# MOBILE STATION POSITION AND VELOCITY COMPUTER-BASED ESTIMATION USING ADAPTIVE ALGORITHMS AND SMART ANTENNAS

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ABSTRACT
The increasing demand for mobile communication services without a corresponding increase in radio frequency spectrum allocation motivates the need for new techniques to improve spectrum utilization. An approach that shows real spectrum utilization for substantial capacity enhancement is the use of smart antennas. The smart antennas are capable of automatically forming beams in the direction of the desired signal and steering nulls in the directions of the interfering signals. Another approach that satisfies the demand for quality of services in a mobile communication system is the communication system's capability to estimate and predict the location of a mobile user. In this paper we present a computer-based system that tracks the position and estimates the velocity of a mobile user, using smart antennas on the base stations. The mobile user is moving in an area where the GSM principles are applied, while the position and velocity estimations' accuracy are checked using four different adaptive algorithms.

KEYWORDS
Mobile communications, mobile station, position estimation, velocity estimation, adaptive algorithms, smart antennas, least mean squares, sample matrix inversion

## INTRODUCTION

During the last decades, the telecommunications field has experienced extraordinary development. The need to exchange information with a user, anywhere and anytime, led to cellular mobile networks integrating several services. The mobile communications revolution pose challenging problems in many issues, i.e. performance modelling, modulation techniques, multiple access schemes, adaptive antennas, user mobility, radio propagation and fading in reduced cell sizes, and interference environment. Therefore, as the landscape of the electronic engineer's profession is continuously changing, universities are realigning telecommunications courses in order to achieve effective learning.

An approach showing real spectrum utilization for substantial capacity enhancement is the use of spatial process with a cell site adaptive antenna array. The adaptive antenna array is capable of automatically forming beams in the direction of the desired signal and steering nulls in the directions of the interfering (undesired) signals (Godara, 1997; Litva and Lo, 1996; Okamoto, 2002). By using the adaptive antenna in a mobile communication station, we can reduce the amount of cross-channel interference from other users within its own cell and its neighbouring cells and therefore increase the system capacity. In order to make the antenna work adaptively many algorithms may be used, some of which will be discussed in this paper.

The adaptive array systems are smart because they are capable to dynamically react to changing RF environments. An adaptive array is controlled by signal processing, which i) steers the radiation beam towards a desired mobile user, ii) follows the user moving, and at the same time iii) minimizes interference arising from other users, by introducing nulls in their directions. The process of focusing the radiation in a particular direction is often referred to as beamforming. The behaviour of the adaptive system is determined by parameters, called weights. The adaptive processor controls the beamforming network to optimize the weights according to a certain criterion. The criterion used in this paper is the minimum mean square error, which is closely related to the adaptive algorithm deriving the adaptive weights. The choice of the adaptive algorithm is very important because it determines both the speed of convergence and hardware complexity, required to implement the algorithm.

In order to have efficient network control and useful additional services in cellular radio networks, it is necessary to know the position and velocity of mobile users at any time. For this reason much research effort has been done (Rappaport, Reed and Woerner, 1996; Hellebrandt, Mathar and Sheibenbogen, 1997). Particularly in hierarchical network structures with large cells and microcells below, allocation and handover algorithms should take account of the mobility of stations. Fast mobile stations (MS), with speed above a certain threshold, should be assigned to large cells, while nearly stationary transmitters can be served by microcells. This strategy reduces the number of handovers and furthermore the network's service quality would not be wasted by a large number of handovers. If the location of a mobile is known, additional services can be offered to subscribers. Knowing the position of vehicles, e.g., allows for an efficient planning and use of resources. Also automatic monitoring of the position would be of great help for immediate assistance.

