Predicted and Corrected Location Estimation of Mobile Nodes Based on the Combination of Kalman Filter and the Bayesian Decision Theory

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Abstract. The main objective of this research is to apply statistical location estimation techniques in cellular networks in order to calculate the precise location of the mobile node. Current research is focusing on the combination of Kalman filter and the Bayesian decision theory based location estimation. In this research basic four steps of Kalman filter are followed which are Estimation, Filtering, Prediction and Fusion. Estimation is done by using Receive Signal Strength (RSS), Available Signal Strength (ASS) and the Angle of Arrival (AOA). Filtering is done by calculating the average location and variation in values of location. Prediction is done by using the Bayesian decision theory. Fusion is done by combining the variances calculated in filtering step. Finally by combining the prediction and fusion results PCLEA (Predicted and Corrected Location Estimation Algorithm) is established. Timestamp is used for recursive step in kalman filter. The aim of this research is to minimize the dependence on the satellite based location estimation and increase its accuracy, efficiency and reliability.

Keywords: Kalman filter, Bayesian decision theory, location estimation.

1 Introduction

Location estimation of a mobile user is a very popular research area from past few years. Due to the growth of cellular architecture the mobile users originating calls are also increasing at the same time. It is estimated that more than 50% emergency calls are originated by the mobile phones [1]. Techniques which are used for location estimation are satellite based techniques, geometric techniques, statistical techniques and the mapping techniques [2], [3]. All techniques have different accuracy level, processing time, coverage and the cost. The location of the mobile node can be estimated by the mobile node itself which is known as self positioning. Otherwise it can be calculated by the server with the help of the reference points, which is known as remote positioning or network centric positioning [4]. Two different approaches are used by the researchers, the direct positioning approach and the two step-step

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positioning approach. In direct positioning approach position is estimated directly from the signal travel between two nodes [5]. In two steps positioning approach first different signals parameters are calculated and in the second part position of the mobile node is estimated by using these parameters. The accuracy level of two step approach is higher as compare to direct approach [5], [6]. Figure 1 is explaining the direct and the two step positioning approaches [3], [5], [6].

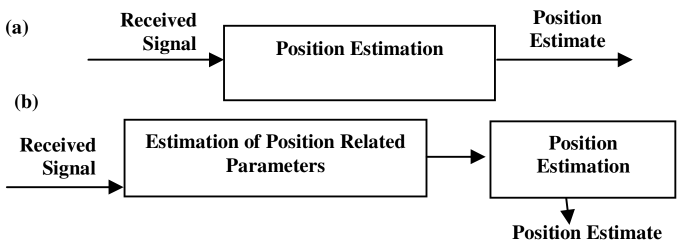


Fig. 1. (a) Direct Positioning, (b) Two-step Positioning [3], [5], [6]

Current research is falling under two step position technique which is focusing on the Kalman filtering combine with the Bayesian decision theory results. The cycle of Kalman is based on prediction and correction. It is very powerful as it supports past, present and future predictions [7]. Kalman filter also use four step procedure for accuracy in measurement updates [7] estimation, filtering, prediction and fusion.

In this research estimation is done by using RSS, ASS and the AOA as a parameters. Filtering is performed by the mean and the variant values of location at different timestamps to calculate the Region of Interest (RoI). Whereas prediction is done by using Bayesian decision theory, overlapping area (**Ω**) is used as a-priori probability in Bayes law. Finally fusion is performed by combining the variances of different timestamps and fuse results with the predicted value calculated by Bayesian decision theory. Based on the Kalman filter cycle [7], an algorithm PCLEA is developed which predicts and corrects the location values based on recursive timestamps.

This paper is divided into six sections; in section II literature survey of previous research work is done. Discussion review is included in section III. Section IV is defining the problem statement. Section V presents proposed architecture which includes estimation, filtering, prediction, fusion and PCLEA. Section VI is dedicated for results and discussion and finally conclusion is added in section VII.

2 Relevant Studies

In [8] authors used Extended Kalman filter approach in WSN for location estimation. Parameter considered was RSSI, where is RSSI=K/R2.

K is considered as the measure of confidence level and R is representing the radius of the sensor network communication range. Authors claimed that their method is showing better results when compare with existing methods.

In AVG [9], authors used Kalman filter very efficiently to control noise and error control. Based on experiments they claimed that derived approach offers better suppression of vision measurement noise and a better performance in the absence of vision measurements.

