ABSTRACT

A time difference of arrival (TDOA) technique has been proposed for providing location services in future UMTS networks. The performance of such a system is limited by errors in the time difference (TD) measurements primarily cause by non-line of sight (NLOS) propagation conditions. In future systems angle of arrival (AOA) measurements at the serving base station (BS) may be available, primarily as a requirement to increase downlink capacity via beamforming. These measurements may also be useful for location purposes, though they will also be subject to errors caused by NLOS propagation conditions between the mobile (MS) and the serving BS. In this paper the performance improvement of a TDOA location system utilizing the AOA measurement from the serving BS, over a TDOA only system is evaluated. Simulation results are presented which show that location accuracy improvement is possible even in highly NLOS conditions. Furthermore location estimation is now possible when only two BS’s are detectable, rather than the three BS’s required in the TDOA only system, thus increasing the coverage of the system.

1. INTRODUCTION

In wireless systems the need for accurate location estimation has been motivated by the US FCC’s E911 mandate for emergency services [1], as well as customer services (e.g. fleet navigation, location billing), and network aspects (e.g. improved traffic management).

In UMTS a TDOA based location estimation technique has been proposed utilising idle period downlink (IDPL) to allow time differences (TD’s) to be calculated between the serving BS’s and more distant BS’s.

Naturally in line of sight (LOS) conditions the performance of such a system can be very accurate. However if any of the TD’s are measured when a BS is non-LOS (NLOS) then sizeable location errors may be generated. In [2] it is noted that NLOS propagation lengths may be typically 400m greater than LOS.

Increasing the number of measurements can increase the location accuracy, but care must be taken not to utilise NLOS measurements where possible. In [3] a robust receiver architecture was introduced in which timing measurements were tracked via a Kalman filter (KF) with a simple LOS state input estimator. The KF variance estimates generated are used as a weighting matrix in the location estimator. The receiver performs well even in a largely NLOS environment.

In future mobile systems antenna arrays may become standard. In this case the MS’s angle of arrival (AOA) will be known at the serving BS (and possibly adjacent BS’s if the MS is in a soft handover region). The AOA measurements will be subject to NLOS errors correlated to the errors in TD’s involving the serving BS, but should still be useful to the location estimator.

In this paper the performance improvement of a TDOA location system utilising the AOA measurement from the serving BS, over a TDOA only system is evaluated. The NLOS problem is first discussed in more detail then the proposed location receiver architecture is described. Simulation results for measurements from a time aligned idle period downlink (TA-IPDL) [4] UMTS system are then presented.

2. NON-LINE OF SIGHT PROBLEM

Timing and AOA measurements in NLOS conditions will be subject to large errors. The received signal in NLOS conditions is made up of a superposition of arriving rays from local and distant scatterers. As the MS moves through the environment, scatterers appear and disappear, thus there is a high degree of spatial correlation in measurements. This correlation is inversely proportional to the MS speed, and also dependent on the environment type.

The NLOS error in timing measurements (or excess delay) is positive only, with a distribution usually considered to be exponentially decaying [5]. In AOA measurements at the BS there is an angular spread around the true LOS AOA. In [6] an angular spread with standard deviation 17.6 degrees in an urban environment is measured.

2.1. LOS model

In modelling the LOS/NLOS characteristics of the environment a LOS model based on the CoDIT model[7] is used. N scatterers exist in each environment, defined in terms of delay (uniformly distributed within a range) and AOA at the MS (uniformly distributed over 2π). Scatterers appear and exist for a length normally distributed around Ls. A LOS path is present with probability \( P_{LOS} \). The LOS path exists for a length normally distributed around \( L_{LOS} \), before the LOS state is re-evaluated. \( L_{LOS} \) is dependent on the...
geometry of, for example, surrounding buildings and streets and thus conceptually the $L_{\text{LOS}}$ might be expected to have a value of the order 10–100 metres.