Two quantities can be used to obtain distance and speed information: the field signal strength (Hellebrandt and Mathar, 1999; Hellebrandt, Mathar and Sheibenbogen, 1997) in different base stations, and the corresponding propagation times (Fisher, Koorapaty, Larsson and Kangas, 1999). Both parameters are subject to strong irregular variations caused by short-term fading, shadowing and reflections. In this paper, we focus on signal strength measurements.

The aim of this paper is to provide an algorithm estimating the mobile user position and velocity. The mobile user is moving in an area, where the GSM principles are applied. This location algorithm is based on adaptive antenna arrays, which are sited on the Base Stations (BS) of the GSM system. We study the accuracy of the proposed position and velocity estimation algorithm by using four different adaptive algorithms: the Least Mean Squares (LMS), the Normalized - Least Mean Squares (N-LMS), the Sample Matrix Inversion (SMI), and a hybrid algorithm based on the SMI and LMS ones (Papadimitriou and Vardiambasis, 2005; Papadimitriou, Vardiambasis and Melesanaki, 2006).

The aforementioned system has been implemented at the Microwave Communications and Electromagnetic Applications Lab of the Technological Educational Institute of Crete, in the context of an advanced undergraduate elective course in antennas and communication systems engineering, called "Smart Antennas and Wireless Communications". This course lets students combine the characteristics of smart antennas and mobile communications systems (like GSM). Studying smart antennas, students apply adaptive algorithms and criteria, which can be applied in GSM systems. On the other hand studying GSM systems, students use communication algorithms, which can estimate the position and the velocity of a mobile station. During this course many exercises, simulations, measurements and lab projects are assigned to the students in order to gain insight to modern wireless communication systems.

## THE POSITION AND VELOCITY ALGORITHM

To determine the 2D position and velocity of an MS, the field strengths from the MS received by a minimum of three BSs are required. The theoretical electric field strengths received by the three BSs are $\bar{E} = [E_1\ E_2\ E_3]$. The measured electric field strengths received at the BSs from a single MS are $\bar{E}_m = [E_{m1}\ E_{m2}\ E_{m3}] = \bar{E} + \bar{n}$, where the subscript m stands for measurements and $\bar{n}$ corresponds to white Gaussian noise (Loo and Second, 1991). The problem is to obtain the position PM(x,y) of the MS. The first step is to get the distance $\bar{r} = [r_1\ r_2\ r_3]$ between the MS and the BSs. The method to get $\bar{r}$ is based in non linear mean square method (Battiti, 1992; Hagan and Menhaj, 1994; Marquardt, 1963). The electric field strength $\bar{E}$ is a non-linear function of $\bar{r}$ and is given by

$$\overline{E}(r) = \overline{E}(r_o) + \frac{\partial \overline{E}}{\partial r}\Delta r + \frac{1}{2!}\frac{\partial\left(\frac{\partial \overline{E}}{\partial r}\right)}{\partial r}\Delta r^2 + \dots \quad (1)$$

We can ignore higher order terms since $\Delta r$ is very small compared with r and we can use the Jacobian matrix of the electric field strengths that follows

$$\overline{J}r_0 = \begin{bmatrix} \partial E_1/\partial r_1 & 0 & 0 \\ 0 & \partial E_2/\partial r_2 & 0 \\ 0 & 0 & \partial E_3/\partial r_3 \end{bmatrix}. \quad (2)$$

The error between the measurement and theoretical values for the field strength is given by

$$\overline{\varepsilon} = \overline{E}_m - \overline{E}(\overline{r}) = (\overline{E}_m - \overline{E}_0) - \overline{J}r_0\,\Delta\overline{r}\,. \quad (3)$$

Assuming $\overline{u} = \overline{\varepsilon}^T\,\overline{\varepsilon}$, we set $\partial\overline{u}/\partial r = 0$ in order to minimize $\overline{u}$. This leads to the main iteration equation

$$\overline{r}_{n+1} = \overline{r}_n + (\overline{J}r_0^T\,\overline{J}r_0)^{-1}\cdot\overline{J}r_0^T\cdot(\overline{E}_m - \overline{E}_n)\,. \quad (4)$$

We focus on calculation of the Jacobian matrix $\overline{J}r_0$. The radiated electric field strength from an array with finite length antenna elements may be written as

$$\overline{E}_n = \overline{E}_0\left[\frac{z_j - z_1}{\sqrt{r_n^{\,2} + (z_j - z_1)^2}} - \frac{z_j - z_2}{\sqrt{r_n^{\,2} + (z_j - z_2)^2}}\right]AF_n\,, \quad (5)$$

where $AF_n$ is the array factor.

