A new Particle Filter for Localization of a Mobile Base Station Based on Microwave Backscatter

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Abstract

This work presents an improved particle filter algorithm for a precise measurement of the local position of a mobile target. The presented measurement system consists of a mobile radar base station to be tracked and several active transponders located at predefined points of the working area. The system measures the range between the transponders and the base station like Frequency Modulated Continuous Wave (FMCW) radar by comparing the instantaneous frequencies of the transmitted and received signals, which has the advantage that the line of sight between the transponders and the base station is not always necessary and the data association problem can be completely avoided. It provides also the radial velocity of the base station to the respective transponder operates in the 5.8 GHz ISM band and can handle measurements up to 369 per µs within a few centimetres accuracy. In this paper we examine four data sets collected using this system. For each data set the base station traversed a repeating path for approximately five hours at different speeds. Range and range measurements to four transponders were collected through out the experiment each time with different distribution of the transponders. The developed particle filter is used to localise the base station after performing a detailed analysis of the noise inherent in the received ranges. Moreover, the noise sources are characterised and a noise model is developed to process the data with the particle filter algorithm.

Introduction

Accurate sensing of a mobile vehicle position is a fundamental requirement in many mobile robot applications, but is a very challenging problem in the cluttered and unstructured environment in real situations. The existing indoor positioning systems provide different levels of accuracy required for indoor navigation, but many are limited in workspace and robustness because they require clear line-of-sight. A ceiling-mounted-camera for example provides a good tracking performance as long as an unobstructed view is available. Indoor RF systems often based on time of flight, lose accuracy if the radiation must detour around obstacles (1,7). The Global Positioning System (GPS) have been brought into full operation and made available to civilian usage. The main disadvantage of this system is that thousands of square meters within buildings are outside the reach of GPS, moreover, the signal of this system isn't designed to penetrate walls of normal buildings, this means, that a large area in which over 90 percent of the daily life business take place in, couldn't profit from the advantages of wireless two- or three dimensional locating system (4,10).
The Active Badge system (5) was a significant contribution to the filed of local positioning systems. A badge worn by a person broadcasts a unique Infra-Red (IR) signal every 10 seconds. Sensors placed at specified location in a building pick up the unique identifiers and relay these to centralised management software. This system has several drawbacks: it scales poorly due to the limited range of IR and performs poorly if there is direct sunlight. The system described in (3) based on DC magnetic fields. Multiple sensors are placed on body mounted peripherals; their output is processed to determine a person's location and direction with a high degree of precision. It is quite expensive and severely range limited.

Our experimental test bed is a local positioning radar system that offers a real-time contact free tracking of a mobile vehicle in a harsh industrial environment. The system was built at Symeo GmbH, Munich, Germany (2). It comprises at least three transponders, which have to be installed in a fixed locations a round the perimeter of the area to be covered, plus a mobile station mounted on the object to be tracked, where the maximum range of the base station is about 60m.Our sample installation is used to track a sample train model in an area 11 m long and 10 wide. Four transponders are installed along the sides of the working area and the base station is installed on the sample train. The transponders are frequency multiplexed, which means they transmit simultaneously and are therefore recorded at the same time. Each transponder consists of: 160°/10° dipole antenna, RF circuit with Led, 230/7.5 V power supply board and stainless steel housing with a transparent plastic cover. The base station is implemented as a real-time embedded system which measures the distance to all transponders within a range of about three times per second. A vertically linearly polarised omni-directional antenna is connected to the base station via a special low-loss high frequency cable. It transmits a frequency modulated signal which is received, amplified, and modulated by each transponder and reflected back to the base station. There, the signal runtime is calculated by comparison of the transmitted and received signal. The base station communicates via WLAN with a centralised PC database, where the received raw data are processed and analysed. The system measures the ranges between transponders and base station within a 10 cm accuracy assuming line of sight between the transponders and base station with an update time of about 200ms. A major advantage of this system is that it doesn't suffer from high temperature, dirt and vibration like laser-based systems (2).

