Annals of DAAAM for 2010 & Proceedings of the 21st International DAAAM Symposium, Volume 21, No. 1, ISSN 1726-9679
ISBN 978-3-901509-73-5, Editor B. Katalinic, Published by DAAAM International, Vienna, Austria, EU, 2010
Make Harmony Between Technology and Nature, and Your Mind will Fly Free as a Bird
Annals of DAAAM International

PARTICLE FILTER BASED ALGORITHM FOR PERSONAL TRACKING

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Abstract: *This paper deals with personal localization and tracking. Particle filter is the backbone of our algorithm. This filter is fusing the system dynamics model dead reckoning solution based on pedometer and velocity motion model with a maximum likelihood estimator (MLE) output. MLE uses the range measurements (received signal strength methodology) and the infrastructure of reference nodes with known position.*
Keywords: *Particle Filter, Maximum Likelihood Estimator, Personnel Localization and Tracking*

1. INTRODUCTION

The terms ubiquitous services or pervasive computing can be heard frequently nowadays. The fast growth in the field of electronics has enabled to start realising these ideas, which fits the smart city concept. These services are directed at the persons, users, inhabitants and are locally determined. So the facility to localize this person - user is crucial feature of this system.

The use of Global Positioning System (GPS) is improper due to high energy consumption and outdoor usage restriction. During last years many effort has been concerned on development of local positioning systems (LPS). The LPS usually consists of reference nodes (RN) and blindfolded nodes (BN). RN knows their actual position, which can be set up by administrator at the installation of network or acquired by supreme positioning system. BN calculates its location from measurements of ranges to RN.

The available computational resources (modern PDAs are equipped with powerful processors and sufficient amount of memory) enable the use of more complex, precise and reliable location algorithms (LA). Since the devices usually use some communication standard to access data, the possibility to involve communication infrastructure in the location task offers. The application of inertial sensors (gyroscope, accelerometer) can bring effective increase of the position estimation accuracy. On the other hand, the need to be independent on the wireless standard is limiting our efforts to received signal strength (RSS) range measurement method, which is giving back only very perturbed data.

The Bayesian Filters (BF) can be used to fuse the data from system dynamics model (inertial sensors) and LA together. The Particle Filter is very promising non-parametrical BF, which is able to deal with non-linear system dynamics and is not restricted only on the Gaussian beliefs.

2. THEORETICAL PRELIMINARIES

2.1 Maximum Likelihood Estimator

MLE (Fox et al., 2003) is coming out from the maximization of the probability of location solution based on the statistical character of propagation channel. If we use the log-normal statistical model for RSS (Hashemi, 1993), we will obtain equation (1).

$$[x_1,\dots,x_n;y_1,\dots,y_n] = \underset{[x_1,\dots,x_n;y_1,\dots,y_n]}{\arg\min}\left[\left(\ln\frac{\tilde{d}^2_{i,j}}{d^2_{i,j}}\right)^2\right] \tag{1}$$

2.2 Particle Filter

The PF (Arulampalam et al., 2002) is nowadays very popular type of BF. It represents the posterior by a set (2) of weighted random state samples drawn from this posterior (3):

$$X(t) = x^{[1]}(t), x^{[2]}(t),\dots, x^{[M]}(t) \tag{2}$$

$$bel(x(t)) = \sum_{i=1}^{M} w^{[i]}\delta\left(x - x^{[i]}\right) \tag{3}$$

Where δ represents the Dirac delta measure. This representation can incorporate much broader area of distributions, than only Gaussian, and enables the modelling of nonlinear state transition transformations. The basic variant of PF consists of these steps (Thrun et al., 2005):

$$\forall m = [1,\dots,M]: x^{[m]}(t) \approx p\left(x(t) \mid u(t), x^{[m]}(t-1)\right) \tag{4}$$

$$w^{[m]}(t) = p\left(y(t) \mid x^{[m]}(t)\right) \tag{5}$$

$$\overline{X}(t) = \overline{X}(t) + \left\langle x^{[m]}(t), w^{[m]}(t)\right\rangle \tag{6}$$

$$\forall m = [1,\dots,M]: draw\ i\ with\ \ probability \propto w^{[i]}(t) \tag{7}$$

$$add\ \ x^{[i]}(t)\ to\ X(t) \tag{8}$$

Initially, there is generated a set of M hypothetical states (4), each based on the control u(t), particles from the last step $x(t-1)^{[m]}$ and system dynamic model p(x(t)|u(t),x(t-1)). To include the measurement y(t) into the particle set, the so-called importance factor $w(t)^{[m]}$ is calculated in (5) for each particle. This step is called importance sampling. Steps (7) and (8) are representing the re-sampling procedure.

2.3 RSS Based Range Measurement

The (indoor) wireless radio propagation channel is a complicated, random and time-varying environment. There are described three types of variations in this channel:

- Small-scale variations (fast fading): These variations are caused by multipath character of the channel.
- Mid-scale variations (slow fading): They are mainly caused by shadowing and terrain contours and may exhibit great differences.
- Large-scale variations (path loss): The increasing distance between nodes is changing the channel's structure and measured parameters. RSS LA are based on this fact.

