Accuracy Enhancement of an Indoor ANN-based Fingerprinting Location System Using Particle Filtering and a Low-cost Sensor

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***Abstract*—This paper presents an accuracy enhancement solution to mobiles location tracking systems in indoor wireless local area network (WLAN) environments. The enhancement method consists of the particle filter application to an artificial neural network (ANN) based fingerprinting technique combined with a low-cost sensor (compass). The application of the particle filter has the advantage of using information about the mobile's motion to reduce location errors (caused by the WLAN received signal strength-RSS variations) and to avoid mobile's trajectory discontinuities (caused by the static estimation of the fingerprinting technique). A digital compass has been added to the fingerprinting system to observe the mobile's heading and then improve the trajectory orientation. To apply the filtering process, two models have been proposed: non-linear and linearized filtering models. The first model is obtained from the characterization of the pedestrian's motion with the heading observation. The second model is obtained after the replacement of the heading variable, in the first model, by the pedestrian's velocities along the x and y axes. Experimental results, conducted in a specific in-building environment, showed that the application of the particle filter to the ANN-based fingerprinting system mounted with a compass improves the location accuracy, in terms of mean error, of about 39 % and 50 % for the cases of non-linear and linearized filtering models, respectively.**

***Index Terms*—Indoor Location/Tracking, WLAN, RSS, Fingerprinting Technique, ANN, Particle Filter, Digital Compass**

I. INTRODUCTION

Over the past ten years, mobile's location has received considerable attention in emergency situation, public safety, commercial and military applications [1]. Various location solutions have been adopted. The classic location systems are those based on satellites, like GPS (Global Positioning System). However, since signals received from satellites are not strong enough to penetrate inside most indoor environments, it has been necessary to develop a location system dedicated for indoor environments to provide better performances. One practical way to implement an indoor location system is to use the WLAN technology, given that it is deployed in many indoor environments (universities, hospitals, airports, etc.). With this new emergence, different approaches have been adopted to estimate the mobile location in indoor environments. The fingerprinting method [2, 3, 4] seems to be more adapted for WLAN technology and more interesting to give an accurate indoor location. This technique is based on the fact that the RSS signal (received from the WLAN access point) is different at each location in the zone of interest, thus each location has a unique signature or fingerprint. From field measurements, a database of RSS fingerprints for different locations is built. Then, to locate the mobile user, measurements are carried out to form the specific fingerprint of the user's location. This observed fingerprint is compared, using a pattern-matching algorithm, with the database consisting of the stored fingerprints and their corresponding locations in order to estimate the mobile user's location. On the other hand, the RSS-based fingerprinting technique fails to provide an accurate location estimate because of the RSS variations over time (due to the dynamic profile of the indoor propagation channel). Moreover, as this technique provides a static location, errors and discontinuities are introduced in the mobile user's trajectory. To reduce location errors and avoid trajectory discontinuities, some filtering is needed. Kalman filtering [5] seems to be more adapted to these location problems since it has the advantage of using information about the mobile's dynamic to improve the estimation. Likewise, if more observations about the mobile's motion are added, the location/tracking performances are improved further. In the case of a pedestrian, the heading measurement data seems to be the most efficient and low-cost information to characterize correctly its motion. However, when the aforementioned information is used, the system becomes non-linear and the application of the standard Kalman filter is no more valid. Consequently, different extensions of Kalman filtering may be used in the case of a non-linear system. Particle filter [6, 7], based on sequential Monte-Carlo methods, is one of these extensions and can be applied to non-linear systems with process and observation noises which do not have to follow necessarily Gaussian distributions.

Consequently, particle filtering is applied to the fingerprinting location system in conjunction with a compass, in order to enhance mobile's location/tracking performances in an indoor environment. To process the fingerprinting location technique, an ANN-based pattern-matching algorithm is considered.

The paper is organized as follows. In section II, a description of the proposed location/tracking system is presented, based on a particle filter applied to an ANN-based fingerprinting location system combined with a compass, where two filtering models are proposed. Section III presents the experimental process and gives results of the particle filter applied to the Generalized Regression Neural Network (GRNN) algorithm in each proposed filtering model. Finally, the paper is closed with a conclusion in section IV.

II. PROPOSED LOCATION TRACKING SYSTEM

The proposed location/tracking system is based on the particle filter application to the combined ANN-based fingerprinting location system with a compass, implemented in a WLAN in-

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building environment. Figure 1 shows the functional diagram of the proposed location/tracking system. The location process is performed using three phases: the measurement phase (data collection), the location estimate phase and the filtering phase (enhancement of the location estimate).