We suppose that the smart antenna consists of M elements. The incoming signals are obliquely incident upon the antenna structure with elevation angle $\theta'$ and azimuth angle $\varphi$. The array factor is given by:

$$AF_n = \left|\mathrm{conj}(\overline{W}_{opt})\begin{bmatrix}1 \\ e^{-j\Phi_r} \\ \dots\dots\dots \\ e^{-jM\Phi_r}\end{bmatrix}\right|, \quad \Phi_r = \frac{2\pi d}{\lambda}\cos\varphi\,\sin\theta\,, \quad \theta = \pi - \theta' = \pi - \tan^{-1}\left(\frac{r}{z_1 + (\lambda/4) - z_j}\right) \quad (6)$$

where $\overline{W}_{opt}$ is the weight vector coming from an adaptive algorithm used for beamforming, and $\theta$ is the supplementary elevation angle of the MS signal impinging to the BS. Using $\overline{J}r_n = \frac{\partial\overline{E}_n}{\partial r_n}$, we have

$$\overline{J}r_n = \overline{J}_1 + \overline{J}_2 \quad (7.a)$$

$$\overline{J}_1 = -\overline{E}_0\left[\frac{z_2 - z_j}{\left[r_n^{\,2} + (z_2 - z_j)^2\right]^{3/2}} - \frac{z_1 - z_j}{\left[r_n^{\,2} + (z_1 - z_j)^2\right]^{3/2}}\right]r_n\cdot AF_n\,, \quad (7.b)$$

$$\overline{J}_2 = \overline{E}_0\left[\frac{z_2 - z_j}{\sqrt{r_n^{\,2} + (z_2 - z_j)^2}} - \frac{z_1 - z_j}{\sqrt{r_n^{\,2} + (z_2 - z_j)^2}}\right]\cdot\frac{\partial AF_n}{\partial r_n}\,, \quad (7.c)$$

where

$$\frac{\partial AF_n}{\partial r_n} = \left|-j\frac{\partial\Phi_r}{\partial r}W_{opt2}e^{-j\Phi_r} - \dots - j(M-1)\frac{\partial\Phi_r}{\partial r}W_{optM}e^{-j(M-1)\Phi_r}\right|, \quad (8)$$

$$\frac{\partial \Phi_r}{\partial r} = \frac{2\pi d}{\lambda} \cos\varphi \cos\theta \frac{\partial \theta}{\partial r} = \frac{2\pi d}{\lambda} \cos\varphi \frac{(z_1 + (\lambda/4) - z_j)^2}{\left[r^2 + (z_1 + (\lambda/4) - z_j)^2\right]^{3/2}}, \qquad (9.a)$$

$$\frac{\partial \theta}{\partial r} = -\frac{z_j - (z_1 + (\lambda/4))}{r^2 + (z_1 + (\lambda/4) - z_j)^2}, \qquad \cos\theta = -\frac{z_1 + (\lambda/4) - z_j}{\left[r^2 + (z_1 + (\lambda/4) - z_j)^2\right]^{3/2}}. \qquad (9.b)$$