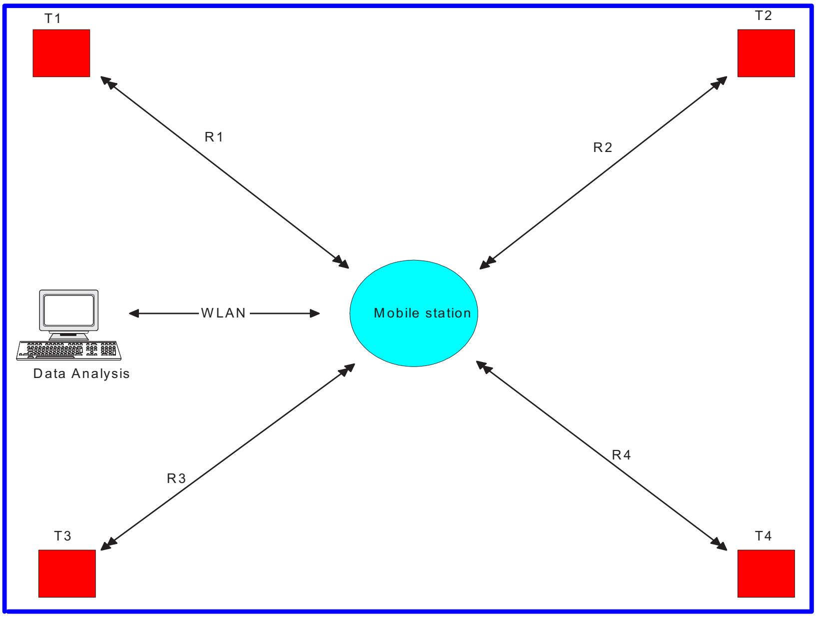

Figure (1)**:** Plot of the measurement system with transponders and mobile station

Measurement principle

The principal of operation is based on high frequency-modulated continuous wave radar, where the transmitter frequency is changed as a function of time continuously. If the transmitter frequency increases linearly with time as shown by the solid line in Figure(2) and if there is an object at a distance *R*, an echo signal will return after a time $T = \frac{2R}{c}$ as shown by the dashed line in Figure (2), where *c* is the speed of light. If the reflected signal is heterodyned with a portion of the transmitter signal in a nonlinear element, a beat frequency (difference frequency) f_b will be produced; this frequency is a measure of the target range if there is no Doppler shift. If the rate of change of the carrier frequency is f_0', the beat is $f_b = \frac{2R}{c} f_0'$.

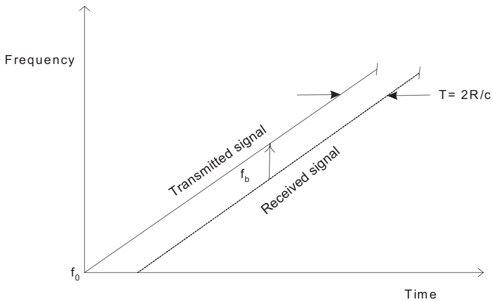

Fig.2 FMCW Radar frequency-time relationship

The frequency in practical CW radar can't be continuously changed in one direction. Periodicity is needed as in triangular frequency modulation; the resulting beat frequency is of constant frequency except at the turn-around region. If the frequency is modulated at a rate f_m, the beat frequency is $f_b = \frac{4R}{c} f_m$. This means that, the measurement of the beat frequency determines the range R, in our case the distance from base station to transponder. The beat frequency is detected through a signal processing unit realized by implementations of FFT algorithms.

Data collection and processing

A key step in our research is the data collection phase. We use a debugging software installed in the base station to record information about the received signal strength, transponders simultaneous radial distances from base station, time stamp and transponder number corresponding to each range measurement. The data is stored in a text file and sent to a data analysis and processing unit installed on a personal computer via WLAN interface. There, the data is filtered and stored in a matrix format with five columns, the first is the time stamp and the other four contains the ranges arranged with respect to transponder number. In our analysis we use the range measurements, transponders pre-assigned coordinates, and time cycles corresponding to each raw of measurement. The process of data collection and processing is controlled using a simple routine written in Mat- lab, where the required information is collected and stores in a text file. this routine searches through the stored data and using the synchronized timestamps, we merge all of the traces collected into a single unified table containing tuples of the form (ts, r_1, r_2, r_3, r_4) corresponding to time instant and the four transponders ranges at that time instant. For each data tupel (r_1, r_2, r_3, r_4) we computed the mean and the standard deviation, we use this later in the update stage in the particle filter algorithm. Figure (3) shows the hardware structure of the main component of the system that we used in our experimental tests. It consists of the main board of the mobile station, an interruptible power supply, wireless LAN connection, and power controller.