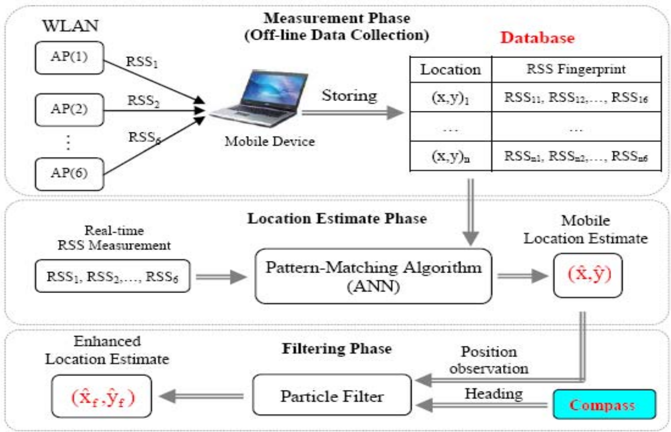

Figure 1 : Functional diagram of the proposed location/tracking system.

II.1 Measurement phase

The measurement process (data collection) was conducted at the 5th floor of the Mckay-Lassonde building (open concept architecture) situated in the campus of École Polytechnique de Montréal. Figure 2 shows the layout of the floor. It has approximately a trapezoidal shape with the dimensions of 95m, 70m and 40m, and it is consisted of rectangular blocs (composed of rest areas and offices) and several corridors.

Figure 2 : Map of the experimental area (5th floor).

The Mckay-Lassonde building, which is consisted of 8 floors, is equipped with an IEEE 802.11g WLAN system, operating in the 2.4 GHz band, where 48 access points (APs) are deployed. For the zone of interest (5th floor of the building), only 6 APs that are well-headed by the receiver's device were selected. The mobile receiver device consisted of a laptop equipped with a wireless network interface card (Intel®PPO/Wireless3945ABG) which had a sensitivity of -94 dBm. The NetStumbler [8] tool was used to measure the RSS values at each location, where a text-file (containing information about the received WLAN signal) was stored. In the present work, only the information about the RSS value and the corresponding MAC address of the detected AP were extracted. To form the database (containing RSS fingerprints with the corresponding locations), a set of RSS measurements has been collected at 555 locations. The spacing between two adjacent locations was set to 1 m. The RSS vector contained 6 components (corresponding to the 6 APs), where each component value was calculated from the mean of 40 RSS measurement samples. Since the wireless card had a sensitivity of -94 dBm, a value of -100 dBm has been assigned as a RSS signature for measurement locations where the signal had not been received from one of the 6 considered APs.

II.2 Location estimate phase

To estimate the mobile user's location, a pattern-matching algorithm has been used. The considered algorithm is a procedure that exploits the correlation between location information and location fingerprint in order to determine the mobile's position from RSS measurements. It is based on two phases: the training phase (off-line) and the real-time location estimation phase (on-line). In the present work, the ANN network with a GRNN (Generalized Regression Neural Network) structure [9] has been used. The choice of this structure is due to the fact that it gave more accurate results than other structures such as the Multilayer Perceptron (MLP). The GRNN structure is related to the radial basis function (RBF) network in which a hidden unit is centred at every training sample. The RBF units of the GRNN architecture are usually characterized by Gaussian kernels. The only parameter that characterizes the GRNN network is the spread. For radiolocation applications, the ANN approach (with a GRNN structure) can be viewed as a function approximation problem, consisting of a nonlinear mapping from a set of input variables containing information about the 6 RSS values onto a set of two output variables representing the (x, y) mobile's position. In the present work, the ANN (GRNN) network has been processed in two phases separately: the learning (training) phase and the real-time estimation phase. For the learning phase, a set of 6 RSS values has been applied to the input of the ANN (figure 3a). This phase, where the weights are iteratively adjusted to minimize the network performance function, is equivalent to the formation of the database (recording of the set of signatures as a function of mobile's location). During the real-time phase (figure 3b), the actual RSS measurement at a specific user's location is applied to the input of the ANN to give an output corresponding to the mobile's location.