In [10] authors proposed Kalman filter based Location estimation with NLOS mitigation. They fused results of geometric approach with the Kalman for location estimation. They suggested that geographical information can be added for better accuracy of mobile location.

In [2], author proposed and implemented GPS free global positioning method for mobile units for indoor wireless environment. He used Bayesian filtering approach for initial measurement, cell-ID of the serving base station, and the predetermined route radio maps. In step one author derived generic recursive Bayesian filter algorithm for prediction and update. In step two global positioning algorithm is derived which is used to track the probable position of mobile unit. Author repeated the experiment for 100 times and claimed the estimated position tracking error is between 15m and 20m.

Sinan Gezici et al [3] investigated and presented various positioning algorithms. Author pointed out that two approaches used for the position estimation

(i) the "Direct approach" in which position of the mobile node is estimated based on the signal travel between two nodes [5],

(ii) and the two-step positioning that first calculate the different position parameters like AOA, TOA, TDOA, ASS, RSS etc and based on these parameters position of the cell phone is estimated. Author also pointed out the geometric and statistical techniques can be used for the accuracy.

In [11] authors introduced a Bayesian hierarchical modeling approach for location estimation. Instead of locating a single node they simultaneously located a set of wireless nodes. Their work is based on prior knowledge and they constructed the network as used in Boltzmann learning. They demonstrate that their model achieved similar accuracy as previously published models and algorithm.

In Selective Fusion Location Estimation (SELFLOC) [12] authors assigned weight to each location and weighted sum gave the SELFLOC estimation. They calibrated the branch weights during the offline stage using the error feedback. Authors adopted the Minimum Mean Square Error (MME) [13] for SELFLOC weight calibration. Authors also applied SELFLOC algorithm with other classical location algorithms to improve accuracy. Classical algorithms they used in their experiments are Triangulation (TN), K-Nearest Neighbour averaging (KNN) and the Smallest M-vertex Polygon (SMP).

In Region of Confidence (RoC) [12] authors attempted to counter aliasing in the signal domain. By using the probabilistic techniques the algorithm first forms a region of confidence within which the true location of a user lies. Through implementation and experiments authors experienced best mean distance error of 1.6m while using SELFLOC weighted localization algorithm. By using RoC with eKNN they experienced that the error can be improved from 6m to 4.5m.

Vinay Seshadri and others et al [14] used Bayesian sampling approach for the location estimation of indoor wireless devices by using RSSI as main sensing parameter. The proposed architecture used posterior probability of the target location using sequential Monte-Carlo sampling, which is capable of using arbitrary a-priori distribution to compute a posterior probability [14]. Based on the simulation results authors believe that the method is less computationally intensive and it is also suited to an indoor wireless environment where other standards may not work.

In [15] author presented a statistical location estimation technique based on a propagation prediction model. Author took signal parameters such as Receive Signal Strength and Angle of Arrival. Propagation delay is considered as random variable which is statistically dependent on the location of receiver, transmitter and the propagation environment. Author comments that statistical approaches include certain type of flexibility.

If the signal propagation environment differs significantly from ideal condition the distance or angle measurements will be unreliable [15].

Different statistical tools are used by researchers for the precise location of wireless nodes specially Bayesian based location estimation is not new but the combination of the kalman filtering with the Bayes theorem for location estimation is a research area which is not extensively touched by researchers.

3 Problem Statement

Location estimation of a mobile node is not new area of research. Global Positioning System (GPS), Cell Identifier (CI), Location Area Identifier (LAI), GSM and WLAN positioning all falls under the location estimation. On the other hand Bayesian decision theory is commonly referred by researchers. But there is a need of mechanism which can reduce error rates from few meters to few centimeters. Current research is trying to cater the same problem with the help of Bayesian decision theory using a-priori condition of overlapping coverage area (**Ω**) and the fusion results of combine variance ($1/\sigma^2$). Kalman filter recursive model of prediction and correction is followed to achieve accuracy.

4 Propose Architecture

The propose architecture is divide into four steps. In step I we use geometric approach by using RSS, ASS and the AOA to calculate the estimate value of mobile node [16], [17]. In step II we calculate average and variance values in order to filter the estimate position. Step III calculates the Bayesian decision theory based prediction by using overlapping coverage area (**Ω**) as a-priori probability. In Step IV we fuse results of Step II by using kalman filter combine variance approach. Finally we propose PCLEA by fusing the results of Step III and IV in order to get the most accurate position of a cellular node.