The probability density function of the NLOS excess delay, $\tau_{\text{ed}}$, in the model or identically the pdf of the arrival time of the first of N paths in the uniformly distributed delay range can be derived as (space does not permit the derivation)

$$f(\tau_{\text{ed}}) = \frac{P_{\text{det}}N}{\tau_{\text{max}} - \tau_{\text{min}}} \left[ 1 - P_{\text{det}} \left( \frac{\tau_{\text{max}} - \tau_{\text{min}}}{\tau_{\text{min}} - \tau_{\text{ed}}} \right) \right]^{(N-1)} \quad \tau_{\text{min}} \geq \tau_{\text{ed}} \geq \tau_{\text{max}}$$

$$= 0 \quad \text{otherwise.}$$

(1)

where $P_{\text{det}}$ is the identical detection probability of each scatterer and $\tau_{\text{min}}$ to $\tau_{\text{max}}$ is the range of scatterer delays. $f(\tau_{\text{ed}})$ has a shape similar to the exponential pdf but over a finite range, and does not always integrate to one. In such cases $P_{\text{det}}$ is too low and there is a probability that the signal is not detected.

The pdf of the AOA of the first received path at the BS in NLOS conditions is complicated to derive in closed form. However Monte–Carlo simulation have shown that as the MS–BS separation increases the angular spread around the true AOA decreases and, even in NLOS conditions, a fair estimate for the AOA may be obtained if there is some spatial diversity.

3. RECEIVER ARCHITECTURE

Figure 1 shows the receiver architecture implementation. The architecture can be thought of in three stages: prefiltering of measurement data to correct/remove as far as possible NLOS data as well as smooth sampling measurement noise; the variance weighted location calculation; and a final KF tracking stage to provide a time continuous smoothed motion.

3.1. Prefilter stage

The received timing measurements, $\tau_{1,m}$, and AOA measurement, $\alpha_1$, may be heavily corrupted with NLOS errors, which ideally would be discarded. However the environment may be such that no good data is available for considerable periods of time, so the function of the prefilter stage should be to make the best use of the available data. Also, in tracking the measured parameters, the manoeuvring capability of the MS must be taken into account.

KFIs are used to track $\tau_{1,m}$ and $\alpha_1$ to their first derivative. If the true parameter value is known the pdf of the parameter’s new value after a time interval can be predicted. For example if the MS has manoeuvred and its velocity is considered uniform in speed (to a maximum speed) and direction, a pdf of the new parameter, $f(\dot{r})$ can be derived as

$$f(\dot{r}) = \int_0^{\cos^{-1}(P/P_{\text{max}})} \frac{1}{\pi P_{\text{max}} \cos \phi} d\phi$$

$$= \ln \left( \frac{P_{\text{max}} + P_{\text{max}} \sqrt{1 - P^2}}{P_{\text{max}}} \right) ^{1/P}$$

(2)

where $P_{\text{max}}$ is the maximum change in parameter in the time interval. (2) is of similar shape to the Gaussian pdf with equal variance; the major difference being that the Gaussian pdf is over an infinite range whereas (2) is limited to 2.5$\sigma$.

This pdf leads to a simple input estimator which discards data that is definitely NLOS and cannot be due to a manoeuvre. A weighting is applied to the measurement noise variance estimate, $\sigma^2_\gamma$, as follows

$$\hat{\sigma}^2_\gamma = \max \left( \sigma^2_{\text{LOS}}, \frac{\gamma_1}{W(r)} \right)$$

(3)

where $\gamma_1$ is the parameter variance estimated by the KF, $\sigma^2_{\text{LOS}}$ is the minimum parameter measurement variance in LOS conditions, and $W(r)$ is a weighting function, a function of the residual $r$ between the measured parameter and the KF prediction. In the following the weighting function is defined as a Gaussian curve normalised to one at its maximum,

$$W(r) = \frac{e^{-\frac{r^2}{2\gamma_1^2}}}{\sqrt{2\pi}\gamma_1}$$

where $\gamma_1$ allows for some magnitude adjustment in the KF output variance estimates, $\sigma^2_{\gamma,1}$ and $\sigma^2_{\gamma,2}$, which were found by simulation to be smaller than anticipated due to correlated NLOS data.