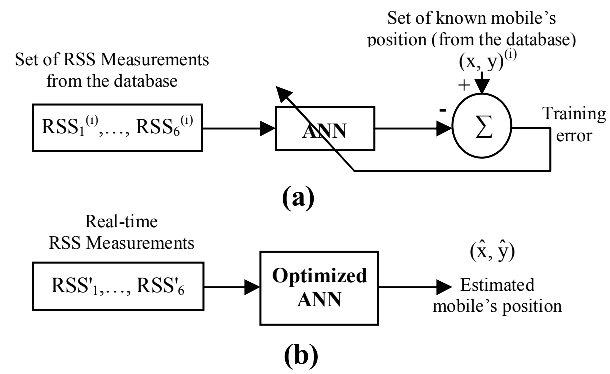

Figure 3 : ANN processing phases : a) Learning phase (off-line phase), b) Real-time estimation phase (on-line phase).

II.3 Filtering phase

The particle filter, applied to the ANN-based fingerprinting system, is a simulation-based sequential Monte-Carlo approach [6, 7] which may be used for state estimation whenever a system is non-linear and/or the noises involved are not Gaussian. This type of filter tries to estimate the posterior probability distribution $p(x_k|z_{1:k})$ by a set of samples (particles) with their associated weights, where x_k is the process state at time step k and $z_{1:k}$ is the set of the observations (measurements) collected up to the k^{th} time step. By considering N samples $x_k^{(i)}$ weighted by $w_k^{(i)}$ weights, the posterior probability distribution is given by :

$$p(x_k|z_{1:k}) = \sum_{i=1}^{N} \mathrm{w}_k^{(i)} \delta(x_k - x_k^{(i)})$$

where $\delta(\cdot)$ denotes the delta Dirac function.

Particle filtering problem is presented in general as follows. At a given time step k, the process state $x_k \in \mathcal{R}^n$ and the observation (measurement) $z_k \in \mathcal{R}^m$ are governed by the following non-linear equations:

$$x_k = f(x_{k-1}) + w_k$$
$$z_k = h(x_k) + v_k$$

where f and h are the non-linear state and observation functions, w_k and v_k are the process and measurement noises, respectively.

The recursive operations of the particle filter are given by the following steps:

- **Initialisation**

  At the initial time-tep (k=0), N random samples $x_0^{(i)}$ are generated from the probability distribution $p(x_0)$ and the weights $\mathrm{w}_0^{(i)}$ are initialized to $1/N$.

- **Prediction**

  The a priori estimation of each particle $x_k^{(i)}$ is given by the following state equation:

$$x_{k|k-1}^{(i)} = f(x_{k-1}^{(i)}) + w_k^{(i)}$$

- **Correction**

  The measurement (observation) z_k involved to evaluate the weights of particles uses the following equation:

$$\mathrm{w}_k^{(i)} = \mathrm{w}_k^{(i)} . p(z_k | x_k^{(i)}) .$$

Then, each evaluated weight is normalized as follows:

$$\tilde{\mathrm{w}}_k^{(i)} = \mathrm{w}_k^{(i)} / \sum_{i=1}^{N} \mathrm{w}_k^{(i)}$$

- **Resampling**

  The resampling step is added within the recursive operations in order to resolve the degeneracy problem (deterioration of performances) of the particle filter. It consists of the fact that after a certain number of iterations, negligible weight values are assigned to the majority of particles and only few particles are associated with high weight values. The problem of degeneracy can be reduced by using resampling which has the role to eliminate particles with small values of weights and replicate particles with large values by assigning the value of $1/N$ to the weights. Various resampling algorithms have been proposed. Systematic resampling [10] is used in this present work because of its implementation simplicity and its optimality in terms of weights variance.

- **Estimation**

  Finally, the posterior estimation of the process is obtained by using the following equation:

$$\hat{x}_k = \sum_{i=1}^{N} \tilde{\mathrm{w}}_k^{(i)} . x_{k|k-1}^{(i)}$$

II.3.1 Application of particle filtering for radiolocation

In the present work, two filtering models have been proposed and adapted for the considered radiolocation system. The first one is a non-linear model extracted from the linear motion of a pedestrian (walking at a constant velocity) in conjunction with its angle of orientation measured by a compass. The digital compass used is a product of the Silicon company [11] (F350-COMPASS-RD) and may be connected to a laptop via its USB port. The second one is a linearized version of the first model obtained by replacing the angle of orientation with the pedestrian's velocities along the x and y axes.

