Pedestrian Tracking Algorithm in NLOS Environments

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Abstract—**This paper presents a cellular network based positioning algorithm in an urban environment characterized by multipath and severe non line of sight (NLOS) errors. The proposed algorithm mitigates localization error up to 75% as shown by the simulation results. The algorithm involves an initial averaging step followed by a prediction step for optimization, confining the estimated location close to the actual location. The proposed algorithm doesn't require additional hardware like sensors, accelerometers, gyroscopes etc. for localization as used in traditional cellular network based positioning methods. This approach can also be utilized in indoor positioning system (IPS) and global positioning systems (GPS) when at most three satellites are available. Low computational complexity of the algorithm is an added advantage. Utilization of orthogonal sources of information for improving accuracy is also explored.**

Index Terms— **NLOS, Pedestrian Tracking, Modelling, Algorithm**

I. INTRODUCTION

Advancements in dynamic mobile localization technologies have constantly been exploited by the police, homeland securities and tourists as mainstream applications in the form of vehicle and pedestrian tracking. With the advent of smartphone technologies, cellular network based positioning methods are fast evolving in pedestrian tracking. However, cellular network based pedestrian tracking still faces major accuracy issues [1] (up to hundreds of meters) primarily due to multipath and non-line of sight (NLOS) error. These factors coupled with limited number of communicable base stations create reliability issues. Severity of NLOS is augmented in urban environments as high-rise buildings and structures impediment signal propagation. These obstructions subject the signal through reflections and refractions thereby hindering the direct flow of signal from the base station to the mobile devices. The more reliable, Global Positioning System (GPS) also incurs these signal propagation aberrances in NLOS environments. Most state of the art methods addressing this problem [2-4] are based on the presumption that the mobile devices are equipped with inertial sensors, gyroscopes or pedometers. However, size and cost constraints prohibit the inclusion of inertial sensors in most mobile devices thereby hindering their practical implementation.

The objective of this research was to develop a pedestrian tracking algorithm which solely requires location estimate from cellular tower. This technological constraint is only a more general and a valid real time situation considering the fact that most mobile devices except smartphones don't facilitate motion information. Also, this is a more ubiquitous and pragmatic situation. Although, the usage of this algorithm with hardware sophistication involving sensor usage would lead to a greater accuracy but in order to maintain generality this has not been addressed.

The algorithm can subdue the disadvantages causal to hardware constraints by involving orthogonal sources of information i.e. statistical information regarding motion of pedestrian, paths, maps etc. However, this may aggravate the inherent computational complexity of the algorithm therefore degrading its adaptability. As an urban environment problem is being addressed, pervasive computing methods may be used to solve computational complexity issue. Migration of computational intensive tasks such as statistical analysis or maps information via 3G, Wi-Fi to the nearby powerful server would result in accurate results. Figure 1 show a pedestrian in a NLOS environment where high rise buildings are obstructing signal propagation.

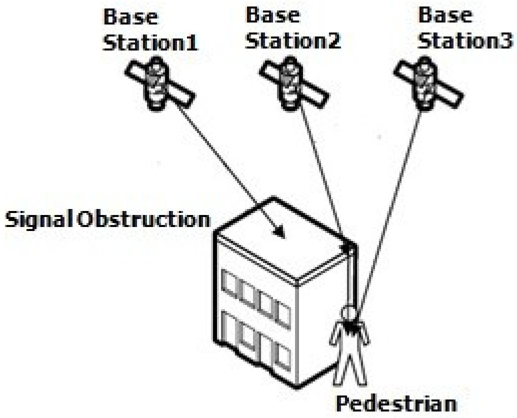

Fig.1 NLOS Environment

II. LOCALIZATION MODEL

In this section, network model is described. Instead of following traditional approaches in pedestrian tracking different modeling is approached. In this network model, three base stations which can communicate with mobiles are considered. However, this model is also applicable for cellular networks having more than three base stations. Unavailability of even three base stations can be countered with pseudo beacon method [5]. This network model is based on the assumption that the estimated position of pedestrian carrying mobile device by base stations lies within a circle of radius *R*, which is centered at true position of the pedestrian. Therefore, it can be inferred that all location points given by base stations would lie randomly in a circle of radius *R*. This model is compared with earlier models through simulations (as described in section 4) and it turns out that most of the estimated points for a given situation indeed lie in a circle of radius *R*.. Figure 2 describes the cellular network model consisting of three base stations. As shown in the figure, the predicted location of the pedestrian by these three base stations lies in a circle of radius *R* centered at true position at k^{th} instant of time. Hollow dots represent predicted positions.

