Body Shadowing Mitigation using Differentiated LOS / NLOS Channel Models for RSSI-based Monte Carlo Personnel Localization

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***Abstract*—Research into localization has produced a wealth of algorithms and techniques to estimate the location of wireless network nodes, however the majority of these schemes do not explicitly account for non-line of sight conditions. Disregarding this common situation reduces their accuracy and their potential for exploitation in real world applications. This is a particular problem for personnel tracking where the user's body itself will inherently cause time-varying blocking according to their movements. Using empirical data, this paper demonstrates that, by accounting for non-line of sight conditions and using received signal strength based Monte Carlo localization, meter scale accuracy can be achieved for a wrist-worn personnel tracking tag in a 120 m^2 indoor office environment.**

Keywords-body centric; localization; channel; off-body; propagation; NLOS; RSSI; Monte Carlo; tracking

I. INTRODUCTION

One of the most desirable features for any personnel tracking system is the ability to localize to meter scale accuracy using tags that are low-cost, long life and unobtrusive. The ability to locate persons to this degree of accuracy, i.e., a root mean square error of less than 2 m, has important commercial and social applications. For example, in healthcare applications high resolution capability allows the accurate monitoring of nursing or medical staff and patient interactions, i.e., bathing, mealtimes, distribution of medication and improved traceability in terms of disease and infection control. While commercial deployments of personnel tracking systems feature a range of technologies such as ultra-wideband, Wi-Fi and proprietary radio, these systems struggle to achieve verifiable meter scale accuracy in the presence of the user with sufficient energy efficiency, battery longevity and wearability.

One approach to personnel localization is to utilize ultra-low cost active RFID. While some active RFID systems are used to establish per-room connectivity-based localization, received signal strength indication (RSSI) information may be used to improve accuracy through trilateration. However, radio wave interactions with the user's body, which are uncontrolled and largely unpredictable, tend to degrade localization accuracy and add significant complexity. In particular, the blocking of the line of sight (LOS) between a tag and a receiver can cause significant range over-estimates [1]. Therefore, consideration of the non-LOS (NLOS) conditions presented by the unique environment of the human body may lead to improved accuracy in personnel localization.

The effect of a user's orientation upon RSSI has been noted in the literature [2] and although NLOS detection algorithms exist [3, 4] they have been largely disregarded in the design of localization systems resulting in location estimates that are skewed from their true positions [l]. It is known that to accurately represent LOS and NLOS conditions in the same environment the channel model requires different parameters for these two conditions. Alternatively, it has also been suggested that to compensate for NLOS conditions one may use statistical methods [5]. One such method is Monte Carlo Localization (MCL) [6] and since its introduction into wireless sensor networks it has seen various improvements that take advantage of ancillary information such as confidence measures [7] or inferred orientation data [8]. However, these schemes only use the connectivity information between nodes, unlike the work in [9] which also uses the range information provided by the signal strength. While signal strength measurement is not as accurate as time difference of arrival or time of arrival [10] it requires no extra hardware to implement and instead relies upon the standard RSSI values reported by most packet-based radio transceivers. This means that unlike other wrist mounted schemes [11] this localization method may be implemented using commercial off the shelf hardware.

In this work empirical data was obtained from a wrist mounted node that uses a MCL scheme to obtain a position estimate within an open plan office environment. The algorithm implementation is outlined in the next section which covers both the channel model and RSSI based formulation of MCL. Section III contains a description of the hardware and software developed for this set of experiments while also outlining the environment and scenarios performed. This is followed in Section IV by a description of the various channel models, leading on to a presentation of the results in Section V. Concluding remarks and the direction of future research are discussed in the final section.

This work was supported, in part, by a research studentship from the Centre for Secure Information Technology, Queen's University, Belfast.

II. Algorithm Overview

A. Channel model

The most common channel model found in signal-strength localization literature, and the one used in RSSI-based Monte Carlo Localization (RMCL) [9], is based on the log-distance path loss model. Here the received power at a distance d is given as

$$\mathrm{RSSI}(d) = P_0 - 10n_p \log_{10}\frac{d}{d_0} + X_n, \tag{1}$$

where P_0 is the received signal strength in dBm at a reference distance d_0, and n_p is the path loss exponent. In (1), X_n is the noise component of the received signal (in dB) and is modeled as a Gaussian distribution with variance σ_n^2 and mean of zero.

