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Filtering techniques for localization based Zigbee protocol in WSN

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***Abstract*— the problems of localization target and estimation in Wireless Sensor Networks (WSNs) have received considerable attention recently, driven by the need to achieve high localization accuracy, with the minimum cost possible. A large range of proposed approaches regarding the localization area have emerged, however most of them suffer from either requiring an extra sensor, high power consumption, or offer high localization error.**

The main focus in this work is on the localization technique and the estimation of outdoor positioning which is based on a RVI algorithm. The particle filter and the extended kalman filter have been implemented with the RVI algorithm to predict and calculate the location of targets where the ultimate aim is to minimize the error distance. The simulation results demonstrate that the suggested combination, for the sake of anticipated accuracy in localization, can be achieved even by the use of few anchor nodes.

***Keywords*— Estimation of location, ZigBee, Link Quality Indicator, Extended Kalman filter, Particle filter.**

I. Introduction

Several approaches based on the communication between sensors nodes have been proposed and developed to achieve localization in WSNs [1]. Most of these techniques rely on wireless technologies, such as, WLAN, RFID, ZigBee, and UWB. Beside several signal metrics have been investigated like basic node to node distance, angle, or numbers of hops [2,3]. Normally, the nodes used in a wireless sensor network have very little resources and need techniques that utilize small resources without the need for extra hardware. Therefore, signal-strength-based methods which generally employ measurements of received signal strength indicator (RSSI), provided by most wireless network devices, present a good solution. According to that, our localization system is based on signal strength-based methods which employ RSSI measurement; these methods do not affect our model since it doesn’t require additional material or increments in energy consumption, size, or cost [2]. Moreover, (RVI) the ratiometric vector iteration [4] is one of the more prevailing algorithms. Consequently, RVI appears as a very convenient option for our localization system which ensures the satisfaction at cost, energy and physical constraints of the problem. Moreover, instead of the usual received signal strength indication used in this localization algorithm, we planned to use the link quality indicator (LQI) measurement, which is a metric introduced in IEEE.802.15.4 that measures the error in the incoming modulating of successfully received packet for distance estimation .

LQI-based localization technology has become a common method in WSN outdoor positioning because of its simple hardware description and easily acquired indication signal. However, it is worth-noting that it is yet flawed in terms of precision, sensitivity and usability, a clear-cut fact which significantly limits and constrains its effective application. This paper is basically about the identification of localization techniques and the estimation of outward positioning, which are mainly based on a RVI system [5] and indistinct filtering.

The purpose of this work is to reduce the estimation error in order to set up a real-world application that uses a ZigBee-based wireless sensor network (WSN), to track objects and people in confined spaces and communicate their information. Most large-scale wireless sensor network applications share common characteristics and services such as low power, limited memory energy constrained due to their small size and deployment in extreme environmental conditions.

Traditional methods are based on linearized models and Gaussian noise approximations so that the Kalman filter can be applied [6]. Research is focused on how different state coordinates or multiple models can be used to limit the approximations. In contrast to this, the particle filter approximates the optimal solution numerically based on a physical model rather than applying an optimal filter to an approximate model.

II. Related Work

To satisfy the needs of energy of our localization system, the ratiometric vector iteration (RVI) was chosen as localization algorithm. This method takes into account the limitations of WSN nodes for computing capacity and use of energy, to obtain good location accuracy with a reduced cost of communication. The algorithm is based on the estimates of distance ratios rather than absolute distances that are often difficult to calculate. By updating the estimation of location of the mobile node in an iterative way, the RVI

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precisely locates the target with the only participation of three sensors.

Also, instead of the usual received signal strength indication (RSSI) as required by the algorithm, since no additional hardware was required for distance estimation, we use the link quality indication (LQI) that have a better approach to estimating the distance in WSNs and which is a standard feature of the ZigBee protocol. Thus the RVI algorithm was implemented and modified to work with LQI measurements.