4.1 Step I: Estimation (W)

At the first step of the proposed architecture geometric position estimation techniques are used. ASS, RSS and the AOA are used as parameters. Our assumption is based on,

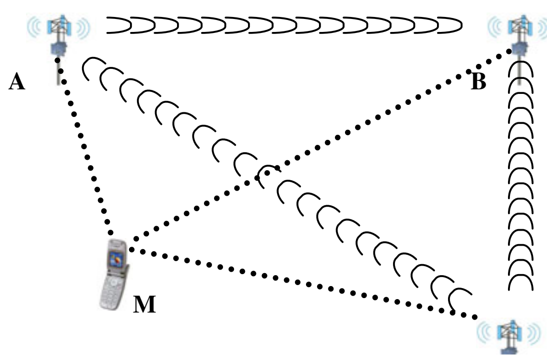


Fig. 2. Mobile node (M) is receiving signals from antennas

that the cell phone is receiving signals from 3 BTS (Base Transceiver Station). In this condition 3 triangles will be constructed i.e. ΔABM, ΔACM and ΔBCM as shown in the figure 2 [16], [17].

By using the ASS and the RSS, the distance between points AB, AM and AC is calculated.

$$D_{(AB)t0} = \frac{ASS_{(A)t0} + ASS_{(B)t0}}{2} - \frac{RSS_{(A)t0} + RSS_{(B)t0}}{2} \quad (1)$$

$$D_{(AM)t0} = ASS_{(A)t0} - RSS_{(M)t0} \quad (2)$$

$$D_{(BM)t0} = ASS_{(B)t0} - RSS_{(M)t0} \quad (3)$$

where
ASS is Actual Signal Strength at A and B at t0.
RSS is Receive Signal Strength from A, B and M at time t0.
$D_{(AB)}$ is distance between point A and B.
$D_{(AM)}$ is distance between point A and M.
$D_{(BM)}$ is distance between point B and M.

As the location of points A, B and C are known and the distance between A, B and M is calculated. By using the simple trigonometry formula angles α and β are calculated at the next step.

$$\text{Cos}\alpha = \frac{\{D_{(AM)t0}\}^2 + \{D_{(AB)t0}\}^2 - \{D_{(BM)t0}\}^2}{2\, D_{(AM)t0}\, D_{(AB)t0}} \quad (4)$$

By using basic trigonometric *formula for angle calculation with three known sides,*   *Cosα = $(b^2 + c^2 - a^2)/2bc$*

$$\text{Cos}\beta = \frac{\{D_{(BM)t0}\}^2 + \{D_{(AB)t0}\}^2 - \{D_{(AM)t0}\}^2}{2\, D_{(BM)t0}\, D_{(AB)t0}} \quad (5)$$

By using the distance between AB, AM and BM and the angles α and β a triangle is plotted to estimate the location of M (Loc M) at time t_0 by using ΔABM as shown in figure 3.

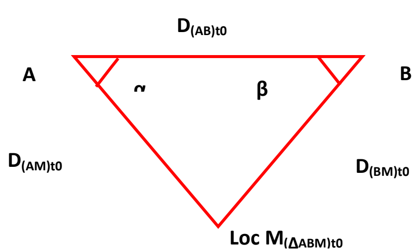


Fig. 3. Mapping of M by using distances AB, AM and BM and the angles α and β

Similarly by using triangles ΔACM and ΔBCM two other locations of M are calculated as shown in figure 4.

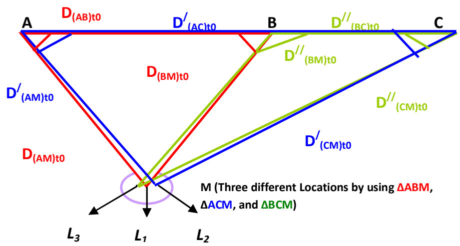


Fig. 4. Location estimation of Mobile by using three triangles, where D is the distance calculated by ΔABM, $D^{/}$ is calculated by ΔACM and $D^{//}$ is calculated ΔBCM

Theoretically calculated locations that we mention above are not accurate because radio waves contain noise. Kalman filter prediction and correction is use with the combination of Bayesian decision theory to minimize errors. As we have three different locations at t_0 we average them to calculate the location of mobile node at this timestamp.