B. RSSI-based Monte Carlo Localization

The principal idea behind RMCL is to represent the posterior distribution of the node's location by a set of samples. Each sample point, $\boldsymbol{\theta}_k^i = (x, y)$, has an associated weight w_k^i. Where k is the time step, $i=1,2,\ldots N_s$, and N_s is the total number of samples.

At each time step a random sample of possible locations are drawn from the sample space according to $p(\boldsymbol{\theta}_k|\boldsymbol{\theta}_{k-1})$. This is the transition distribution which describes how the new location estimates are distributed in relation to the previous set. For the experiments in this paper the transition distribution is

$$p(\boldsymbol{\theta}_k^i|\boldsymbol{\theta}_{k-1}^i) = \begin{cases} \frac{1}{\pi d_{max}^2}, & \mathrm{dist}(\boldsymbol{\theta}_k^i, \boldsymbol{\theta}_{k-1}^i) \le d_{max} \\ 0, & \mathrm{dist}(\boldsymbol{\theta}_k^i, \boldsymbol{\theta}_{k-1}^i) > d_{max} \end{cases}, \tag{2}$$

where d_{max} is the maximum distance between sequential location predictions and $\mathrm{dist}(\boldsymbol{\theta}_k^i, \boldsymbol{\theta}_{k-1}^i)$ is the Euclidean distance between $\boldsymbol{\theta}_k^i$ and $\boldsymbol{\theta}_{k-1}^i$. For each sample, its weight can be calculated as follows,

$$w_k^i = \frac{w_k^{*i}}{\sum_{j=1}^{N_s} w_k^{*j}}, \tag{3}$$

where w_k^{*i} is the non-normalised weight. Setting the transition prior as the importance density allows recursive calculation of the non-normalized weight using

$$w_k^{*i} = w_{k-1}^{*i} p(\boldsymbol{m}_k|\boldsymbol{\theta}_k^i), \tag{4}$$

where $\boldsymbol{m}_k$ is the set of measurements made at time step k. Following the assumption that RSSI is normally distributed the probability of a given signal strength being received a given distance is

$$p(P|d_{ij}) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{P - P_0 + 10n_p \log_{10}\frac{d_{ij}}{d_0}}{2\sigma^2}\right\}, \tag{5}$$

where P is the power received and d_{ij} is the distance between node i and j. With the set of samples and their associated weights the posterior distribution is approximated as

$$p(\boldsymbol{\theta}_k|\boldsymbol{m}_{1:k}) \cong \sum_{i=1}^{N_s} w_k^i \delta(\boldsymbol{\theta}_k - \boldsymbol{\theta}_k^i), \tag{6}$$

where $\delta(\cdot)$ is the Dirac delta function. To avoid the degeneracy problem, where all but one sample will have a negligible weight value, an estimate of the effective sample size is calculated using the following formula.

$$\widehat{N}_{\mathrm{eff}} = \frac{1}{\sum_{i=1}^{N_s}\left(w_k^i\right)^2}. \tag{7}$$

If $\widehat{N}_{\mathrm{eff}}$ is below the threshold value of $N_s/10$ then systematic resampling is applied and each sample weight is reset to $1/N_s$.

When the algorithm is started, $p(\theta_0)$ is initialized as a random collection of samples selected uniformly throughout the sample area, with all the weights set to $1/N_s$. With this as the starting point, RMCL predicts possible new locations and calculates their weights at every time step. Each time step is also accompanied by a check of the effective sample size with re-sampling taking place if it is found to be too small. At each time step the location is estimated as the weighted mean of all the sample points, as is shown in (8)

$$\widehat{\boldsymbol{\theta}}_k = \sum_{i=1}^{N_s} \boldsymbol{\theta}_k^i \cdot w_k^i. \tag{8}$$

III. Experimental Setup

A. System Overview

The localization system was based on *activCampus,* a commercial, ultra-low power, secure, active RFID system supplied by ACT Wireless Ltd. The selected arrangement consisted of a wrist-worn tag acting as the mobile node. Four *activReader* RFID reader units operating at 868 MHz took the place of anchor nodes. These readers were placed at the four corners of an open plan 120 m^2 modern office area within the ECIT Institute, see Figure 1.