The localization algorithm implemented, updated in an iterative way the estimated distance of the mobile node according to the distance between each anchor and the sensor node mobile. From the perspective of refining its estimates, we used a co-operative approach. So, not only distance from anchors but also from neighboring sensors were used in the algorithm to adjust cooperatively their locations and give a more accurate result. [5]

This section mentions the two conventional methods: Extended Kalman Filter and particle filter, which are a localization method based on pre-measured data.

A. Extended kalman filter

The Kalman filter is a recursive predictive filter that is based on the use of state space techniques and recursive algorithms; it estimates the state of a dynamic system. This dynamic system can be disturbed by some noise, mostly assumed as withe noise. To improve the estimated state the Kalman filter uses measurements that are related to the state but disturbed as well.

In many cases, interesting dynamic systems are not linear by nature; so, the traditional Kalman filter cannot be applied in estimating the state of such a system. In these kinds of systems, both the dynamic and the measurement processes can be nonlinear or only one of them. In this section, we describe the extended Kalman filter (EKF) [7].

In the monitoring process, the Kalman filter looks for an object when it moves; that is, it takes the information about the state of the object to time. Then, it uses this information to predict where the object is located in the next frame. he position of the object is then corrected considering the prediction and observation as well [8].

1) Equation of Extended Kalman Filter

The Extended Kalman Filter is suitable to determine the x and y-position of the mobile target with the measured distances to the anchors. Using the trilateration method, the anchor distances di with $i \in \{1, 2 \ldots .9\}$ are calculated as follow:

$$d_i = \sqrt{\left(x - x_i\right)^2 + \left(y - y_i\right)^2} \quad (1)$$

Where $(x_i\ , y_i\ )$ is the coordination of beacon i .

Recall the equations of the extended Kalman filter:

$$\begin{cases} X_{k+1} = f(X_k, U_k) + \varepsilon \\ Y_k = h(X_k) + \varepsilon_{obs} \end{cases} \quad (2)$$

$$X_k^* = f(X_k, U_k) \quad (3)$$

$$P_k^* = A.\hat{P}_{k-1}.A^T + Q \quad (4)$$

$$Y_k^* = h(X_k^*) \quad (5)$$

$$K = P_k^*.H^T.\left(H.P_k^*.H^T + R\right)^{-1} \quad : \text{ Kalman gain } (6)$$

$$\begin{cases} \hat{X}_k = X_k^* + K\left(Y_k - Y_k^*\right) \\ \hat{P}_k = P_k^* - K.H.P_k^* \end{cases} \quad (7)$$

Where $\boldsymbol{A}$, and $\boldsymbol{H}$ are Jacobien matrices with the partial derivatives

$$\begin{cases} A_{i,j} = \dfrac{\partial f_i}{\partial x_j} \\ H_{i,j} = \dfrac{\partial h_i}{\partial x_j} \end{cases} \quad (8)$$

The state vector X_k contains the target position to be estimated:

$$X_k = (x, y)^T \quad (9)$$

The optional input control vector $\boldsymbol{U}_k$ is set to zero. The observation vector Y_k represents the observations at the given system and defines the entry parameters of the filter, in this case the results of the range measurements. The process function **f** relates the state at the previous time step k to the state at the next step $k + 1$. The measurement function $\boldsymbol{h}$ acts as a connector between X_k and Y_k.

Referring to the state estimation, the process is characterized with the stochastic random variables $\boldsymbol{\varepsilon}$ and $\boldsymbol{\varepsilon_{obs}}$ representing the process and measurement noise. They are assumed to be independent, white and normal probably distributed with given covariance matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$.

The state transition matrix $\boldsymbol{A}$ arises from the respective equations, the matrix becomes:

$$A = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \quad (10)$$

The related Jacobien matrix H describes the partial derivatives of h with respect to Xk :

$$H_k = \begin{pmatrix} \dfrac{\partial d_1}{\partial x} & \dfrac{\partial d_1}{\partial y} \\ \dfrac{\partial d_2}{\partial x} & \dfrac{\partial d_2}{\partial y} \\ \vdots & \vdots \\ \dfrac{\partial d_9}{\partial x} & \dfrac{\partial d_9}{\partial y} \end{pmatrix} \quad (11)$$

with
$$\begin{cases} \dfrac{\partial d_i}{\partial x} = \dfrac{x - x_i}{\sqrt{(x-x_i)^2 + (y-y_i)^2}} \\ \dfrac{\partial d_i}{\partial y} = \dfrac{y - y_i}{\sqrt{(x-x_i)^2 + (y-y_i)^2}} \end{cases}$$

Given that h contains non-linear difference equations the parameter (d1, d2 ……d9) as well as the matrix H must be calculated newly for each estimation.