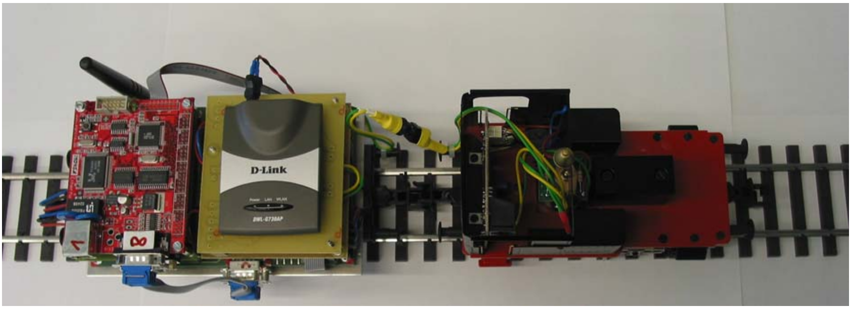

Fig.3 System hardware architecture

Applying particle filter to the collected data

In this section we will describe a particle filter implementation for localising the mobile vehicle. The filter consists of three stages: a particle set representing the different possible stages of the mobile vehicle, the weights of the particles which are updated according to a given formula using the measurement equation, and the resampling step in order to avoid degeneracy of the particles (3, 8, and 9). The filter operates by maintaining a set of samples representing the probability distribution of the vehicle states. In this context, arbitrary distributions will be used, so that each particle being weighted based on its probability given incoming measurements. The particle filter represented estimates the vehicle planar position, so that each particle is a point in the *xy* plane and represents a particle solution. The filter is initialized with a number of particles $N = 1000$, with each particle is initialized to a random state $\begin{bmatrix} x & y \end{bmatrix}$. Initially, the particles are uniformly spread over the *x y* plane within pre-assigned set boundaries. The filter is initialised by sampling *N* samples from the following probability density function which has a uniform distribution in $\begin{bmatrix} x_{\min} & x_{\max} \end{bmatrix}$.

$$p(x) = \begin{cases} \dfrac{1}{N(x_{\max} - x_{\min})} & x_{\min} < x < x_{\max} \\ 0 & otherwise \end{cases} \tag{1}$$

During run, accumulative probability distribution is maintained for each particle, where the cumulative probability of the i^{th} particle is $\dfrac{i}{N}$ and the probability of the i^{th} particle at the beginning is $\dfrac{1}{N}$.

The drift of the particles is computed as the translation in *x* and *y* coordinates according to the received measurements. Since the translation is done in *x y* only, all the particles are drifted by the same amount at each time step. Diffusion is the next step after drifting, where a random number is added to each particle coordinate and a diffusion rate of $D = 0.05$ m/s is considered, so that the random diffusion amount is scaled by $D.\Delta t$, where Δt is the amount of time since the last measurement.

Sampling is done by assigning a probability density to each of the particles according to the standard normal formula:

$$prob.(p/d_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{(\hat{d} - d_i)^2}{2\sigma^2}) \tag{2}$$