In this work, the wrist worn tag was an eZ430-Chronos from Texas Instruments that was programmed with custom firmware that allowed control of the interrogation rate for each experiment. The proprietary active RFID reader units utilized a meander line printed monopole antenna and allowed all interrogations from the RFID tags to be forwarded using an on-site Wi-Fi network for processing at a remote server. This allowed the data analysis to be conducted off-line, in post processing. Overall, the system was configured to allow synchronous recording of RSSI at multiple readers during each interrogation.

The tag's interrogation rate was set to 6.67 Hz, allowing RSSI to be sampled every 150 ms. The proprietary protocol used in the measurement system included a packet sequence number which allowed the identification of any missing RSSI data during initial post-processing. Missing values were then synthesized via linear interpolation with the surrounding data. To reduce the effect of small scale fading, the RSSI data was smoothed using a moving average window of 18 samples long (2.7 s).

B. Environment and Scenario Overview

A number of experiments were conducted using the system described above where a user with the wrist-worn RFID tag navigated a number of different paths within the testing environment. A single tag was used for all scenarios and it was always worn on the subject's left wrist. The same subject (weight 83 kg, height 182 cm) was used for all tests. Additionally during these measurements great care was taken to ensure the immediate area was unoccupied as it was anticipated that other pedestrians would act as slow moving scatterers and shadowing objects [12].

The building was of recent construction, consisting mainly of metal studded dry wall with a metal tiled floor covered with polypropylene-fiber, rubber backed carpet tiles, and a metal ceiling with mineral fiber tiles and recessed louvered luminaries suspended 2.7 m above floor level. This office measured 10×12 m and contained a number of desks constructed from medium density fiberboard, PCs and, low-level soft partitions, which have a maximum height of 1.3 m. To minimize multipath generated from the partitions, the readers were placed 2.2 m above the floor.

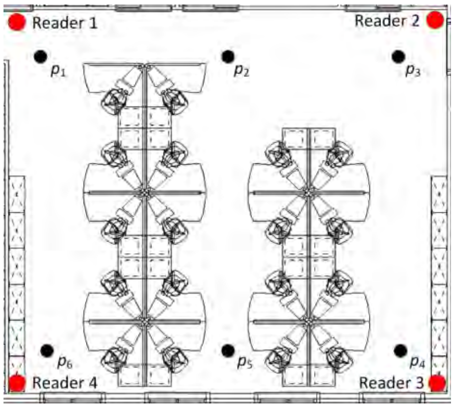

Figure 1. Office floor plan showing reader positions and path waypoints.

For each of the three scenarios carried out in this environment the user travelled at a constant target speed of 0.6 m/s from the starting location to a different point within the office and then walked back to the starting location. The starting and end locations are marked by the points p_1 to p_6 in Figure 1. The tag's location on the left wrist creates a situation in each scenario in which the tag is NLOS to two of the readers and LOS to the remaining readers. Combining time and known location information of the tag allowed manual differentiation of the channel into LOS and NLOS.

IV. Channel Modeling

In these experiments four different arrangements of channel models were tested. First was a simple model that was generated from all of the recorded RSSI sample data. The second split the data into LOS and NLOS models, based on the manual differentiation mentioned above. The third saw the data split into four models, one for each of the readers. The final arrangement had eight models which are made up of separate LOS and NLOS channel models for each reader.

Only the data gathered in the first two runs of each scenario was used to create the channel models. The data from the third run was reserved for testing the models and accuracy of the localization algorithm. This ensures that the results obtained were not specific to the data from which the channel was estimated. For each of the channel scenarios under consideration the model parameters are estimated using MATLAB by calculating the curve following (1) that best fitted the data in a least squares sense.