B. Particle filter

The particle filter is a sequential Monte Carlo algorithm, a sampling method for approximating a distribution that makes use of its temporal structure. It does assume the development of the probability density function (pdf) of a dynamic system's true state from noisy observations over time. Based on [8] and [9] a general description of the Bayesian inference process will be given.

In particular, we will be concerned with the distribution $P(x_t \mid z_{0:t})$ here x_t is the unobserved state at time t, and $z_{0:t}$ is the sequence of observations from time 0 to time t. In the previous lecture on Kalman filters, this distribution $P(x_t \mid z_{0:t})$ was a multivariate Gaussian due to assumptions regarding the transition model $P(x_{t+1} \mid x_t)$ and sensor model $P(y_t \mid x_t)$. The particle filter is more general, and makes few assumptions on these models [10].

Without restrictive linear Gaussian assumptions regarding the transition and sensor models, $P(x_t \mid z_{0:t})$ cannot be written in a simple form. as an alternative, we will represent it using a collection of N weighted samples or particles, $\{ x_t(i), w_t(i) \}_{i=1}^{N}$, where $w_t(i)$ is the weight of particle $x_t(i)$, a particle representation of this density:

$$P(x_t \mid z_{0:t}) \approx \sum_i w_{t=1}(i)\delta(x_t - x_{t-1}(i)) \quad (12)$$

Consider the integral that needed to be performed at each filtering step from the previous lecture:

$$P(x_t \mid z_{0:t}) = \alpha P(z_t \mid x_t) \int P(x_{t-1} \mid z_{0:t-1}) P(x_t \mid x_{t-1}) dx_{t-1}$$

(13)

As before, we are using this recursive definition to compute the filtered distribution $P(x_t \mid z_{0:t})$ given the distribution $P(x_{t-1} \mid z_{0:t-1})$ with a particle representation for$P(x_{t-1} \mid z_{0:t-1})$, Equation 13 can be approximated as:

$$P(x_t \mid z_{0:t}) \approx \alpha P(z_t \mid x_t) \sum_i w_t(i) P(x_t \mid x_{t-1}(i)) \quad (14)$$

How do we create the "right" set of particles for representing the distribution $P(x_t \mid z_{0:t})$? One answer is to use importance sampling. The particle filter can be viewed as operating as an importance sampler on this distribution. The technique of importance sampling is a method for generating fair samples of a distribution *P(x)*. Suppose *P(x)* is a density from which it is difficult to draw samples, but it is easy to evaluate $P(x_i)$ for some particular x_i. Then, an approximation to *P(x)* can be given by:

$$P(x) \approx \sum_{i=1}^{N} w(i)\delta(x - x(i)) \quad (15)$$

Where $w(i) = P(x)/q(x(i))$ (16)

Make a note of that any distribution q(·), known as a proposal distribution, can be used here. However, with such a uniform sampling strategy, most samples will be wasted, having small *w (i)* values. Instead, we use a more direct proposal distribution, our approximation to $P(x_t \mid z_{0:t-1})$ (the integral in Equation 13). With this proposal distribution, the weights *w (i)* end up being relatively simple due to cancellation.

Concretely, the particle filter consists of the following steps (from [10], equivalent to Algorithm 4, SIR, in [11]):

Represent N samples xt (j) from the proposal distribution q(xt):

$$x_t(j) \sim q(x_t) = \sum_i w_{t-1}(i) P(x_{t-1} \mid x_{t-1}(i)) \quad (17)$$

by selecting a random number r uniformly from [0, 1], choosing the corresponding particle i, and then sampling from $P(x_t \mid x_{t-1}(i))$. This transition model is typically a linear Gaussian model, but any model from which samples can easily be drawn will suffice.