Where: d_i is the range measurement obtained from the FMCW system, $\hat{d}$ is the range estimate from the particle p to the transponder, and σ is the standard deviation for that range measurement. The estimate range d_i is calculated using the standard formula:

$$d_i = \sqrt{(x_{pi} - x_{tj})^2 + (y_{pi} - y_{tj})^2} \tag{3}$$

Where: x_{pi} , y_{pi} gives the position of particle *i, i* = 1, 2 . . . *N,* and x_{ti} , y_{ti} are the coordinates of transponder *j, j* = 1,2,3,4. Resampling is done by inverting the cumulative probability distribution during the update stage to represent the current probability distribution of the particles. In resampling, the particle set is refocused to regions in state space with posterior probability, which focuses the computational resources of the filtering algorithm to regions in state space where they matter the most. The main idea behind the resampling algorithm is to represent the posterior pdf, $p(x_{0:k} / y_{1:k})$ by an updated set of random samples, $x_{0:k}^i$, $i = 1,\ldots, N$ with associated weights, g_k^i , $i = 1,\ldots, N$, and to find optimal estimates based on these samples and weights. The weights are normalised such that $\sum_i g_k^i = 1$ and $x_{0:k} = \{x_l, l = 0,\ldots, k\}$ represents the set of all states up to time k . The algorithm approaches the optimal estimate as the number of samples is large; an approximate of the posterior estimate used is given by:

$$p(x_{0:k} / y_{1:k}) \approx \sum_{i=1}^{N} g_k^i \delta(x_{0:k} - x_{0:k}^i) \tag{4}$$

The importance sampling method is used to choose the weights. This method depends on the assumption of an importance density $\pi(x_{0:k} / y_{1:k})$ from which the samples $x_{0:k}^i$ were drawn provided that $p(x_{0:k} / y_{1:k}) \; \alpha \; \pi(x_{0:k} / y_{1:k})$, then the weight equation is given by:

$$g^i = \frac{p(x_{0:k}^i / y_{1:k})}{\pi(x_{0:k}^i / y_{1:k})} \tag{5}$$

The importance sampling method can be modified such that the $\pi(x_{0:k} / y_{1:k})$ admits at time k as a marginal distribution at time $k-1$ the importance function $\pi(x_{0:k-1} / y_{1:k-1})$, that is $\pi(x_{0:k} / y_{1:k}) = \pi(x_k / x_{0:k-1}, y_{1:k}) \pi(x_{0:k-1} / y_{1:k-1})$, using this in (5) yields the weight update:

$$g_k^i = g_{k-1}^i \frac{p(y_k / x_k^i) p(x_k^i / x_{k-1}^i)}{\pi(x_k^i / x_{0:k-1}^i, y_{1:k})} \tag{6}$$

It follows that the posterior density can be approximated with:

$$p(x_k / y_{1:k}) \approx \sum_{i=1}^{N} g_k^i \delta(x_k - x_k^i) \tag{7}$$

The resampling algorithm described above is a recursive propagation of weights and sample points as each measurement is received sequentially and can be summarized by the following steps:

- for *i* = 1:*N*

1. generate $\{x_0^i\}_{i=1}^N$ from $p(x_0)$, and set $\{g_k^i\}_{i=1}^N = \frac{1}{N}$
2. update the weights and normalize according to (6)
3. resample with replacement $x_k^i \in \{x_k^j\}_{j=1}^N$, where $p(x_k^i = x_k^j) = g_k^j$, $g_k^i = \frac{1}{N}$
4. predict the particles: $x_{k+1}^i \quad \in \quad p(x_{k+1}^i / x_k^i)$

Results and discussion

To evaluate the performance of the developed filter, Figure (4) shows the output filtered x-y positions of the mobile station illustrated with respect to the actual path of mobile station. The histograms shown in Figures (5) and (6) display the distribution of localisation error results from applying two different data sets to the filter. In the first case, the standard deviation (σ) and mean (μ) error are 3.1464 cm and 5.9448 cm respectively. For the second data set, $\sigma =$ 3.4870 cm and μ = 6.1048 cm. Figure (7) presents an approximate density function of the resulted error. It formulates a Log-normal distribution with 6.10479 cm mean and 3.48698 cm standard deviation. It is obvious that, the accuracy of the system lie within about 12 cm. Sample of the output position data with computed error, corresponding standard deviation and confidence measure is listed in Table (1).The main sources of errors which cause this uncertainty are multi-path fading, resulted in the closed work space because of some metal objects and concrete walls, and inter-modulation of transponder signals as a result of nonlinear signal mixing. In this environment with a large distortion, the mean and variance of the measured radians depend also on the signal strength and the speed of the mobile station; this affects greatly the systematic error. Our approach to the good filter performance was to analyse the noise processes of the range measurement and the interference of the transponders signals. The transponders are placed in a way to decrease the interferences between the received and reflected signals by transponders.

