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Real Time Guidance For Indoor Navigation Using Bluetooth Technology

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Abstract

The emergence of the modern mobile devices and ubiquitous connectivity have attracted applications related to pervasive computing environment. We propose a method to implement localization and indoor navigation using a Bluetooth-capable handheld device. The range estimation of the positioning system is based on an approximation of the relation between the RSSI (Received Signal Strength Indicator) and the associated distance between sender and receiver. We suggest use of the linear predictive method to minimise mean square error in the noisy measurements, to produce a better estimate of the user's position.

The Bluetooth device of the user can be used to detect his/her location, using signal strength analysis of signals received from Access Points (APs) enabled with Bluetooth fixed inside a building environment.

Introduction

A. Motivation

Imagine that it is a tourist's first visit to a large museum and the tourist has a strong desire to see a particular artefact. Due to shortage of time, the tourist likes to admire his/her favourite painting/artefact. Walking through different galleries, the tourist has trouble locating the artefact.

Example for such scenarios is that people find it difficult to locate a particular user, place or object in an unfamiliar indoor environment such as airport, school and university campus, hospital, corporate premises, railway station, museums and other complex indoor environment. These motivates the presents of navigational aiding equipment that provides the users in online the path towards the destination through a sequence of steps. Such a navigation device also find uses in navigating autonomous robots and providing guidance to the differentially abled or visually impaired people through the safe path in an environment in addition to guiding the people in real time.

At present scenario, people find difficult to locate a particular user, place or object in an unknown indoor environment such as airport, school, university campus etc., and other complex indoor environment. This motivates the presence of navigational aiding equipment that provides the users the path towards the destination through a sequence of steps. A navigation device of this type aids in navigating autonomous robots. It also provides guidance to the visually impaired people through the safe path in an environment

Architectural Overview

Different definition has been used to define the context and most commonly definition of context is given Dey [1]. Applications that are aware of context are known as Context-aware applications. It provides the user , flexible and adaptable services. In addition, it also yields information about user's surroundings.

Examples for such applications[2] are guidance for navigation and resource discovery, call for user localization. If the user's position in a given environment is identified, then the real time tracking of the user is determined using various predictive methods, such as the shortest path to a desired location.

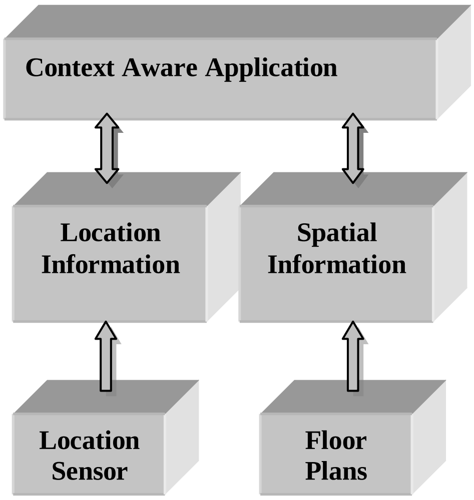


Figure 1: Basic Requirements For A Context Aware Indoor Navigation System

Fig.1 shows the basic elements for a context aware navigation system. Indoor environment is created by fixing the wireless access points inside the room, while the position of the target (user PDA) to be determined is chosen randomly. The navigation system requires the knowledge of floor plan of the indoor environment and the fixed position of the access points or sensors.

We propose to use Bluetooth technology enabled users' PDA and access points for this purpose.

Bluetooth Technology For Navigation

The advantages of Bluetooth in context aware indoor localization are described in [3], which makes Bluetooth the most versatile and inexpensive technology suitable for real time guidance for indoor navigation [3, 4 and 5].

In our system the Bluetooth device of the user detects its location using signal strength analysis of signals received from Access Points placed at strategic locations. The Access Points transmit their IDs over the RF channel which are received by listeners attached to the user's PDA and are processed for user localization purposes.