Set the weight wt (j) as the likelihood:

$$w_t(j) = P(y_t \mid x_t(j)) \quad (18)$$

The samples {xt (j) } above are fair samples from P(xt |z0:t−1). Reweighting them in this fashion accounts for evidence zt .

Normalize the weights {wt (j) }:

$$w_t(j) = \frac{w_t(j)}{\sum_k w_t(k)} \quad (19)$$

Another point is that there is an optimal proposal distribution, which is not the one used here. The optimal proposal distribution, minimizing variance in weights w(i) , turns out to be p(xt |xt−1, zt).

The most important property of the particle filter is its ability to handle complex, multimodal (non-Gaussian) posterior distributions. However, it has difficulties when xt is high dimensional. Effectively, the number of particles N required to adequately approximate the distribution grows exponentially with the dimensionality of the state space.

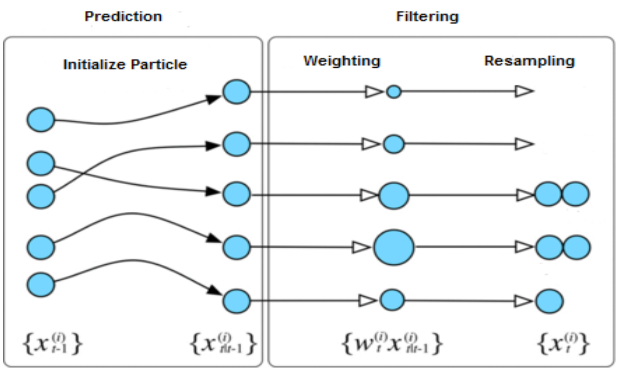

Fig 1 : Illustration of one cycle of the Particle Filter

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III. EXPERIMENTS AND RESULTS

A. *Material*

The whole system contain a wireless sensor network based on the ZigBee protocol, a set of ZigBee boards miniaturized and Jennic JN5139 wireless [14] microcontrollers that two different models are used. JN5139-Z01 the M00/M01 with integrated antenna or SMA connector for M00 for M01 and high power JN5139-Z01-The M02 with a SMA omnidirectional antenna Titanis of Antenova. The JN5139 is a device with low power consumption and low cost (1.2 uA in standby mode) with a 32-bit processor and a 2.4 GHz IEEE802.15.4/ZigBee compatible transceiver. The transceiver of JN5139 provides an LQI measure which is used to estimate the distance.

Then, the ZigBee network has three types of devices, namely, the network coordinator (implemented with a JN5139-Z01-M02 device) connected through a UART interface to a PC in which data was registered and the localization algorithm was executed; the anchor nodes or routers (implemented with JN5139-Z01-M02 devices) which were placed in fixed and known locations; the mobile node (implemented with a JN5139-Z01-M00/01 device) which was worn by the user and the problem consists in determining its location.

B. *Parameters exploration*

The performance of the proposed localization method was evaluated using a network composed of anchors nodes to properly cover a surface of 120m × 120m. The algorithm was implemented in Matlab. We used our system for the localization of, respectively, 9, 16, 25 and 49 different anchors nodes.

In our first experience [5] we implemented EKF with white noise after the estimation RVI algorithm using the position of targets and their estimates as parameters of extended Kalman filter that overcomes the linearization of the model prediction and measurements. In this work we propose a combination between the RVI system and the particle filter for locating the sensor node based on LQI provided by JenNet protocol. The goal of our approach is the minimization of the localization error so as to improve location accuracy.