The large-scale variation in power path-loss over distance d_{ij} between nodes observes inverse-exponential pattern (9).

$$P_{i,j}(dBm) = P_0(dBm) - 10n_p \log\frac{d_{i,j}}{d_0} \qquad (9)$$

Since wireless radio channel is a complicated environment, the logical way of describing such an environment is by a statistical model. There can be used a log-normal (Gaussian in dB) distribution for modelling the measurement errors (10).

$$f\left(\widetilde{P}_{i,j}(dBm)\right) = N\left(P_{i,j}(dBm); \sigma^2_{dB}\right) \qquad (10)$$

The probability of received power has Gaussian probability density function (PDF) with mean P_{ij}(dBm) and variance σ^2_{dB} (the standard deviation is in literature described as constant with distance and typically between 4 and 12 (Hashemi, 1993)).

3. ALGORITHM CONCEPT

The LA could be divided on subsequent parts, which form two layers (see Fig. 1).

The lower layer is based on MLE. This algorithm uses RSS range measurement methodology and the known position of RN to estimate the unknown BN position.

The main part of upper layer is PF. PF fuses the system dynamics solution (prediction step) with the correction step, in our case represented by the lower layer (MLE).

The inputs to the system dynamics model is formed by the dead reckoning system with underlying velocity motion model. The velocity motion model computes the new position based on the previous position, horizontal angular velocity integration and the linear shift (one foot step length). The prediction step is enumerated whenever is by the pedometer detected the person step. Measurements from accelerometer and gyroscope must be preprocessed first. The forward and vertical acceleration is needed for pedometer and horizontal angular (rotational) velocity and step length is needed for dead reckoning system.

The final position is computed during the correction (measurement update) step of PF.

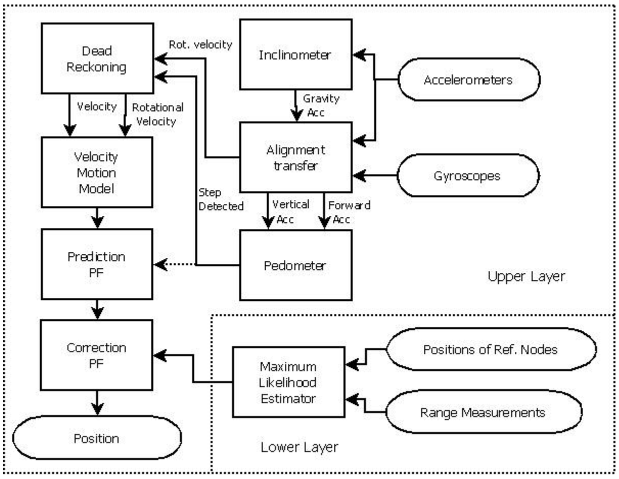

Fig. 1. Two level tracking engine

4. OFF-LINE ALGORITHM EVALUATION

The algorithm was evaluated on the reference measurement data set which is freely available from the German Aerospace Centre (Angermann et al., 2009). This data set contents these sensors measurements: accelerometer, gyroscope, electronic compass, and altimeter; supplemented with active RFID tags measurements, GPS and accurate ground truth.

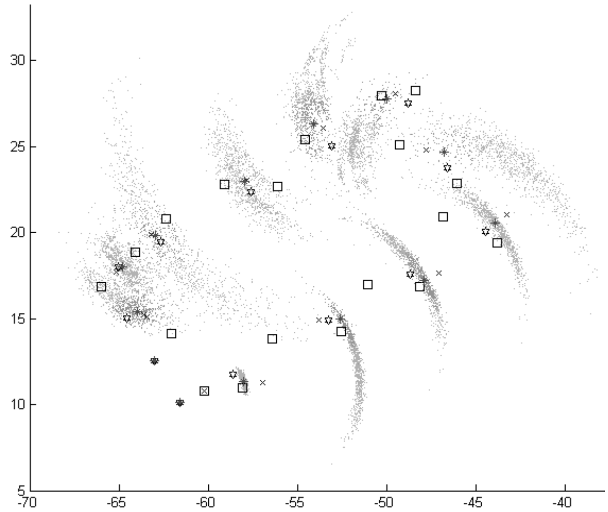

Fig. 2. Algorithm outcomes

We used accelerometer, gyroscope and RFID tags measurements for our algorithm testing. The outcomes can be seen on Fig. 2, which shows: RFID tags (rectangles), particles (dots), MLE outcomes (crosses), our algorithm estimation (stars) and the true positions (diamonds).

5. CONCLUSION

There can be found the numerical outcomes from our algorithm. Comparing it with the MLE, we see the 23.5% accuracy increase.

If the system is well modelled the PF gives supreme outputs, since it is able to deal with non-Gaussian uncertainties and non-linear model. High computational demands and the fact that sometimes the PF doesn't give a solution are the main PF drawbacks.

Averaged absolute position error [m]			
Used LA	MLE	MLE + Particle Filter	Accuracy incr.
	1.08	0.82	23.5%

Tab. 1. Algorithm outcomes, accuracy increase

6. ACKNOWLEDGEMENTS

This work has been supported in part by Ministry of Education, Youth and Sports of the Czech Republic (Research Intent MSM0021630529), Grant Agency of the Czech Republic (102/09/H081 SYNERGY - Mobile Sensoric Systems and Network) and by Brno University of Technology.

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