In TOA filtering, the NLOS error pdf is not symmetric about the true LOS TOA. If a TOA is measured that is earlier than the predicted TOA LOS measurement noise region the filter outputs are forced to take the measured value on the assumption that a manoeuvre has occurred (the parameter velocity estimate should also be adjusted). In this way the filter attempts to track to the LOS edge of the data.

In AOA filtering, the NLOS error pdf is symmetric about the true pdf. The KF should naturally converge to the true LOS direction given enough uncorrelated NLOS measurements. Simulation shows that convergence can be slow if the initial measurements have large NLOS errors. In such cases resetting the KF greatly improved performance.

3.2. AOA–TDOA estimator

A time difference vector, $\Delta \hat{r}(n)$, and covariance matrix, $Q_r$, can be formed from $\hat{r}(n)$ and $\hat{\dot{r}}(n)$, defined as

$$\Delta \hat{r}(n) = \begin{bmatrix} \hat{r}_1(n) - \hat{r}_1(n) - s_{1,2} \\ \hat{r}_1(n) - \hat{r}_1(n) - s_{1,2} \end{bmatrix}$$

$$Q_r = \begin{cases} \sigma^2_{\hat{r}_1}(n) + \sigma^2_{\hat{\dot{r}}_1}(n) & i = j, \\
0 & i = 1|j = 1, \quad \text{otherwise} \end{cases}$$
where $s_{i,j}$ represents the measured synchronisation offset between BS$_i$ and BS$_j$, and $Q_r$ is an $N$ by $N$ matrix with terms as defined.

The most likely MS location, $\theta^0(n)$, can be found from the $N-1$ time difference hyperbolae defined by

\[
\begin{align*}
    r_2 - r_1 &= c\Delta \hat{r}_{2,1}(n) \\
    \vdots \\
    r_N - r_1 &= c\Delta \hat{r}_{N,1}(n)
\end{align*}
\]  

(4)

where $r_1$ is the distance between the MS at $(x, y)$ and BS$_i$ at $(x_i, y_i)$; and the AOA such that

\[
\tan \alpha_1 = \frac{x - x_1}{y - y_1}
\]

(5)

In [8] a linearization of (4) in terms of dependent variables $(x, y, r_1)$ is demonstrated which yields a standard weighted least squares (WLS) solution. The further constraint from equation (5) is added to yield the WLS solution of the form

\[
\hat{Z} = (X^T Q^{-1} X)^{-1} X^T Q^{-1} Y
\]

(6)

where

\[
X = \begin{bmatrix}
    x_2 - x_1 & y_2 - y_1 & c\Delta \hat{r}_{2,1} \\
    \vdots & \vdots & \vdots \\
    x_N - x_1 & y_N - y_1 & c\Delta \hat{r}_{N,1} \\
    -1 & \tan \alpha_1 & 0
\end{bmatrix}
\]

\[
Y = \frac{1}{2} \begin{bmatrix}
    (c\Delta \hat{r}_{2,1})^2 + x_1^2 + y_1^2 - x_2^2 - y_2^2 \\
    \vdots \\
    (c\Delta \hat{r}_{N,1})^2 + x_1^2 + y_1^2 - x_N^2 - y_N^2 \\
    2x_1 - 2y_1 \tan \alpha_1
\end{bmatrix}
\]

and

\[
Q = \begin{bmatrix}
    Q_r & 0 & \ldots & 0 \\
    0 & 0 & \ddots & \vdots \\
    0 & \ldots & 0 & \sigma^2_{\alpha_1}
\end{bmatrix}
\]

In the definition of $Q$ the covariance terms between $\tau_1$ and $\alpha_1$ are taken as zero for simplicity. In reality these covariances will lie in the range 0 to $\sigma_\tau_1 \sigma_{\alpha_1}$.