4.2 Step II: Filtering (X)

Filtering of the estimated location is done by calculating average and variance by using different timestamps. In current scenario we are considering four timestamp.

$$Loc\ M_{to} = \frac{Loc\ M_{(\Delta ABM)t0} + Loc\ M_{(\Delta ACM)t0} + Loc\ M_{(\Delta BCM)t0}}{3} \tag{6}$$

Similarly the average at t_1,t_2 and t_3 are calculated .

$$Loc\ M_{t1} = \frac{Loc\ M_{(\Delta ABM)t1} + Loc\ M_{(\Delta ACM)t1} + Loc\ M_{(\Delta BCM)t1}}{3} \tag{7}$$

$$Loc\ M_{t2} = \frac{Loc\ M_{(\Delta ABM)t2} + Loc\ M_{(\Delta ACM)t2} + Loc\ M_{(\Delta BCM)t2}}{3} \tag{8}$$

$$Loc\ M_{t3} = \frac{Loc\ M_{(\Delta ABM)t3} + Loc\ M_{(\Delta ACM)t3} + Loc\ M_{(\Delta BCM)t3}}{3} \tag{9}$$

Refer to Kalman filter [7], to calculate variation in location at different timestamps the variance computing formula is used.

$$\boxed{\sigma^2 = \frac{\sum (X - \overline{X})^2}{N} \quad [7]}$$

$$\sigma^2_{(Loc\ M)\ t_0} = \frac{\Sigma\ (L_{n(t_0)} - Loc\ M_{t_0})^2}{N} \tag{10}$$

Where n= 1, 2, 3 and N= 3

Similarly variation of location can be recorded by calculating variance at $t_1, t_2 \ldots t_k$.

$$\sigma^2_{(\text{Loc M})\, t_1} = \frac{\Sigma\ (L_{n(t_1)} - \text{Loc } M_{t_1})^2}{N} \tag{11}$$

$$\sigma^2_{(\text{Loc M})\, t_2} = \frac{\Sigma\ (L_{n(t_2)} - \text{Loc } M_{t_2})^2}{N} \tag{12}$$

$$\sigma^2_{(\text{Loc M})\, t_3} = \frac{\Sigma\ (L_{n(t_3)} - \text{Loc } M_{t_3})^2}{N} \tag{13}$$

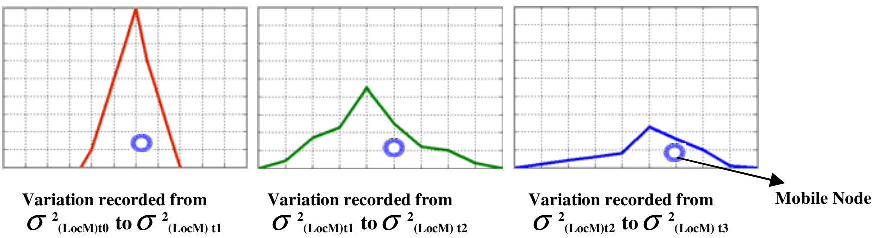


Fig. 5. Variation in location of M at t_0 to t_1, t_1 to t_2 and t_2 to t_3

Figure 5 is representing the variations at three different timestamps. Although the location of mobile node is falling inside the Region of Interest (RoI) but still it is only pointing out only the region of high availability and unable to predict the actual position (each box in a region is representing 2 square meters).

4.3 Step III: Prediction (Y)

Overlapping Coverage Area (Ω). It is also possible that at any time t_n mobile node receive signals from less than three BTS (Base Transceiver Station). Overlapping coverage area is considered as condition in Bayesian decision theory for the location estimation. Ω is representing the overlapping coverage area of three BTS.

where $\Omega = (A \cap B \cap C)$, $\Omega_1 = (A \cap B)$, $\Omega_2 = (A \cap C)$, $\Omega_3 = (B \cap C)$

If the location of mobile node is confirm from all of the three BTS then the probability of precision will be higher whereas in case of Ω_1, Ω_2 and Ω_3 probability of precision will be lesser. Figure 6 representing the signal coverage and the overlapping coverage areas.