II.3.1.1 Non-linear filtering model

The non-linear model is characterized by the following state and measurement equations.

- **State (process) equation :**

  The model of the state equation $x_k = f(x_{k-1}) + w_k$ is given by:

$$\begin{bmatrix} \mathrm{x}_k \\ \mathrm{y}_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} \mathrm{x}_{k\text{-}1} + \mathrm{T}\mathrm{v}_0 \cos(\theta_{k\text{-}1}) \\ \mathrm{y}_{k\text{-}1} + \mathrm{T}\mathrm{v}_0 \sin(\theta_{k\text{-}1}) \\ \theta_{k-1} \end{bmatrix} + \begin{bmatrix} \frac{1}{2}\mathrm{T}^2 w_k^{\mathrm{x}} \\ \frac{1}{2}\mathrm{T}^2 w_k^{\mathrm{y}} \\ w_k^{\theta} \end{bmatrix}$$

where T is the sampling time step, (x_k, y_k) are the 2D coordinates of the mobile's location at time step k, v_0 is the pedestrian's tangential velocity (supposed constant), θ_k is the pedestrian's angle of orientation, (w_k^{x}, w_k^{y}) are the process noise components that are characterized by the pedestrian's accelerations (along the x and y axes) which have not been considered in the mobile's motion model (considered as a constant velocity). w_k^{θ} is the process noise component defined by the modelling error of the state θ_k. The standard deviation of this last component has been taken a little bit higher than the usual value in order to neglect the a priori estimation obtained from the equation of the state θ_k. Finally, at each time step k, N independent samples of the process noise w_k have been generated.

- **Measurement (observation) equation :**

  The model of the measurement equation $z_k = h(x_k) + v_k$ is given by:

$$\begin{bmatrix} \mathrm{z}_k^{\mathrm{x}} \\ \mathrm{z}_k^{\mathrm{y}} \\ \mathrm{z}_k^{\theta} \end{bmatrix} = \begin{bmatrix} \mathrm{x}_k \\ \mathrm{y}_k \\ \theta_k \end{bmatrix} + \begin{bmatrix} v_k^{\mathrm{x}} \\ v_k^{\mathrm{y}} \\ v_k^{\theta} \end{bmatrix}$$

where ($\mathrm{z}_k^{\mathrm{x}}$, $\mathrm{z}_k^{\mathrm{y}}$) are the observed mobile's location obtained by the GRNN algorithm, z_k^{θ} is the angle of orientation measured by the digital compass, (v_k^{x}, v_k^{y}) are the measurement noise components defined by location estimation errors obtained by the GRNN algorithm, and v_k^{θ} is the measurement noise component defined by the error observed during the orientation angle measurement of the compass. The standard deviation of this last component has been taken close to zero in order to solve the problem related to the correct modelling of the orientation angle. Hence, the value of the observed angle was considered relatively close to the estimated one.

II.3.1.2 Linearized filtering model

The model is proposed to linearize the previous model. It also solves the difficult task of modelling the angle of orientation with its replacement, in the non-linear model, by pedestrian's velocities along the x and y axes as follows:

$$\begin{bmatrix} v_k^x \\ v_k^y \end{bmatrix} = \begin{bmatrix} Tv_0\cos(\theta_k) \\ Tv_0\sin(\theta_k) \end{bmatrix}$$

where (v_k^x, v_k^y) are the pedestrian's velocities along the x and y axes. Therefore, the linearized model is obtained by characterizing the state and measurement equations as follows.

- **State (process) equation :**

  The model of the state equation is given by:

$$\begin{bmatrix} x_k \\ y_k \\ v_k^x \\ v_k^y \end{bmatrix} = \begin{bmatrix} x_{k-1} + Tv_{k-1}^x \\ y_{k-1} + Tv_{k-1}^y \\ v_{k-1}^x \\ v_{k-1}^y \end{bmatrix} + \begin{bmatrix} \frac{1}{2}T^2 w_k^x \\ \frac{1}{2}T^2 w_k^y \\ Tw_k^x \\ Tw_k^y \end{bmatrix}$$

where x_k, y_k, w_k^x, w_k^y and T are defined as in the non-linear filtering model.