A key advantage of the particle filter used is that in few seconds of data collection and about 40 range measurements, the filter converges to a single compact block estimating the distribution of the vehicle position. Compared to the extended kalman filter, particle filter requires no initial estimate of the mobile position, this means it can converges without a good initial estimate. Moreover, particle filter can smoothly compensate for nonlinearities in the received measurements while kalman approach is more restricted to linear models. On the other hand, more tuning of the particle filter is still required to compensate for the errors, namely at the four edges of the tracking path, where the largest error is occurred as illustrated in Figure (4) below.

Conclusion

We described and implemented an algorithm for estimating the position of a mobile vehicle given noisy input range measurements. The algorithm provides a position estimate which is very close to the actual vehicle position and computes standard deviation and mean of error of the estimated position, where in some measurements large errors can be found. It gives no information about the orientation of the mobile vehicle, this will be considered in future work by tracking the angular variations in the measured ranges. Future improvements will be to extend the sensing capabilities of the systems by adding extra sensor structure, namely, GPS and relative sensors. The main objective is to compare the performance of these sensors with radar sensors and to solve the interfacing problems between GPS and LPR, such that GPS can make use of the LPR systems to obtain a considerable tracking accuracy in indoor tracking environments. Moreover, the effect of systematic and statistical errors on the performance of the system will be tested. In this context, an efficient filtering will be developed as a combination of particle filter and extended kalman filter, where a few runs of the particle filter will be used at the beginning to obtain a good initial estimate to seed the extended kalman filter. Compensation of the nonlinearities in the system with particle filter will contribute greatly in the bootstrap of the entire real time system.

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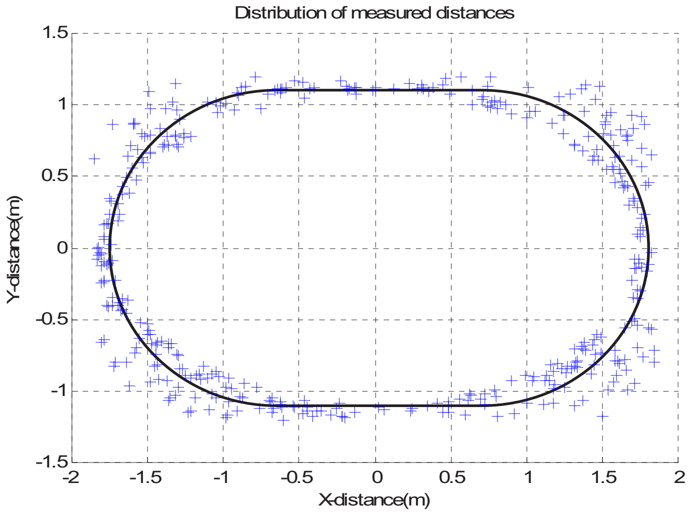

Fig.4 Actual track of the mobile station shown with estimated *x-y* positions

MeanX(m)	MeanY(m)	Error(cm)	Standard Deviation(SD)	Confidence =Error/SD
6.41656	7.51	5.06	1.11	4.56
6.40520	7.50	3.48	0.43	8.03
6.31659	7.32	7.58	0.72	10.55
6.10421	6.95	7.63	0.95	8.02
5.96038	6.61	2.46	0.34	7.13
5.90509	6.49	5.61	0.20	28.50
5.59343	5.81	5.16	0.30	17.04
5.35278	5.46	5.39	0.37	14.58
5.30338	5.37	0.78	0.17	4.57
4.99739	4.92	3.72	0.17	22.15