The probability of selecting the location with the condition of posterior probability Ω will be higher than the posterior probability of Ω_1 and Ω_2. By applying the Bayesian theorem we will get

$$P(\boldsymbol{L_1} | \Omega) = \frac{P(\Omega | \boldsymbol{L_1}) \times P(\boldsymbol{L_1})}{P(\Omega | L1) \times P(L1) + P(\Omega |\sim L1) \times P(\sim \boldsymbol{L_1})} \quad (14)$$

$$P(\boldsymbol{L_2} | \Omega) = \frac{P(\Omega | \boldsymbol{L_2}) \times P(\boldsymbol{L_2})}{P(\Omega | \boldsymbol{L_2}) \times P(\boldsymbol{L_2}) + P(\Omega |\sim \boldsymbol{L_2}) \times P(\sim \boldsymbol{L_2})} \quad (15)$$

$$P(\boldsymbol{L_3} | \Omega) = \frac{P(\Omega | \boldsymbol{L_3}) \times P(\boldsymbol{L_3})}{P(\Omega | L3) \times P(L3) + P(\Omega |\sim L3) \times P(\sim \boldsymbol{L_3})} \quad (16)$$

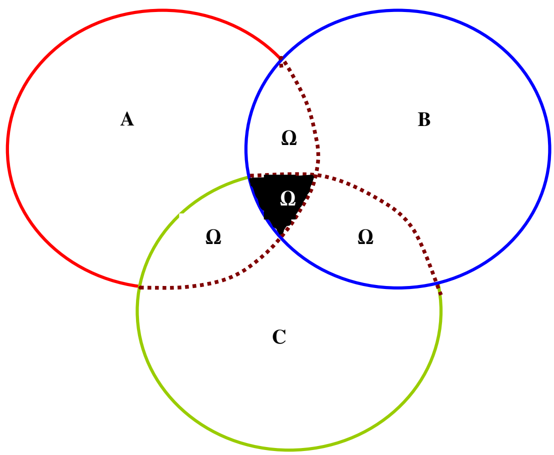


Fig. 6. Footprint of BTS A, B and C, showing the overlapping area

For a given Ω if any estimated location is falling outside the Ω then the chances of precision will be lesser. It will be considered only if all the locations falling outside the Ω. This rule will minimize the average probability of error. By applying the Bayesian decision theory on equation 14, 15 and 16 we will get the following equation.

$$P(\boldsymbol{L} | \Omega) = \max [P(\boldsymbol{L_1} | \Omega), P(\boldsymbol{L_2} | \Omega), P(\boldsymbol{L_3} | \Omega)] \quad (17)$$

4.4 Step IV: Fusion (Z)

By combining the variances [7] of step II we will get combine variation area for the location estimation. This overlapping variant area is considered as a most powerful candidate for the location of mobile node. Simulation results in figure 7 are explaining and justifying the scenario.

$$1/\sigma^2 = 1/\sigma^{2(\mathrm{LocM})\ t0} + 1/\sigma^{2(\mathrm{Loc\ M})\ t1} + 1/\sigma^{2(\mathrm{Loc\ M})\ t2} + 1/\sigma^{2(\mathrm{Loc\ M})\ t3} \quad (18)$$

$$\text{Let } \varsigma = 1/\sigma^2$$

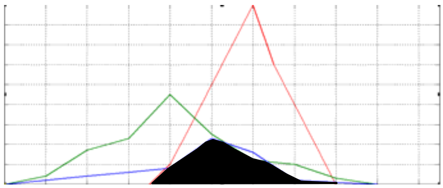


Fig. 7. Overlapping variant area by combining variences

Figure 7 is the combine variance representation in Matlab, which is combining the overlapping variance area shown in figure 5. The shaded portion is representing the combine variances. We use fusion here to minimize the region of interest of step II. Although fusion is helpful to minimize the Region of Interest (RoI), but does not support to pinpoint actual position. Based on the above four steps (estimation:W, filtering:X, prediction:Y and fusion:Z) predicted and corrected location estimation algorithm is proposed base on kalman filter recursive approach of prediction and correction. In our algorithm prediction is based on W, X, Y and Z whereas correction is obtained by combining their results.