RSSI Based Triangulation

Received Signal Strength Indicator (RSSI) is a measure of received RF energy. We use the Log-distance model[6] for the purpose of estimating the position using RSSI values.

$$p(d)[dBm] = p(d_0)[dBm] - 10nlog(\frac{d}{d0})$$

where,

$p(d)[dBm]$ - at a distance d meter received power from transmitter

$p(d_0)[dBm]$ - at a reference distance d_0 power received from transmitter

n - Path loss slope factor

The relationship between RSSI and distance is required for precise estimation of the target location. It means using the RSSI value extracted from the signals transmitted by the Access Points, the distance between AP and a mobile user can be determined. Hence the position estimation based on signal strength begins with conversion of RSSI measurements to distances.

B. Conversion of RSSI to Distance

The first step in this conversion of RSSI measurements to distance is that the measured RSSI in dB accounts for three terms such as path loss model between the transmitter and set of receivers, shadow fading and fast fading.Therefore, the received RSSI from the AP i with coordinates (a_i, b_i) at time *n* to the moving target is given by

$$p_{n,i} = k_i - 10\gamma \log\ d_{n,i} + \psi_{n,i}$$

where,

k_i denotes a constant determined by the power transmitted, wavelength, height of the antenna and its gain at i^{th} AP,

γ is a slope index (varies from 2-5 depending on the environment),

$\psi_{n,i}$ is a zero mean, stationary Gaussian process with standard deviation σ_ψ .Its value lies between 4 - 8 dB,

The distance between the moving target at (x_n, y_n) and ith Access Point at $(a_i, b_i)$is represented by $d_{n,i}$

$$d_{n,i=}\sqrt{(x_n - a_i)\ ^2 + (y_n - b_i)^2}$$

C. 2D Triangulation

The bidimensional representation of the mobile user requires three distance measurements, from APs to user PDA. The observation vector consists of the three largest RSSIs from which the three smallest distances are calculated. By providing these distance values as input to the triangulation algorithm, along with the corresponding beacon coordinates, 2D triangulation is performed and the absolute coordinates of the user's PDA are calculated. Triangulation is achieved by identifying the intersecting point of three imaginary circles, as shown in the fig.2. Each circle is centred at an Access Point and has a radius equal to the distance between the Access Point and the user's PDA.

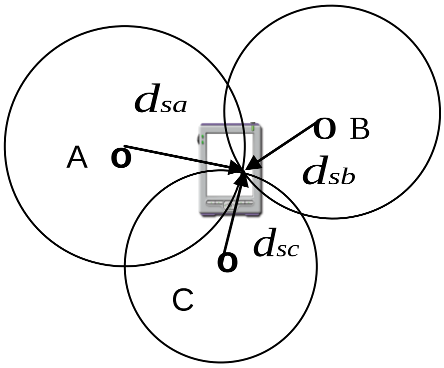


Figure 2: 2D Triangulation Using 3 Access Points

Given (x_a, y_a),(x_b, y_b) and $(x_c, y_c)$the locations of the Access Points A, B and C, the absolute co-ordinates (x, y) of the user's PDA is calculated from the following [7]:

- Distance of the user's PDA from APs A, B and C.
- Absolute co-ordinates of the APs A, B and C.

Kalman Filter For Estimation

For reliable performance of the wireless system, it is necessary to know what conditions the digital system must tolerate. The state estimate of a dynamic system is probabilistically estimated by Bayes's method from a set of noisy observations. An estimator computes an estimate of the system state with each observation of the system. Linear estimators such as the Predictive Kalman Filters are commonly applied[8 and 9].

A. Kalman Filter

It is a linear Predictive Filter for optimally estimating the state of the process [10], with the help of the assumption[8]

- Dynamic nature of the system and measurement device

- Statistical behaviour of system noise, measurement device error and unpredictability in the dynamic models.
- Initial conditions of the variables of interest.