TABLE I. Single Channel Model (All Data)

Channel Parameters		
***P_0* (dB)**	***n_p***	***σ(dB)***
–61.4	1.363	5.488

TABLE II. LOS and NLOS Channel Models

Channel	**Channel Parameters**		
	***P_0* (dB)**	***n_p***	***σ(dB)***
LOS	–59.1	1.526	5.54
NLOS	–63.6	1.209	5.27

TABLE III. Separated Channel Models For Each Reader

Reader	**Channel Parameters**		
	***P_0* (dB)**	***n_p***	***σ(dB)***
1	–61.6	1.393	5.65
2	–62.7	1.359	5.24
3	–58.1	1.633	5.15
4	–58.9	1.551	5.51

TABLE IV. Channel Models Separated by Reader and LOS

Reader	**Channel**	**Channel Parameters**		
		***P_0* (dB)**	***n_p***	***σ(dB)***
1	LOS	–58.5	1.643	5.58
	NLOS	–64.7	1.143	5.37
2	LOS	–60.8	1.490	5.56
	NLOS	–64.4	1.243	4.76
3	LOS	–55.3	1.829	5.20
	NLOS	–61.4	1.404	4.83
4	LOS	–58.6	1.498	5.40
	NLOS	–58.5	1.610	5.59

V. Results

The location error was calculated as the Euclidean distance between the tag's estimated location using RMCL and the tag's true location. To provide an overall accuracy figure, the root mean square (RMS) of the error was used since it is better at representing large but infrequent localization errors. Note that much of the localization literature quotes the more favorable 50th percentile (median) or even mean error.

The RSSI resolution of the readers was 0.5 dB which gives an estimated range variance of approximately 1.3 m at 15.6 m, the length of the longest diagonal in the office, and a variance of approximately 0.6 m at 7.8 m, the distance from each reader to the centre of the room.

At each time step RMCL was given the manually determined current LOS condition between the tag and the individual reader and used this information to select the appropriate channel model. The selection of the channel model was restricted depending on how many channel models were being tested. Additionally, since RMCL is statistically based, the calculated location estimate will vary over different iterations of the same data. To account for this the results shown in Table V are the average error of 100 trial runs.

TABLE V. OVERVIEW OF RMCL RMS ERROR

Scenario	Number of Models				User Path	Average Speed (m/s)
	1	*2*	*4*	*8*		
1	1.27	1.20	0.68	1.18	p_6, p_1, p_6	0.68
2	3.09	2.98	0.69	2.63	p_5, p_2, p_5	0.69
3	2.40	1.98	0.64	1.29	p_4, p_3, p_4	0.64
4	2.80	2.33	0.75	1.92	p_3, p_1, p_3	0.75
5	2.06	1.77	0.70	1.40	$p_6, p_1, p_2, p_5, p_2, p_1, p_6$	0.70
6	2.37	2.08	0.74	1.56	$p_6, p_1, p_3, p_4, p_3, p_1, p_6$	0.74
All	2.36	2.07	1.87	1.65	N/A	N/A

It can be seen that, in general, as more models were added to account for the various LOS and NLOS situations the more accurate the location estimate became. Viewing these errors on a cumulative distribution function (CDF) graph, see Fig. 2, shows that every refinement on the channel model increases the location accuracy of the system, despite any deviation from this trend by the result of an individual scenario. An example of this deviation can be seen in Scenario 1 (Table V).

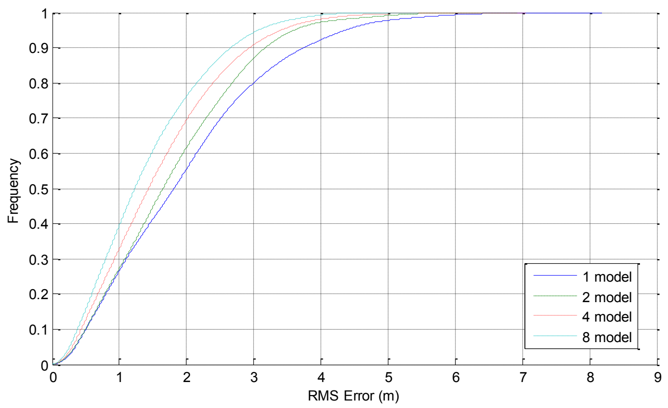

Figure 2. The cumulative destribution function of RMS error in all scenarios using all channel model arrangements.