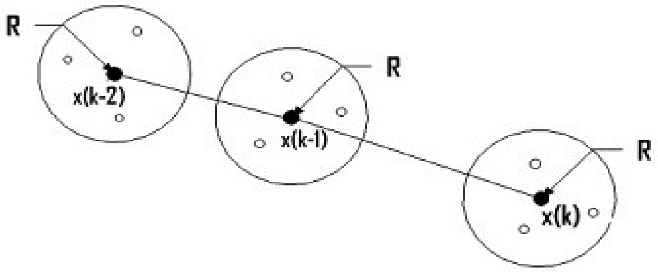

Fig.2 Cellular Network Estimation Model

III. Algorithm

The algorithm involves location estimate from base stations of the mobile device and results in a more accurate location estimate of the pedestrian. As described in previous section, estimated location points by cellular network lies in a R meters radius circle centred at the true point i.e.

$$(x_{i,j}-x_c)^2+(y_{i,j}-y_c)^2\le R^2 \tag{1}$$

where, (x_c, y_c) is the true position of the mobile device. The estimated coordinate for the true point is $(x_{i,j}, y_{i,j})$ at j^{th} time interval by the i^{th} base station.

In this paper, mobile device and pedestrian are used interchangeably. The algorithm is divided in two steps namely initial estimation and prediction optimization.

A. Initial Estimation Step

The initial estimated position is calculated in first step by determining the arithmetic mean of respective coordinates of the estimated points of the base stations.

$$X_{est,j}=\sum_{i=1}^{n}(x_{i,j}/n)\ ,\quad Y_{est,j}=\sum_{i=1}^{n}(y_{i,j}/n) \tag{2}$$

where, n is the number of base stations and $(X_{est,j}, Y_{est,j})$ represents the estimated position.. Here, least square method was also analysed but better results were observed through arithmetic mean approach.

B. Prediction optimization step

The estimation from the previous step is able to reduce localization error but it still has a high value of variance. The prediction step has been introduced with the purpose to minimise this variance. This prediction step makes use of the linear motion equation for displacement.

$$s_{x,j}=v_{x,j-1}(t_j-t_{j-1})+\tfrac{1}{2}a_{x,j-1}(t_j-t_{j-1})^2 \tag{3}$$

where velocity and acceleration are

$$v_{x,j}=\frac{1}{3}\Big([(x_j-x_{j-1})/t_1]+[(x_{j-1}-x_{j-2})/t_2]+[(x_{j-2}-x_{j-3})/t_3]\Big) \tag{4}$$

$$a_{x,j}=\frac{1}{3}\Big([(v_{x,j}-v_{x,j-1})/t_1]+[(v_{x,j-1}-v_{x,j-2})/t_2]+[(v_{x,j-2}-v_{x,j-3})/t_3]\Big) \tag{5}$$

Similarly '$s_{y,j}$', '$v_{y,j}$' and '$a_{y,j}$' can be calculated. 'x_j' represents final predicted location by this algorithm at j^{th} time interval. '$t_{k=1,2,3}$' represents time interval over which position $(x_{i-k+1}-x_{i-k})$ and velocity data $(v_{x,j-k+1}-v_{x,j-k})$ were determined. Similar techniques are used in literature [6] to estimate velocity and acceleration. These equations can be applied only after estimating first four points (initially acceleration is assumed to be zero). Accurate velocity, heading angle direction, acceleration data can be obtained by using sensors and other hardware sophistications. As pointed out earlier, to maintain generality these are avoided. Here, orthogonal sources of information such as statistics regarding pedestrian mean velocity over a certain period of time can be utilised to improve accuracy.

$$X_{pre,j}=X_{j-1}+s_{x,j}\,,\qquad Y_{pre,j}=Y_{j-1}+s_{y,j} \tag{6}$$

where $(X_{pre,j}, Y_{pre,j})$ is the predicted location of pedestrian at j^{th} time interval and (X_{j-1}, Y_{j-1}) is the final predicted location at $(j-1)^{th}$ time interval.

The final estimated location at j^{th} time interval is calculated by finding the weighted average of the initial estimated location, predicted location and previous location of the pedestrian

$$X_j=(w_1X_{j-1}+w_2X_{pre,j}+w_3X_{est,j})/(w_1+w_2+w_3) \tag{7}$$

$$Y_j=(w_1Y_{j-1}+w_2Y_{pre,j}+w_3Y_{est,j})/(w_1+w_2+w_3) \tag{8}$$

where (X_j, Y_j) represents the estimated location of pedestrian at j^{th} time interval and this process goes on for $(j+1)^{th}$, $(j+2)^{th}$ and so on. Weighted mean is obtained empirically by simulating different values of w_1, w_2 and w_3 to minimize localisation error. Best results were achieved by using values of w_1, w_2 and w_3 to be 1, 2 and 3 respectively. Due to insufficient parameters for first four estimations, arithmetic mean of initial estimated position (in first step) and estimated position by least square method is considered as final estimated location of pedestrian.

