4.78%
6	30.76%	11.58%	8.86%
7	19.44%	8.32%	4.78%
8	15.08%	10.94%	3.79%
9	14.09%	7.24%	3.98%
10	16.41%	9.03%	3.76%

Figure 6 shows, respectively, using the maximum likelihood estimate have significantly increased, and finally we will Kalman filter algorithm combined weighted maximum likelihood estimate of the unknown node position, further improve positioning accuracy can be seen from table6 positioning error percentage statistics, using the maximum likelihoodaverage positioning error is estimated as 21.45%.

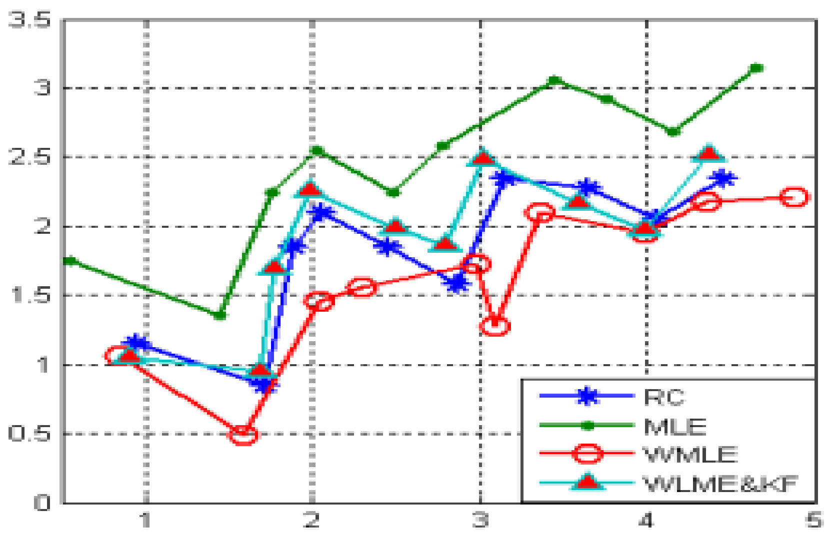

Figure 6. Comparison of the three algorithms

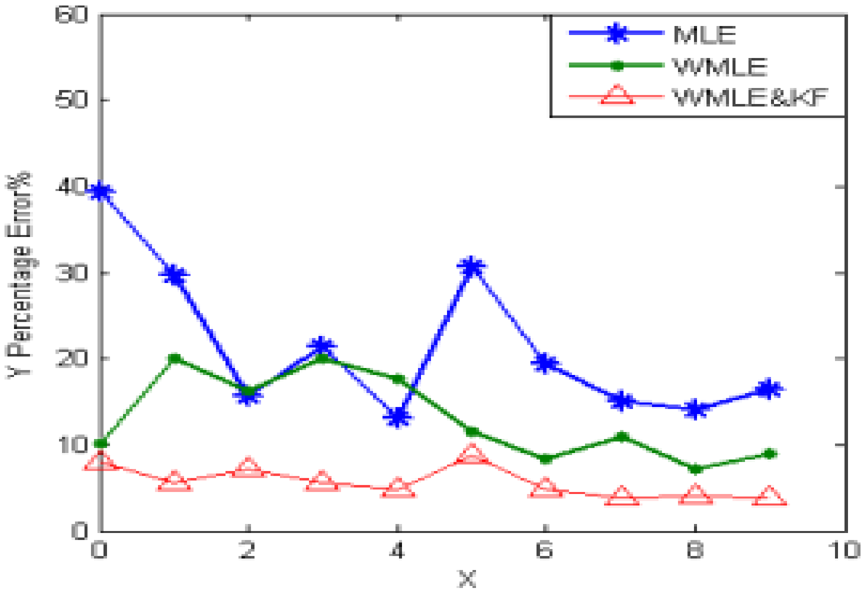

Figure 7. Three methods of positioning error percentage graph

By figure 7, we can see that, in the three position, using maximum likelihood estimation positioning error is relatively large, weighted maximum likelihood estimation, can be seen on the positioning accuracy than the maximum using the weighted maximum likelihood estimate of the average location error of 13.14%, based on weighted maximum likelihood estimate of the Kalman filter method average location error of 4.86%, shown in Figure 7, respectively three methods of positioning error percentage graph.

In this paper, we compared the proposed algorithm with the existing algorithm. We have given both of the average error for the two algorithm. The existing algorithm is using SDS-TWR for ranging and EKF (extend KF) for positioning. Table 7 shown both of the two algorithms' average error of positioning.