PCLEA (Predicted and Corrected Location Estimation Algorithm)

```
1.  estimation: W
2.  filtering: X                       Prediction
3.  prediction: Y
4.  fusion: Z
5.  if  P (L1| Ω) →S
6.                  select: L1
7.  goto 15
8.  else if P (L2| Ω)→ S
9.                  select: L2
10. goto 15                            Correction
11. else if P (L3| Ω)→ S
12.                 select: L3
13. goto 15
14. else goto 1
15.              timestamp:            Recursion
16. estimation: W
17. filtering: X
18. prediction: Y                      Prediction
19. fusion: Z
20. goto 5
```

Above algorithm is based on the prediction and the correction rule of the Kalman filter. As shown in figure 7 the overlapping area of the most variant values of locations L_1, L_2, L_3 and in figure 6 "Ω" is the receive signal overlapping area for same L_1, L_2, L_3 locations. Line 5, 8, 11 of algorithm are analyzing either L_1, L_2 and L_3 are falling in the variant area, If selected then that location will be the most precise value otherwise as mention in line 16, 17, 18 and 19 after a described timestamp it will start the kalman filter cycle of prediction and correction. Figure 8 is representing the tracking architecture of above algorithm.

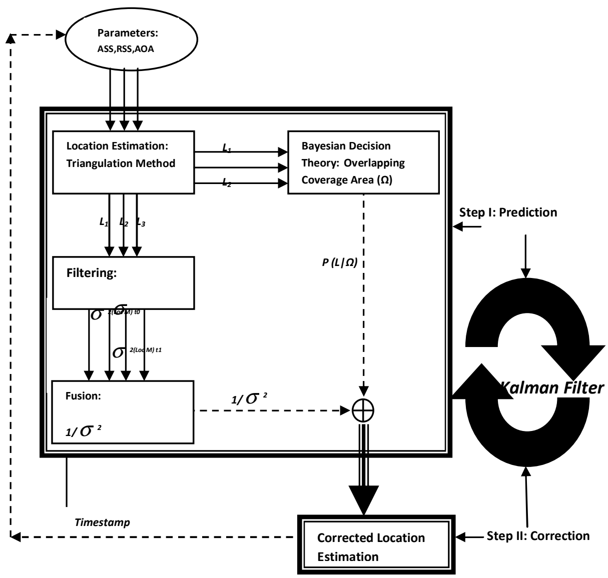


Fig. 8. Tracking architecture of PCLEA

5 Results and Discussion

Figure 9 is base on estimation which is using triangulation method for location estimation at time t_0, t_1, t_2 and t_3. Circle is representing a mobile node. Recorded variation is representing in figure 10, while prediction step is simulated by using P ($L|\Omega$) P ($L|\Omega_1$) P ($L|\Omega_2$) and P ($L|\Omega_3$), as shown in results in figure 11 that estimated location by using Ω is more precise as compare to Ω_1, Ω_2 and Ω_3. Figure 12 is representing fusion with the combine variance approach. Shaded area is the overlapping variance area which is the most appropriate are for location. Figure 13 is representing the comparison between each step (estimation, filtering, prediction, fusion) results with PCLEA. As shown in figure 13, estimation has maximum error rate which is 9.5 to 10 M. Average of the calculated variance area showing error in distance at the maximum of 7M. Based on estimation results prediction is done by using Bayesian decision theory, which is showing huge improvement in location estimation which is with the error rate of 2M. As also shown in figure 11 Ω_1, Ω_2 and Ω_3 results provide less precision in location estimation which is 3.5 to 3M (figure 13). Figure 13 is representing overall comparison of estimation, filtering, prediction and fusion with the PCLEA. Note that the error of fusion and Ω_1, Ω_2 and Ω_3 is almost same (2.6 M and 3 M - 3.5M respectively) but if we combine the fusion results with prediction (as in PCLEA) then the estimated location of mobile node is almost approaching the actual position, which is with the error rate of 0.6M. PCLEA is actually combining benefits of Kalman filter and the Bayesian decision theory for location estimation.

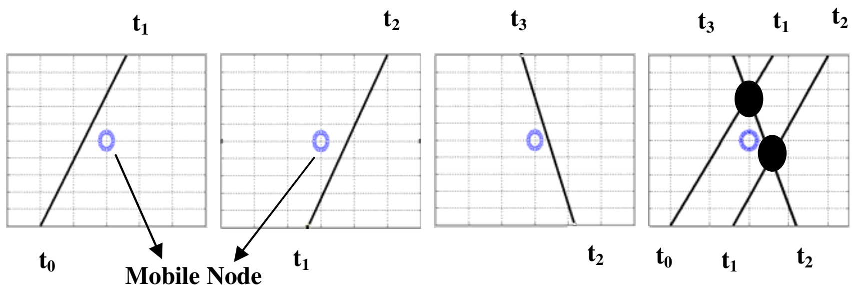


Fig. 9. Estimation

Mobile node is represented by circle, whereas t_0, t_1, t_2 and t_3 are representing the estimated location by using triangulation in figure 9. The error rate is almost 10M in this case. By combining trend lines of all four points we get intersection which is still unable to achieve precision (each box is representing 2 square meters).