Low computational complexity of this algorithm is an added advantage for its mobile device installation. This algorithm requires the mobile device to store locations of only six previous points thereby reducing memory occupation.

IV. SIMULATION METHODOLOGY

NLOS occurrence is by large an urban phenomenon, consideration of urban environments for analysis is pragmatic. A typical pedestrian path in an urban environment can be assumed to be straight line. However, right angle turns must be included in path. Furthermore, similar observations would be expected when different path geometries are used for simulation. Similar assumptions have been made in literature regarding path of the pedestrian [7, 8]. The whole simulation is carried out in a plane. However, this could be easily extended for z direction also [1]. The distance measurements are made simultaneously once per second at all base stations. Considering our localization model, R was taken to be 125m. Simulations were also performed by modeling distance measurement errors as the sum of a zero-mean Gaussian noise variable and an exponential NLOS-induced bias variable as performed earlier in literature. The standard deviation of the distance measurement noise was set at 75 m, whereas the mean of the exponential component of the distance error was varied from 10m to 100 m to model different NLOS conditions. It was observed that most of the erroneous data points lies inside a circle of radius R (125m). Thus, it is reasonable to produce simulations over proposed network model. Locations predicted by base stations were randomly distributed in the described circle of radius R. Algorithm as described in earlier section mitigates NLOS error and provides estimated location of the pedestrian. The simulation performance metric is the mean error of the position estimation computed according to

$$e_{BS} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\sqrt{(X_{true,j} - x_{i,j})^2 + (Y_{true,j} - y_{i,j})^2} \quad (9)$$

$$e_{est} = \frac{1}{n}\sum_{j=1}^{n}\sqrt{(X_{true,j} - X_j)^2 + (Y_{true,j} - Y_j)^2} \quad (10)$$

$$\text{Mitigation } \% = \left(\frac{e_{BS} - e_{est}}{e_{BS}}\right) \times 100 \quad (11)$$

Here, n is the total number of time intervals over which the tracking is performed and m denotes the number of base stations. ($X_{true,j}$,$Y_{true,j}$) and (X_j,Y_j) represents true location and estimated location at j^{th} time interval respectively. Simulated results shows 75% mitigation of mean error induced due to NLOS and multipath occurrences. An urban environment simulation is shown in Fig.3. It is reasonable to assume that this path is surrounded by the high rise buildings.

Here, use of orthogonal sources of information was also explored. Using maps, accuracy can be significantly improved as 85-90% mitigation of mean error was achieved. But simulation results may differ from actual implementation, more research is required to fully utilise these information. In this paper, google maps, pedestrian mean velocity data was used to improve accuracy. Approximately an error of more than 10m in urban environment would predict pedestrian location either in a building or on other side. This was rectified by using google maps and pedestrian location was modified accordingly. However, numerous assumptions were taken during simulations. Thereby, a more rigorous analysis is required to utilise this approach.

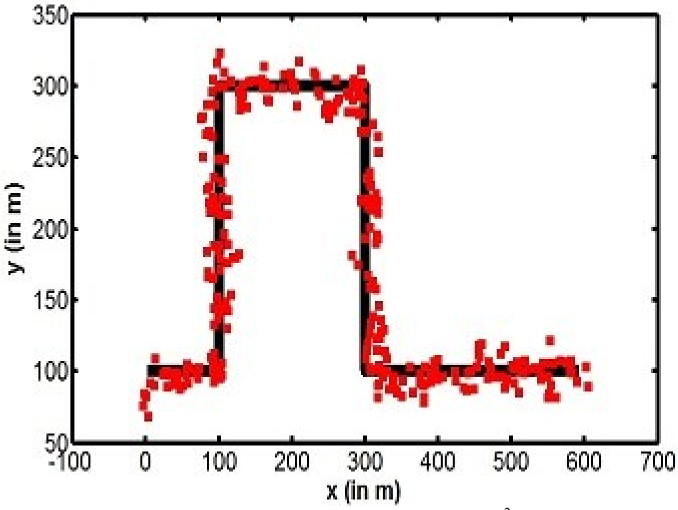

Fig.3 Simulation results over a urban area of 600 X 300 m^2. Markers represent estimated location and solid thick line represent true pedestrian path

V. CONCLUSION

A two-step NLOS induced error mitigation algorithm for pedestrian positioning is presented in this paper. This approach has an inherent advantage of avoiding the use of hardware sophistications such as sensors, gyroscopes etc. The proposed algorithm mitigates localization error up to 75% as shown by the simulation results. Utilization of orthogonal information through pervasive computing environment is also explored. However, further research is needed to turn this into a viable solution to the tracking problem.

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