B. Modelling a person walking along a straight line

Considering a person walking along a nearly straight-line path, the state vector consists of the user's location p and velocity v as described in [9]. Assume, the input *u* in process equation is zero and the measurement *y* is the noisy measured location of the user and the velocity is constant. The location is measured every *dt* seconds. The position is related to the velocity by the following equation:

$$p_{k+1} = p_k + v_k dt + \tilde{p}_k$$

where,

Position noise is denoted as $\tilde{p}_k$.

The position and velocity are the two important elements present in the state vector *x* and given by:

$$x_k = \begin{pmatrix} p_k \\ v_k \end{pmatrix}$$

Finally, knowing that the measured output is equal to the position, the linear system equations are as follows:

$$x_{k+1} = \begin{pmatrix} 1 & dt \\ 0 & 1 \end{pmatrix} x_k + \mathrm{w}_k$$

$$\mathrm{y}_k = 1\;0\;x_k + \mathrm{z}_k$$

where,

The process and measurement noises are represented by w_k and z_k *respectively.*

It is assumed that both w and z are uncorrelated. Then the process noise covariance and measurement noise covariance are expressed by matrices *Sw* and *Sz* defined as

Process noise covariance: $S_w = E(w_k, w_k^T)$

Measurement noise covariance: $S_z = E(z_k, z_k^T)$

The Kalman gain factor plays an important role in giving credibility to the measurements. For large measurement noise results in larger the value of *Sz* but smaller the Kalman gain and not much importance is given to the y *for* the next $\hat{x}$. The smaller the measurement noise leads to smaller *Sz* but larger the Kalman gain, more importance is given to the measurement y when computing the next state.

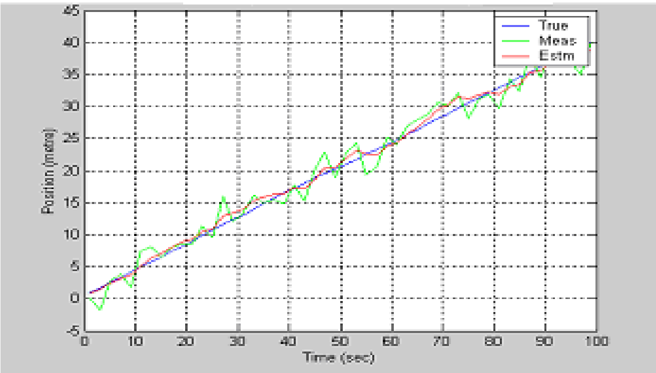
Simulation Results

The simulations of an indoor navigation model were performed for different values of sampling intervals and the observations made are shown. Each pair of graphs

(Figures. 3.A, 3.B, and 3.C) shows the true, measured and estimated positions and the errors in the measured and estimated positions for 2s, 1s and 0.1s sampling intervals.

- From the graphs, it can be observed that the estimated position is accurate to within 2 metres whereas the measured position deviates as much as 4.5 metres. The graphs also show that the accuracy increases with increasing sampling rate.

True, Measured And Estimated Position



Measured And Estimated Position Error

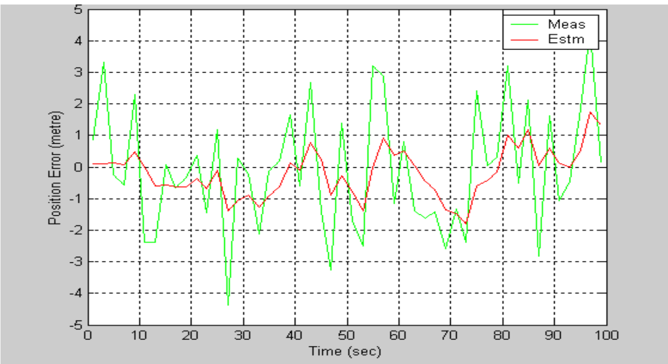
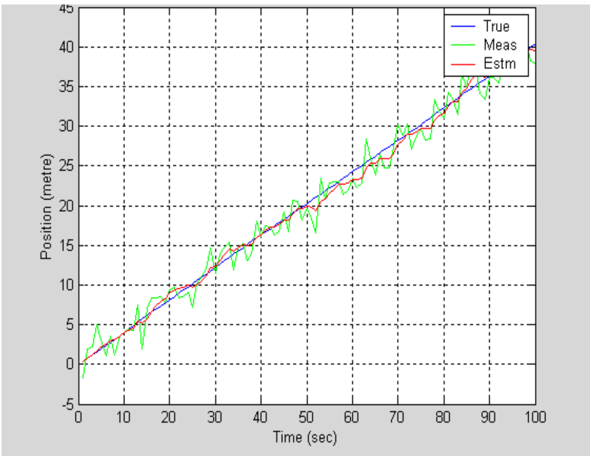