The distance between the MS and any of the BSs is obtained using (4). However, our goal is to get the exact position of the MS, namely PM. So, using the estimated vector $\bar{r}$, which gives the distances between the BS and the MS, an estimated MS position can be obtained. Since the circle radii of the $\bar{r}$ estimates are arriving at an exact cross intersection, further processing is necessary for a better estimate of the actual MS position. The main iteration equation to get PM resembles (4) and is given by

$$P\bar{M}_{k+1} = P\bar{M}_k + (\bar{J}p_k^T \bar{J}p_k)^{-1} \bar{J}p_k^T (0 - err\bar{p}_k), \qquad (10)$$

where $err\bar{p}_k = |P\bar{M} - P\bar{B}| - \bar{r}$, with $P\bar{B} = [PB_1 \; PB_2 \; PB_3]$ representing the position of the three BSs that the MS uses. These three BSs change as the MS moves. $\bar{J}p_k$ is redefined as

$$\bar{J}p_k = \begin{bmatrix} \partial errp_1 / \partial x & \partial errp_1 / \partial y \\ \partial errp_2 / \partial x & \partial errp_2 / \partial y \\ \partial errp_3 / \partial x & \partial errp_3 / \partial y \end{bmatrix}. \qquad (11)$$

Finally the MS velocity can be obtained from the sequential MS position and is estimated by

$$\bar{V}_m = \frac{P\bar{M}_m - P\bar{M}_{m-1}}{T}, \qquad (12)$$

where T is the time interval between two discrete MS positions.

## COMPUTER SIMULATION AND RESULTS

The position and velocity algorithm is tested in an area of interest with region of about 6500x6500 meters that contains 16 cells-BS, each with a cell radius of about 1500 m. In this area we assume that the specifications of GSM system are valid. A BS is located at the center of each cell and is indicated by "A". The mobile user travels along a route in the region that BSs cover. The mobile user is changing its velocity, while moving in the region specified. Along the route, forty samples are taken at a time interval of 4.8 sec. This interval is relevant with the fact that the field strength is reported every 0.48 sec, in GSM. For every 10 reports the algorithm estimates the position and velocity of the MS. The estimated position and velocity is indicated by "x". While the MS is moving, handovers are taken into account. The criterion of a handover is the distance between the MS and the three nearest BSs. We also use a triangle method to find the three nearest BSs in every position of the MS.

We consider that the antenna array consists of M-elements, placed along x-axis having distance d in between. We also consider a signal of interest and two interferers, which obliquely incidents upon the antenna with elevation angle and azimuth angle $(\theta,\phi)$ respectively. All signals are simulated with random generated bits ($\pm 1$) which are modulated by using MSK modulation. We generate 142 bits representing a normal burst of the GSM system. The bits we use are up-sampled and consequently, the adaptive algorithms are tested by using 1136 samples-iterations. We assume that the signal of interest is affected by Gaussian noise with zero mean value and variance depending on the signal to noise ratio (SNR). The power of the interfering signals depends on signal to interference ratio (SIR). For simulation purposes we assume SNR=10 dB and SIR=-10 dB for all interferers.

When position and velocity algorithm is tested, the beamforming (adaptive) algorithms are applied. The output of the beamforming algorithms, that we are interested in is the value of the normalized array factor in the direction of interest. In Figure 4 we compare the convergence speed and stability of the LMS, N-LMS and hybrid algorithms using the value of the normalized array factor in the direction of interest. In hybrid algorithm we use 26 training bits in order to evaluate the initial weight vector applying SMI algorithm. As shown, the normalized array factor in the desired direction converges in higher values using the LMS and hybrid algorithms than using the N-LMS algorithm. Moreover N-LMS is the most unstable algorithm, which means that the value of the normalized array factor may lead us to unpredictable results.