Tab.1 Sample of the filtered output data

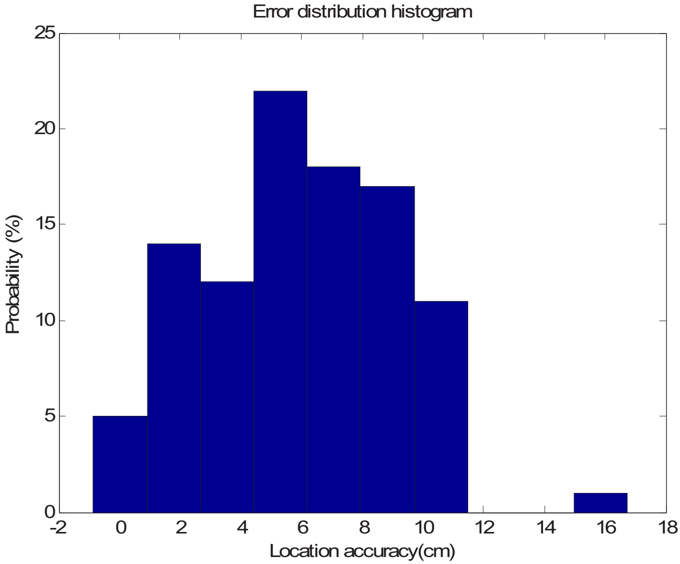

Fig.5 Distribution of errors in the predicted position (first data set)

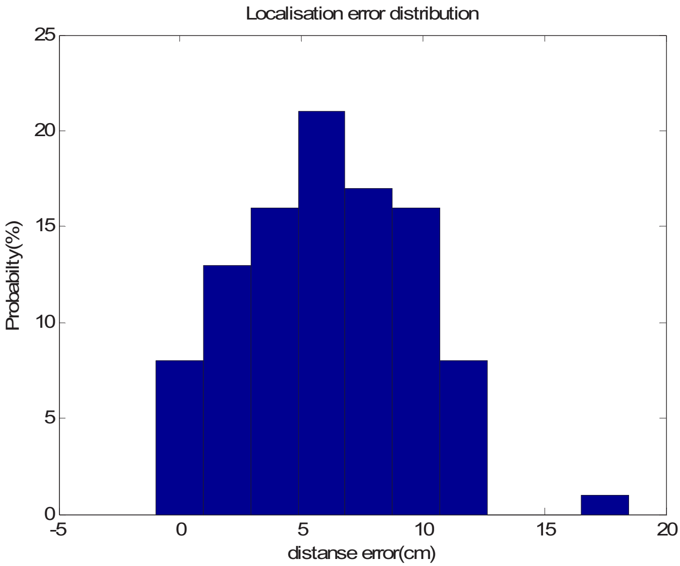

Fig. 6 Distribution of errors in the predicted position (second data set)

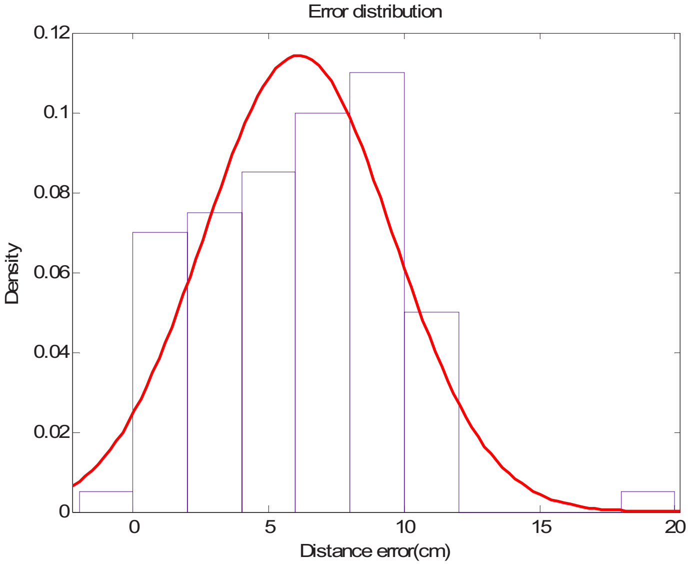

Fig.7 Error distribution with approximate error density function

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