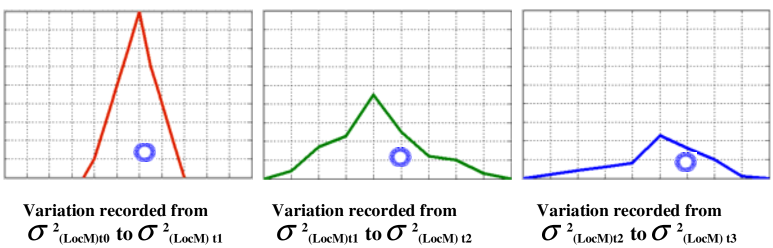


Fig. 10. Filtering

By using the variance we are able to minimize the area in figure 10. By averaging the selected area we still face the error rate of almost 7M (figure 13).

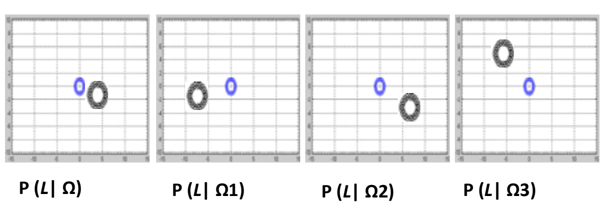
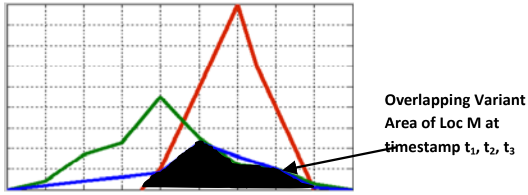


Fig. 11. Prediction

We apply Bayesian decision theory with the condition of overlapping area Ω for prediction. Simulation results shows if the mobile node is receiving signals from all three antennas (i.e. constructing three triangles), then the error rate will be almost 2M. In case of Ω_1, Ω_2 and Ω_3 it may increase by 3 to 3.5M.



$$1/\sigma^2 = 1/\sigma^{2(\mathrm{Loc\ M})\ t1} + 1/\sigma^{2(\mathrm{Loc\ M})\ t2} + 1/\sigma^{2(\mathrm{Loc\ M})\ t3}$$

Fig. 12. Fusion

Figure 12 is representing fusion. The shaded portion is representing the combine variances. Fusion is use to minimize the Region of Interest of filtering step.

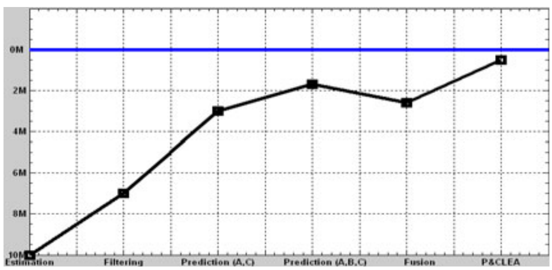


Fig. 13. Comparison of Predicted & Corrected Location Estimation Algorithm (PCLEA) with single step calculation

Figure 13 is representing the distance error recoded at estimation, filtering, prediction at Ω_1, Ω_2 and Ω_3, prediction at Ω, fusion and PCLEA. The error of PCLEA is up to 0.6M. If we compare our region of Interest (RoI) with Region of Confidence (RoC) [12], it shows that RoI has more distance error (2.6M), whereas RoC claimed 1.6M error. The distance error of PCLEA is less with RoC [12] and Selective Fusion Location Estimation (SELFLOC) [12].

In terms of computational complexity the PCLEA is heavier as it is combining four different algorithms; also it is using recursive approach to reach the minimum distance error. It might not produce better results where computational cost is more important like WSN.

6 Conclusion

This research is focusing the prediction and correction rules of kalman filtering in a recursive way to estimate the precise location of a cellular node. In prediction we combine the triangulation, means, variances, Bayesian decision theory and kalman filter fusion whereas for correction we combine results of Bayesian with Kalman filter fusion. Timestamp is use before the recursive iterations. Our results shows that PCLEA is producing less distance error as compare to old location estimation techniques. Infect PCLEA is combining benefits of triangulation, RoI, Bayesian decision theory and the fusion with the kalman filtering.

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