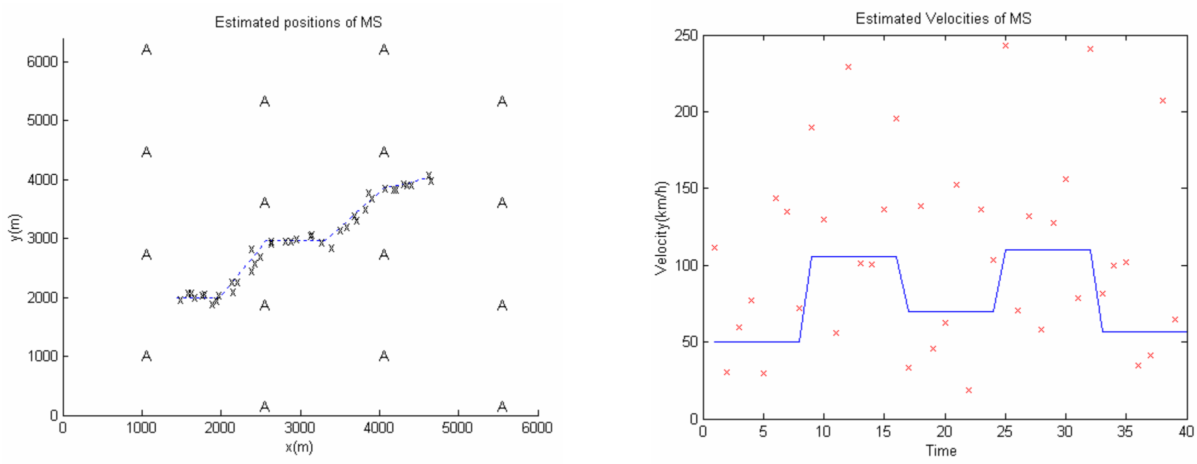


Figure 3. Real and estimated positions and velocities of a moving MS.

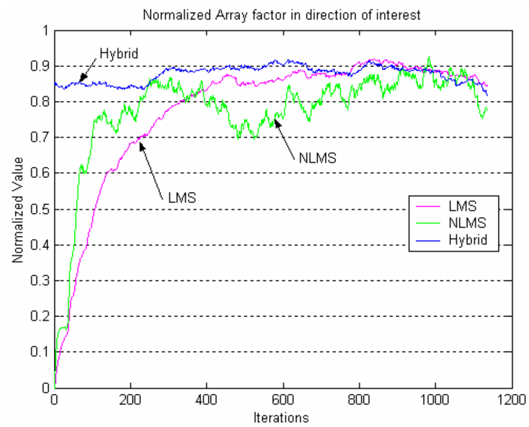


Figure 4. Normalized array factor for the LMS, N-LMS and hybrid adaptive algorithms.

Figure 5, using only the LMS algorithm, summarizes the relation between position and velocity accuracy versus antenna elements. As expected, the accuracy increases rapidly as antenna elements increase. Moreover, for 9 and 16 antenna elements the position accuracy does not change significantly.

In Figure 6 we simulate the position and velocity algorithm in conditions of Rayleigh noise channel (Loo and Second, 1991). Assuming M=9 antenna elements and the LMS adaptive algorithm, the average position and velocity errors for different values of SNR are presented. As Figure 6 shows the average position and velocity errors have smaller values in case of a channel with Gaussian noise than in case of a Rayleigh noise channel. In both cases, the average errors decrease as SNR increases.

In Figure 7 we compare the accuracy of position and velocity algorithm using the LMS, N-LMS and hybrid adaptive algorithms for several elements' numbers. As showed, the N-LMS algorithm derives the lower array factor's value, achieving the worst accuracy compared to the LMS and hybrid algorithms. This holds true even if we have M=16 antenna elements. In the case of the hybrid algorithm, even if we increase the number of elements, the accuracy does not substantially improve.

The hybrid algorithm has better performance than the LMS one, when the antenna elements are few. On the other hand, for more antenna elements, the LMS algorithm is preferred.