This WLS solution implies independence between the variables $(x, y, r_1)$ which is not the case. Chan [8] suggests a further calculation which imposes the true dependencies on the variables which is shown in [8] to be a more efficient estimator. In this paper both WLS and Chan’s method are assessed.

The accuracy of $\hat{Z}$ is determined by evaluating its covariance matrix, $\hat{R}$. In the case where the solution is precisely determined, i.e. one TD and one AOA, the Cramér Rao lower bound (CRLB) is used as an estimate of $\hat{R}$. The CRLB, $\Phi^0$, for the AOA-TDOA estimator can be derived as

\[
\Phi^0 = G^T Q^{-1} G
\]

(7)

where

\[
G = \begin{bmatrix}
    \frac{(x_1 - x)}{r_1} & \frac{(x_2 - x)}{r_2} & \ldots & \frac{(x_N - x)}{r_N} \\
    \frac{(y_1 - y)}{r_1} & \frac{(y_2 - y)}{r_2} & \ldots & \frac{(y_N - y)}{r_N} \\
    \frac{1}{(y - y_1)^2 + (x - x_1)^2} & \ldots & \frac{1}{(y - y_N)^2 + (x - x_N)^2}
\end{bmatrix}
\]

Simulation shows that $\text{trace}(\hat{R})$ is often smaller than the true mean squared error. The variance calculation assumes no bias in the measured TD’s. Clearly the prefilers can never correct perfectly the NLOS bias, thus a multiplicative factor, $\gamma_\tau$, is applied to $\hat{R}$ before the final KF tracking stage to give a more realistic error measure.

4. SIMULATION AND RESULTS

A UMTS system incorporating TA-IPDL was simulated. Cells were arranged in a hexagonal grid around the serving BS. Timing measurements are made from the pulsed pilot
channel during idle periods when all BS's stop transmitting traffic channels. Table 1 shows the system parameters. Four 90 second scenarios were simulated: fast car in rural terrain (150kmph, curve), car travelling in suburban terrain (50kmph, zig-zag), car travelling in urban terrain (50kmph, zig-zag), and pedestrian walking in urban terrain (5kmph, zig-zag). Table 2 shows the scenario dependent parameters. Table 3 shows reasonable values for γ_1 and γ_2. Ten statistically identical runs at each scenario were made. The receiver architecture is simulated with and without AOA information and with both WLS and Chan's estimator to calculate the location.

Figure 2 shows the simulated measured AOA data from the serving BS and KF outputs of a typical track in the urban car scenario. Figure 3 shows the simulated measured TOA data from a non-serving BS and KF outputs of a typical track in the urban car scenario.

Figure 4(a1) shows the results of simulations for the rural scenario with varying Gaussian noise power on the AOA measurements. The mean number of BS's detectable (or hearability) in each idle period was approximately 2.5. It is clear that Chan's algorithm outperforms the WLS algorithm, and it is noted that the gain achieved by using the AOA can easily be lost by using an inefficient estimator. Using the AOA measurements gives a substantial improvement (up to 60%) in 67% location accuracy if the measurement noise power, σ^2_{A LOS}, is less than 10^-4 rads^2. By similar triangles it is reasonable to assume a smaller cell radius would further desensitise the location error to σ^2_{A LOS}. Subsequent simulations use 10^-5 rads^2 as an attainable value for σ^2_{A LOS}.

- (a1) Rural ( dipped)
- (a2) Rural (hurt)
- (b1) Suburban ( dipped)
- (b2) Suburban (hurt)
- (c1) Urban (dipped)
- (c2) Urban (hurt)
- (d1) Urban (dipped)
- (d2) Urban (hurt)

Figure 4: 67% circular location error against (a1) AOA noise power, for the rural scenario; (b1)–(d1) P_{LOS} for the suburban, urban car, urban pedestrian scenarios; (a2)–(d2) hearability, for all scenarios.
In Figure 4(a2) the hearability is varied. In TA-IPDL this is possible by increasing the pilot channel power; in interference limited systems the processing gain would require to be increased. Each point on the graph corresponds to a 3dB change in SNR (after processing). It can be seen that the receiver performance does not improve greatly as the number of BS’s detectable increases. Due to the KF prefilters the location accuracy remains good even when the mean number of BS’s detected per idle period is very small (i.e. < 3).