- **Measurement equation :**

  The model of the measurement equation is given by:

$$\begin{bmatrix} z_k^x \\ z_k^y \\ z_k^{v_x} \\ z_k^{v_y} \end{bmatrix} = \begin{bmatrix} x_k \\ x_k \\ v_k^x \\ v_k^y \end{bmatrix} + \begin{bmatrix} \nu_k^x \\ \nu_k^y \\ \nu_k^{v_x} \\ \nu_k^{v_y} \end{bmatrix}$$

where z_k^x, z_k^y, ν_k^x and ν_k^y are defined as in the non-linear model and ($\nu_k^{v_x}$, $\nu_k^{v_y}$) are measurement noise components defined by errors obtained during the orientation angle measurement of the compass.

III. RESULTS AND DISCUSSION

To validate the filtering approach proposed for the enhancement of the location tracking performances, an experimental test has been conducted over a rectangular trajectory formed by 92 locations with a spatial separation of 1m from each other. The GRNN-based pattern-matching algorithm has been used to estimate the mobile's location. The algorithm has been coded with the neural network toolbox of Matlab and its parameters have been dimensioned as follows. The architecture of the network has been defined by using the function "newgrnn" composed of 6 RSS inputs, one hidden layer (with RBF activation functions) and an output layer (special linear layer) with 2 neurons corresponding to the mobile's location (x, y). The optimal spread value was set to 8. As for the filtering parameters, the constant of the pedestrian's velocity was set to v_0=0.5m/s, which corresponded to a sampling time of T=2s. The process noise was generated at each time step k according to a normal distribution ("randn"). The standard deviations of its components (w_k^x, w_k^y), defined by the pedestrian's accelerations along the x and y axes, were set to 0.05m/s^2 and the one corresponding to its component w_k^θ (defined by errors obtained from the orientation angle modelling) was set to 90°. On the other hand, the measurement noise has been chosen Gaussian, where the standard deviations of its components (ν_k^x, ν_k^y) were set to 3.5m (corresponding to the confidence interval on location estimates obtained by the GRNN), and those corresponding to its components (ν_k^{vx}, ν_k^{vy}) were set to 0.01m/s (due to errors obtained during the orientation angle measurement by the compass). The number of the particles was taken equal to N=200.

Figure 4 gives the CDF (cumulative distribution function) of the estimated location error (in terms of Euclidian distance) before and after applying the particle filter (PF) to the GRNN network for the cases of non-linear (NL.Model) and linearized (LZ.Model) models. Results show that after applying the particle filter to the GRNN network, the CDF curve is considerably improved. On the other hand, the CDF obtained from the linearized filtering model gives better results than the one obtained from the non-linear filtering model, where errors at 50% of CDF (median error) are equal to 1.45m and 0.97m, respectively. Likewise, error values at 75% of CDF are equal to 1.83m and 1.38m, respectively. This confirms the advantage of proposing the linearized model to solve the orientation angle modelling problem.

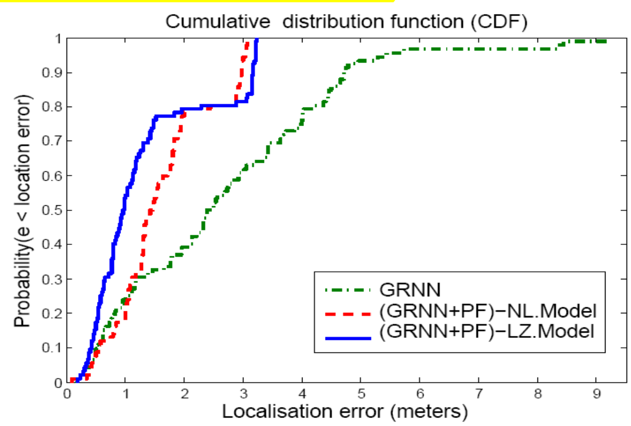

Figure 4 : CDF of mobile's location error.

Table 3 gives a comparison between the location tracking performances (in terms of mean error and processing time) obtained by the particle filter (PF applied to the GRNN considering the non-linear and linearized models), the Kalman filter (KF applied to the GRNN without using the compass) and the extended Kalman filter (EKF applied to GRNN considering the non-linear model). Results in Table 3 show that the application of filtering, using the three filters (KF, EKF and PF), improves the accuracy of the location estimate. Moreover, the table shows that after adding a compass to the GRNN-based fingerprinting system, the location/tracking performances are improved considerably with a location accuracy enhancement (in terms of mean error) of about 39% and 50% for the particle filter using non-linear and linearized models, respectively. This shows the advantage of having more observations about the mobile's motion. Also, the table shows that the particle filter (PF) gives better location/tracking performances than the Kalman and extended Kalman filters

(KF and EKF). However, it has the drawback of consuming a higher processing time. Consequently, if the sampling time "T" is in the same order of the processing time, the use of the particle filter will not be convenient.