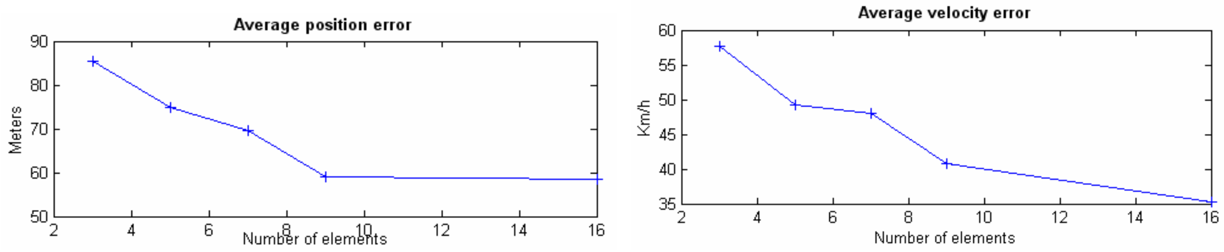


Figure 5. Position and velocity accuracy versus antenna elements.

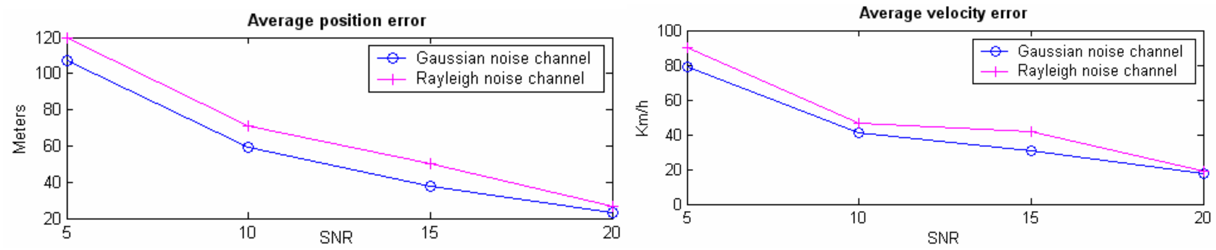


Figure 6. Position and velocity accuracy versus SNR, for Gaussian and Rayleigh noise channels.

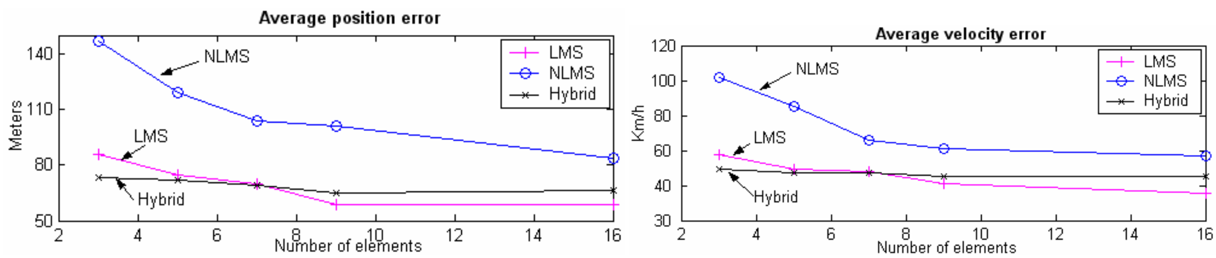


Figure 7. Accuracy comparison using LMS, N-LMS and hybrid adaptive algorithms.

## CONCLUSIONS

A mobile station position and velocity computer-based estimation algorithm has been developed using smart antennas and adaptive algorithms. Various simulations point out that when the number of the antenna array's elements increase, then i) the position and velocity accuracy improves, and ii) the computer-based estimation system has better performance, regardless of the adaptive algorithm used. On the other hand depending on the antenna array's elements, either the hybrid algorithm is preferred, when the BSs use antenna arrays with M=3,5,7 elements, or the LMS algorithm is preferred, when the antenna arrays use more than 7 elements. The N-LMS algorithm has the worst performance and accuracy, compared with the other two algorithms. Finally, it is noted that the position accuracy, for all cases, has a spread of about 7%.

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