Table 6. Using the coordinate information obtained by the different algorithms

Number	Coordinate information comparison			
	MLE	WMLE	WMLE&KF	RC
1	(0.5507,1.7521)	(0.8507, 1.0609)	(0.9017,1.0512)	(0.95,1.15)
2	(1.4508,1.3509)	(1.5823, 0.4905)	(1.6821,0.9512)	(1.72,0.85)
3	(1.7509,2.2420)	(2.0408, 1.4521)	(1.7762,1.6918)	(1.88,1.85)
4	(2.0208,2.5508)	(2.2924, 1.5621)	(1.9809, 2.2515)	(2.05,2.10)
5	(2.4816,2.2501)	(2.9818, 1.7308)	(2.4908, 1.9908)	(2.45,1.85)
6	(2.7803,2.5818)	(3.0906, 1.2804)	(2.7926, 1.8621)	(2.86,1.58)
7	(3.4512,3.0521)	(3.3621, 2.1012)	(3.0215, 2.4842)	(3.15,2.35)
8	(3.7508,2.9209)	(3.9864, 1.9505)	(3.5821, 2.1616)	(3.65,2.28)
9	(4.1503,2.6817)	(4.3512, 2.1812)	(3.9908, 1.9726)	(4.05,2.05)
10	(4.6518,3.1508)	(4.8826, 2.2108)	(4.3621, 2.5174)	(4.45,2.35)

We get the exsiting algorithm's positioning average error from Hyeonwoo Cho, Chang Woo Lee, Sung Jun Ban, Sang Woo Kim's paper [12]. Comparing with the algorithm which uses SDS-TWR algorithm to range and EKF algorithm to position, we can get a conclusion that it has an advantage for using the proposed algorithm with the existing algorithm.

Table 7. compared proposed algorithm with exsiting algorithm

Algorithm	proposed algorithm	EKF&SDS-TWR
Positioning Error	4.86%	8.78%

6. Conclusion

This paper studied on the node location in wireless sensor networks.We have proposed a new scheme for positioning mobile nodes in WSNs—Kalman filter localization algorithm based on SDS-TWR ranging and WMLE method. The simulation results show that the proposed algorithm can mention reduce positioning errors, and improve positioning accuracy.

Aknowlegement

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References

[1] Xiaofan Wu, Chun Chen, Jiajun Bu. An Interference-Aware Transmission Power Control Scheme for Vehicular On-board Monitoring Wireless Sensor Network. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(5): 1077-1080.
[2] Xijun Yan, Xiangwei Meng, Yan Yan. A Wireless Sensor Network in Precision Agriculture. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(4).
[3] J Liu, Y Zhang, and F Zhao. *Robust distributed node localization with error management*. In Proc. ACM MobiHoc, Florence, Italy. 2006: 250–261.
[4] Qingjiang Shi, Chen He, Hongyang Chen and Lingge Jiang. Sensor network localization via nondifferentiable optimization. *IEEE Transactions on Signal Processing*. 2010; 58(6).
[5] Hakyong Kim. Double-Sided Two-Way Ranging Algorithm to Reduce Ranging Time. *IEEE Comm. letters*. 2009: 13(7).
[6] H Kim. *A ranging scheme for asynchronous location positioning sys-tems*. The 6th Workshop on Positioning, Navigation and Communication 2009 (WPNC'09). 2009.
[7] DR Jeske. On the maximum likelihood estimation of clock offset. *IEEE Trans. Commun*. 2005; 53(1): 53–54.
[8] Qasim M Chaudhari, Erchin Serpedin, and Khalid Qaraqe. On Maximum Likelihood Estimation of Clock Offset and Skew in Networks with Exponential Delays .*IEEE Trans. Signal Process*. 2008; 56(4).
[9] YANG C, BLASCH E. Kalman filtering with nonlinear stateconstraints. *IEEE Trans. Aeros. Electron. Syst*. 2008, 45(1): 70–84.
[10] EB Song, YM Zhu, J Zhou, and ZS You. Optimal Kalmanfil-tering fusion with cross-correlated sensor noises. *Automatica*. 2007; 43: 1450–1456.
[11] YANG Q ingyu, YU Ning, WANG Xiao, FENG Renjian. Research on Ranging with Chirp Spread Spectrum Techniquein Wireless SensorNetworks. *Chinese journal of sensors and actuators*. 2010; 23(12).
[12] Hyeonwoo Cho, Chang Woo Lee, Sung Jun Ban, Sang Woo Kim, An enhanced positioning scheme for chirp spread spectrum ranging. *Expert Systems with Applications*. 2010; 37: 5728–5735.