Figure 3: A Observation Interval : 100s Sampling Interval : 2s True, Measured and Estimated Position



Measured and Estimated Position Error

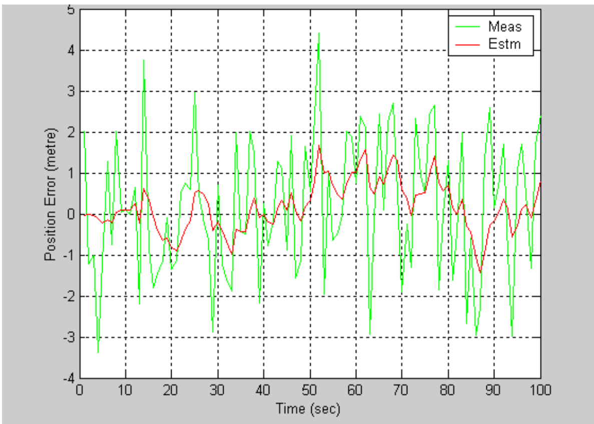
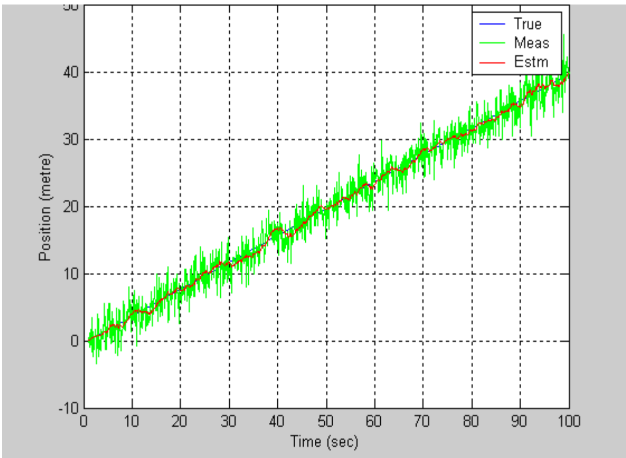


Figure 3: B Observation Interval : 100s Sampling Interval : 1s True, Measured and Estimated Position



Measured and Estimated Position Error

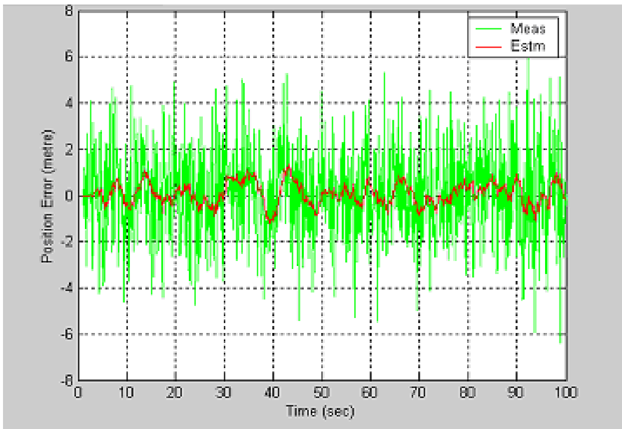


Figure 3: C Observation Interval : 100s Sampling Interval : 0.1s

Statistical Parameters for measured and estimated positions SI – Sampling Interval