Inspection of the results from the individual scenarios reveals that the greatest improvement in accuracy is in Scenario 3 which has an improvement of over 46% (Table V). The cause of the improvement can be seen by examining a typical estimated path for the two of the channel model arrangements. Inspection of Fig. 3 shows that with only one channel model a major deviation from the true path has been calculated as the user travels from p_4 to p_3 (*path up*). In that situation the tag was in NLOS relative to its two closest readers 2 and 3, as the LOS paths were obstructed by the user's body. The effect of this was to cause path deviation as these two readers, which should have the most accurate range measurement, overestimate their distance from the tag. This overestimation was greatly reduced by using differentiated (NLOS-LOS), reader specific channel models, as appropriate for this scenario (Fig. 4). Viewing these errors on a CDF, see Fig. 5, shows that 50% of all the errors are below 1 m in the 8 model case. However, when the number of channel models is reduced the localization scheme becomes less accurate and the median error increases to 2.17 m.

The accuracy improvements gained by having specific LOS and NLOS channel models are not restricted to the simple linear paths displayed in the first four scenarios. They can also be seen in more complex paths such as those shown in the last two scenarios. Using only one channel model in Scenario 6 a significant deviation from the true path can be seen as the user walked in an anticlockwise direction around the office from p_4 to p_6 (Fig. 6). In a similar situation to that observed in the linear scenarios the LOS paths to the closest readers were obstructed by the user's body causing path deviation which was accounted for by using a more accurate channel model (Fig. 7). For the 8 model arrangement the median error was 1.34 m and when using a single channel model the median error was 2.13 m.

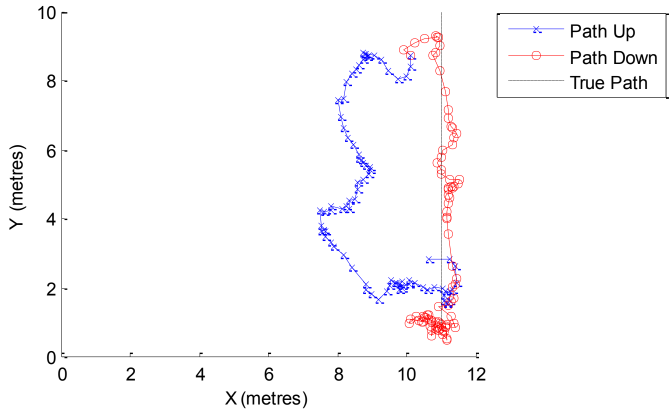

Figure 3. A typical estimated path calculated using 1 model in scenario 3.

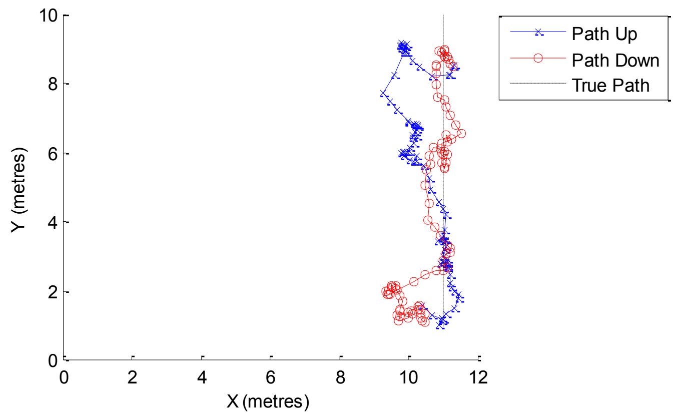

Figure 4. A typical estimated path calculated using 8 models in scenario 3.