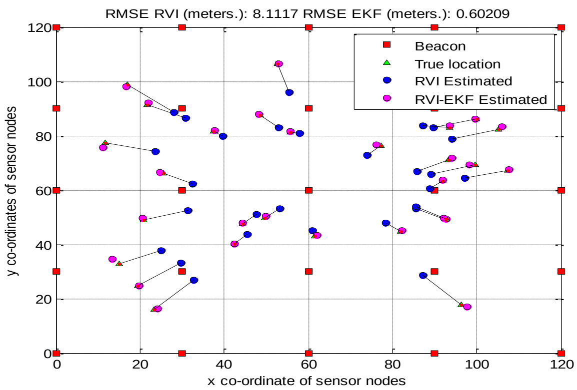

Fig 2: Estimation of position with the RVI - Extended Kalman Filter

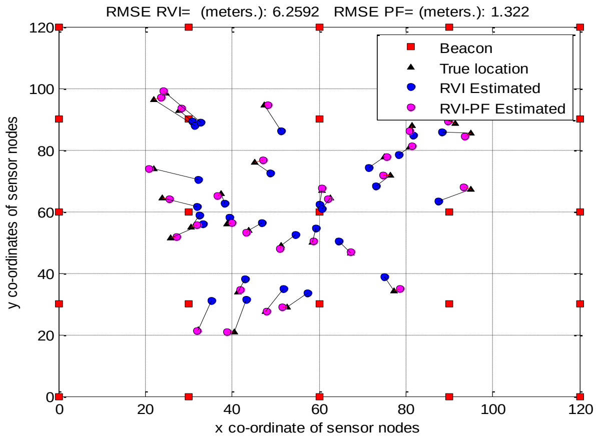

Fig 3: Estimation of position with the RVI- Particle Filter

To evaluate the performance of the filter, Figure (2) and (3) shows the output filtered x-y positions of the targets station illustrated with respect to the actual path of targets station.

C. *Result*

TABLE I
COMPARISON OF DIFFERENT METHODS

Number of beacons	Methods of estimation		
	RVI	RVI_KF	RVI_PF
9	9.51	0.66	1.42
16	9.23	0.74	1.4
25	7.83	0.94	1.13
49	5.51	1.20	1.15
63	5.35	1.4	1.10
81	5.16	0.95	1.35
117	5.28	0.88	1.47
169	5.23	0.82	1.22

The localization accuracy was estimated in four different scenarios. In all of them, the localization error was tested in 20 different locations of anchors. As presented in table 1 , the RVI based system offers an average localization error of (~ 7.83) meters depending on the number of beacons, while the RVI filtering systems proposed in this paper achieves an average localization error of (~0.76) and (~1.32) meters as presented in Figures (4). Therefore, the presented work in this paper achieves better localization accuracy than RVI_E. Kalman filter. Also it achieves much better localization accuracy in RVI_ Particular filter when the mobile target moves from one point to another with different number of beacons.

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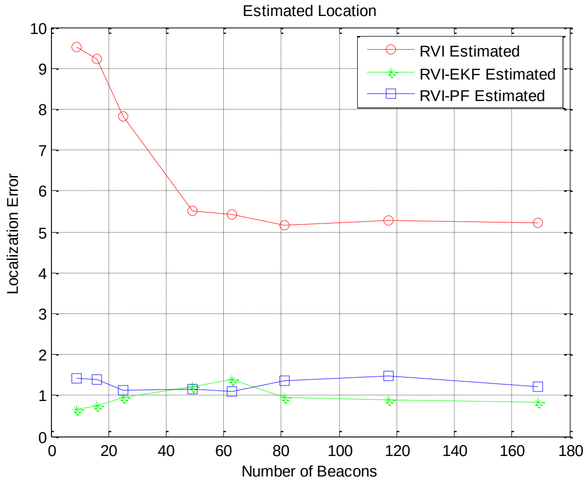

Fig 4: Estimating the location for different systems

IV. Conclusion

In this paper we proposed a comparison of tow filter based on RVI algorithm. The presented work in this paper has been estimate the locations of targets with the combination of RVI algorithm and the tow filter proposed (extended kalman filter and particle filter), the experimental results show that the position accuracy of the estimation is 1.3 m obtained with particle filter and almost 0.76 m obtained with extended kalman filter, the both of them are minimize the error distance. Moreover, the localization system was performed taking key aspects into accounts such as cost, energy consumption and independence from additional hardware.

For future work we aim to expand our proposed system and combine the tow filter to obtain the advantage of the particle filter in term of robustness and the extended kalman filter in term of precision.

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