Table 1: SI = 2 s

PARAMETER (in m)	**MEAS**	**ESTM**
MIN	-4.366	-1.8070
MAX	4.341	1.7490
MEAN	-0.0786	-0.1817
MEDIAN	-0.2393	-0.1103
STD DEV	1.952	0.7767
RANGE	8.708	3.5560

Table 2: SI = 1 s

PARAMETER (in m)	**MEAS**	**ESTM**
MIN	-3.385	-1.4410
MAX	4.405	1.6640
MEAN	0.1782	0.1707
MEDIAN	0.08945	0.1109
STD DEV	1.683	0.6070
RANGE	7.79	3.1050

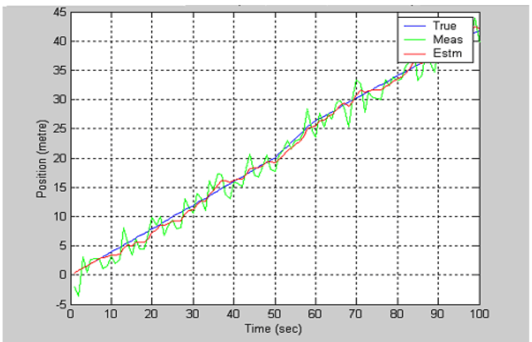
Table 3: Si = 0.1 S

PARAMETER (in m)	MEAS	ESTM
MIN	-3.9940	-1.6880
MAX	4.6680	2.5700
MEAN	0.2660	0.2027
MEDIAN	0.1760	0.0872
STD DEV	1.8550	0.7907
RANGE	8.6620	4.2580

From the above tables, it is seen that the estimation error decreases as the sampling interval decreases. Also the filter performs satisfactorily by keeping the estimation error within the specified bound of 2 metres.

- When the deviation in the velocity is greater than the specified maximum for a small duration of time, the filter still performs satisfactorily to some extent. The results are shown, for an observation period of 100s and a sampling interval of 1s, in Figure 4.

True, Measured And Estimated Position



Measured And Estimated Position Error

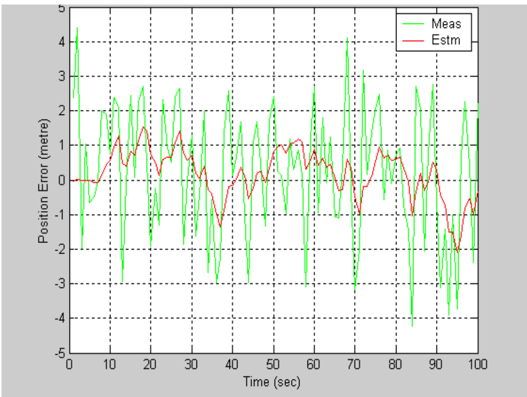


Figure 4: Results For A Velocity Deviation Greater Than The Modelled Value

Table 5: Position Error Parameters For Velocity Deviation Greater Than Specified Value

Duration in seconds	MSE for measured position (m^2)	MSE for estimated position (m^2)
50	.0141	.00026139
100	.0022	.00020192
150	.0014	.00012224
200	.0024	.000064713
250	.0013	.000063864
300	.00086582	.000050591
350	.00032461	.000036524
400	.00084440	.000025800
450	.00088611	.000027173
500	.00050052	.000028299

It can be seen from the above table, that when the velocity deviation is greater than the maximum, estimation error increases. In indoor environments, not much velocity deviations occur as the velocity of a walking person does not vary greatly. Hence the velocity deviation is not a serious problem.

- The error in position estimation is not unacceptably large. The following graph shows a plot of the average position measurement and estimation errors for ten different trials.