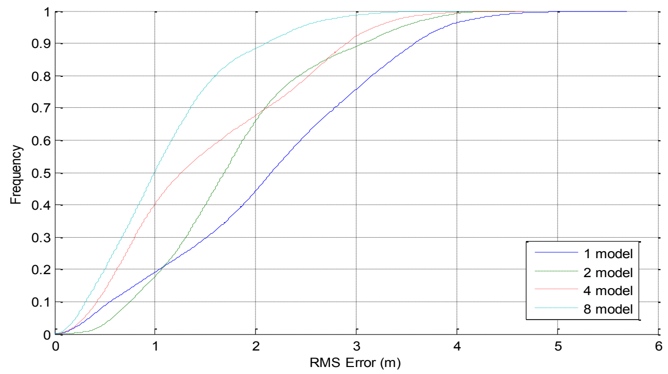

Figure 5. Cumulative distribution function of the RMS errors in Scenario 3 using all four model arrangements.

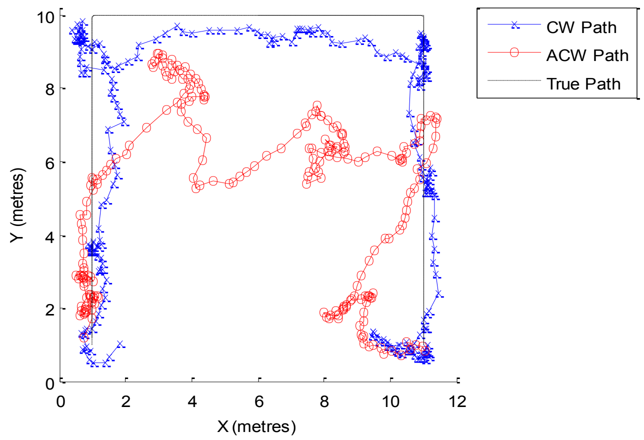

Figure 6. A typical estimated path using 1 model in Scenario 6. The user travels clockwise (CW) from p_6 to p_4 then anticlockwise (ACW) from p_4 to p_6.

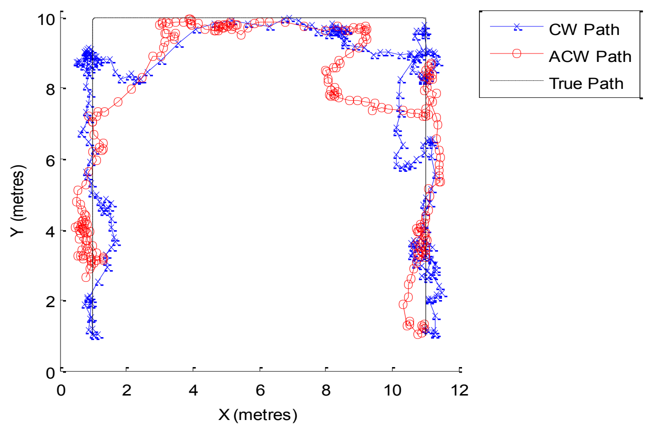

Figure 7. A typical estimated path using 8 models in Scenario 6. The user travels clockwise (CW) from p_6 to p_4 then anticlockwise (ACW) from p_4 to p_6.

VI. CONCLUSION

This paper has shown that RMCL, a statistically based localization method, may be used without special alteration to provide an acceptable localization error of less than 2.5 m overall for the scenarios considered in this study. In addition it was shown that by employing channel models that properly account for the difference in the signal strength characteristics between LOS and NLOS, RMCL may be made even more accurate, with a RMS error as low as 1.18 m.

While the greatest improvement in location accuracy can be achieved by using a combination of LOS and NLOS models that are unique to every link, the associated overheads may prove undesirable in resource constrained systems. Moreover, additional anchor nodes would further increase the time needed to calculate the necessary localization models. Despite this, even two channel models have been shown to improve the accuracy of localization, illustrating how extra effort during system installation can lead to improved accuracy. The demonstrated ability of separate LOS and NLOS channel models to increase the accuracy of localization algorithms suggests that NLOS detection algorithms warrant further investigation. The presented work involved manual differentiation of the LOS conditions but an algorithm for determining the appropriate channel would be needed in order to expand the scope and utility of this work. In keeping with the RSSI ranging method used in this paper, future work will focus upon signal strength characterization as its primary channel differentiation mechanism.

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