Table 3 : Comparison of location/tracking performances.

Algorithm		Location mean error (m)	Gain (%)	Processing time (ms)
GRNN		2.68	-	25
Without compass	KF+GRNN	2.08	22.40	25 + 16
NL Model	EKF+GRNN	1.79	33.21	25 + 17
	PF+GRNN	**1.62**	**39.18**	25 + 56
LZ Model	KF+GRNN	1.83	31.75	25 + 17
	PF+GRNN	**1.33**	**50.37**	25 + 53

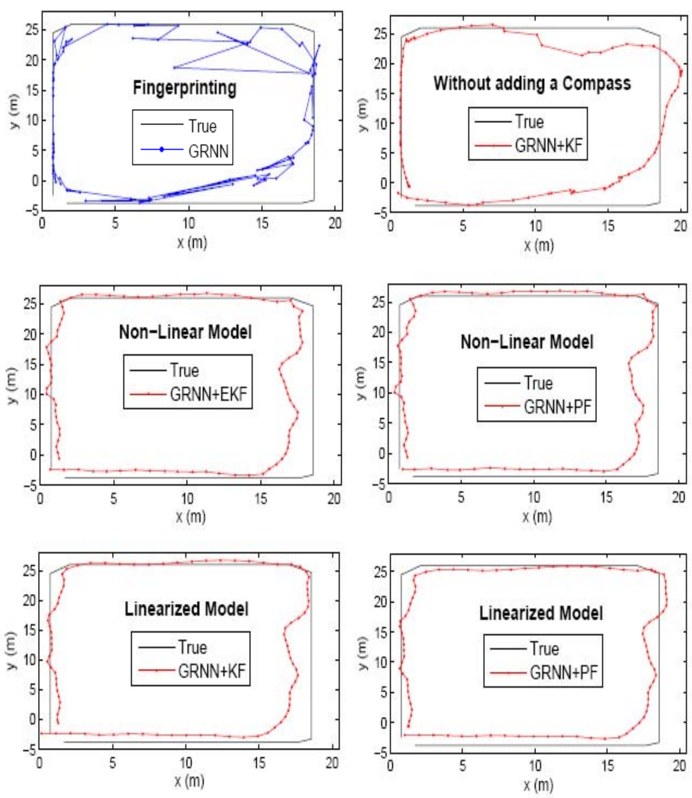

Figure 5 : Mobile's tracking trajectories.

Figure 6 gives mobile tracking trajectories obtained before and after applying to the GRNN: the Kalman filter (the case without using a compass and the case where a compass is used with the linearized model), the extended Kalman filter (the case where a compass is used with the non-linear model), and the particle filter (the case where a compass is used with the non-linear and linearized models). Results show that if filtering is not used, the mobile's trajectory contains discontinuities and is not well-oriented. Moreover, when filtering (KF, EKF and PF) is applied, the mobile's trajectory is more accurate and tends to be closer to the true trajectory. It can be seen from figure 5 that after using a compass, the mobile's trajectory is well-orientated and is closer to the true one. Finally, mobile's trajectories obtained from particle filtering (for non-linear and linearized models) are more accurate than those obtained by the Kalman and extended Kalman filters.

IV. CONCLUSION

In this paper, a dynamic approach based on particle filtering was applied to the RSS-based fingerprinting location system combined with a compass to enhance the accuracy of location/ tracking of a mobile in an indoor environment equipped with a WLAN technology. The ANN pattern-matching algorithm was used to process the fingerprinting technique with the GRNN architecture. To apply the filtering to the radiolocation system, two models have been proposed (non-linear and linearized). Experimental results showed that after applying the particle filter to the GRNN network, location/tracking accuracy has been improved (in terms of mean error) up to 50% (for the case of the linearized model). On the other hand, results showed the advantage of adding a compass to the fingerprinting location system (used to observe mobile's orientation angle), where the location accuracy was better and the mobile's tracking trajectory was well-oriented and closer to the true one. Results showed also that the particle filter has given better location/tracking performances than the Kalman and extended Kalman filters but at the cost of a higher processing time. As future work, it is convenient to implement, in form of a prototype, the proposed location/tracking system for indoor environments.

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