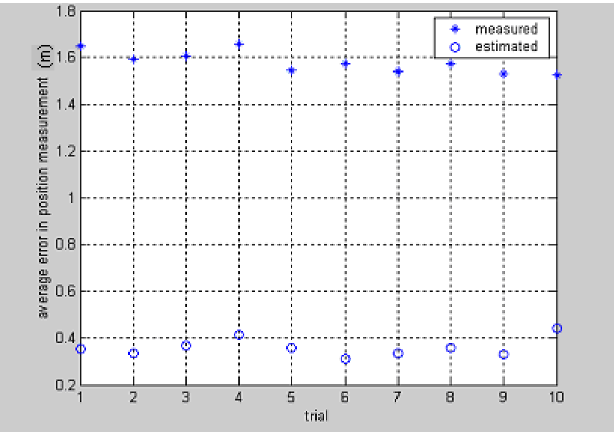


Figure 5: Average Position Estimation And Position Measurement Error

It is clear that the error in the estimation is much smaller than the error in the measurement

Results and Conclusion

A. Results

In this work, we describe a method for user localization in a noisy indoor environment such as a museum. A simplified set of formulae for 2D user triangulation, using distance measures from three Access Points, was used.

A Kalman Filter, for distance estimation, was used. The filter provides a good estimate of the distance measure, based on the motion and noise models and noisy measurement data provided to it as input. The estimated distance values, to three Access Points, provided by the Kalman Filter, are used to triangulate the user's position. The Kalman Filter estimates distances to within an error of 2 metres.

We suggest a passive architecture using the Bluetooth technology, in which the Access Points actively transmit their IDs over the wireless channel and the user's Bluetooth enabled PDA receives these signals and uses them for triangulation.

The following two figures show screenshots of a map of the Pondicherry Bharathi museum with an interactive menu asking the user for a choice of destination and a display of directions to the destination.

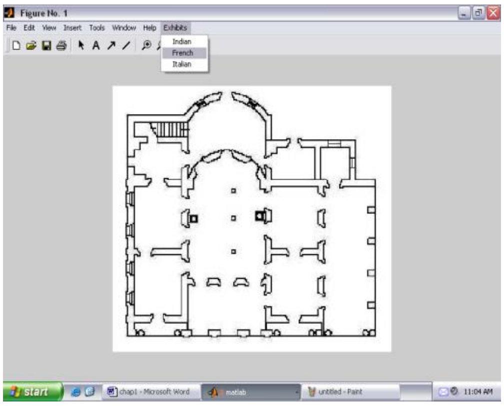


Figure 6: Map Of Museum With Drop Down Menu For Choice Of Destination

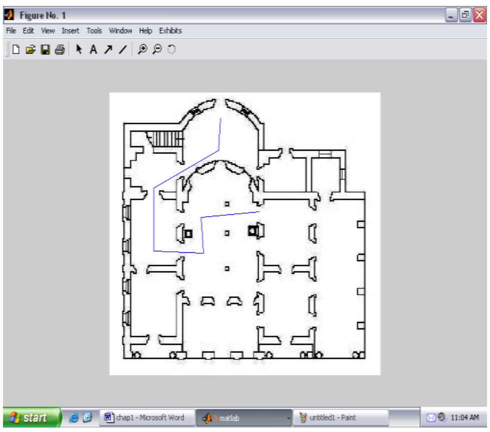


Figure 7: Screen Shot Showing Display Of Path To Destination

The program was implemented in MATLAB 6.1. The user's position once triangulated, the shortest path leading from his co-ordinates to the desired artefact is computed as shown below.

B. Scope For Future Work

The Kalman Filter assumes a Gaussian noise model and a linear system model. The performance of the system can be further improved by eliminating the linearity assumption and describing the system dynamics by a more complex set of non-linear equations. Such a model could be a better approximation of the system dynamics and an Extended Kalman Filter may be designed for distance estimation. By taking into account the 3rd dimension, namely height, a 3D triangulation of the user's position can be performed.

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