Figures 4(b2), 4(c2), 4(d2) show the effect of varying the hearability in the suburban, urban car and urban pedestrian scenarios respectively. As in the rural case a practical limit is reached above which increasing hearability does not improve performance. Utilising the AOA data improves location accuracy in the suburban and urban car scenarios. This improvement is not as great as in the rural (simple LOS) scenario, but is upwards of 20%. In the urban pedestrian scenario the performance is worse using the AOA data. In this case the KF operation is poor due to the high level of correlation between AOA samples.

Figures 4(b1), 4(c1), 4(d1) show the effect of varying \( P_{LOS} \) in the suburban, urban car and urban pedestrian scenarios respectively. The suburban model is only realistic for high values of \( P_{LOS} \). As would be expected performance improves with increasing \( P_{LOS} \). This is most noticeable in the pedestrian example where at low \( P_{LOS} \) due to low spatial diversity performance is poor.

It should be noted that during the urban car and suburban scenarios the MS underwent unrealistic instantaneous direction changes so the actual location errors predicted are probably quite pessimistic as they include errors as the filters adapted to the manoeuvre.

5. CONCLUSIONS

The simulation results show that utilising potentially available AOA information at the serving BS in the location function can lead to a significant improvement in location error performance (20%-60%) in most scenarios.

In the pedestrian environment no improvement was possible as the KF implementation fails to cope with the high level of correlation in the NLOS AOA errors. In such a scenario long term averaging of the filtered AOA may be a sensible strategy and this is the subject of ongoing work.

A further advantage of using the AOA measurement is in coverage. The system can operate with reduced detection of surrounding BS’s that might, for instance, occur at the edge of a cell network or in rural areas where BS’s are distantly spaced.

REFERENCES


<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier frequency</td>
<td>1.92GHz</td>
</tr>
<tr>
<td>Chip rate</td>
<td>3.86Mcips/s</td>
</tr>
<tr>
<td>Over sampling rate</td>
<td>4</td>
</tr>
<tr>
<td>Sample distance ( @c=3e8\text{ms}^{-1} )</td>
<td>19.5m</td>
</tr>
<tr>
<td>Modulation scheme</td>
<td>QPSK</td>
</tr>
<tr>
<td>Pilot length</td>
<td>256 chips</td>
</tr>
<tr>
<td>Max. frame desynchronisation</td>
<td>0 chips</td>
</tr>
<tr>
<td>Pulse shaping roll off rate (( \alpha ))</td>
<td>0.22</td>
</tr>
<tr>
<td>Idle period frequency</td>
<td>5Hz</td>
</tr>
<tr>
<td>Idle period length</td>
<td>2560 chips</td>
</tr>
</tbody>
</table>

Table 1: System parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Rural</th>
<th>Suburban</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td>CoDIT model</td>
<td>rural</td>
<td>suburban</td>
<td>urban</td>
</tr>
<tr>
<td>Cell radius (km)</td>
<td>10.0</td>
<td>2.0</td>
<td>0.5</td>
</tr>
<tr>
<td>( P_{LOS} )</td>
<td>1.0</td>
<td>0.8</td>
<td>0.2</td>
</tr>
<tr>
<td>( L_{LOS} ) (m)</td>
<td>N/A</td>
<td>30</td>
<td>15</td>
</tr>
<tr>
<td>( L_{S} ) (m)</td>
<td>N/A</td>
<td>20</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 2: Scenario specific parameters

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( \gamma_1 )</th>
<th>( \gamma_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rural</td>
<td>1</td>
<td>1–16</td>
</tr>
<tr>
<td>Suburban</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Urban car</td>
<td>4</td>
<td>25</td>
</tr>
<tr>
<td>Urban ped</td>
<td>4</td>
<td>40</td>
</tr>
</tbody>
</table>

Table 3: Values for variance correction factors