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AUGMENTATION OF ANTI-JAM GPS SYSTEM USING SMART ANTENNA WITH A SIMPLE DOA ESTIMATION ALGORITHM

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Abstract—Smart Antenna system analysis presented with multipath and null constraint for reducing interference and efficient use of spectrum with the help of LMS algorithm for GPS (Global Positioning System) System. A new simple DOA (Direction of Arrival) estimation method by rotation of antenna plane proposed. Simulated Result obtained using MATLAB$^{\text{TM}}$.

1. INTRODUCTION

The GPS jamming should turn out to be an issue for the defence was foreseeable. In the precedent few years, the world's corporate sectors have become dependent on satellite-based navigation. The network of GPS satellites provides precise location information everyplace in the world. GPS is particularly vulnerable to jamming, because the receivers are very sensitive, they have to receive the extremely weak signal from orbiting satellites. A relatively low-powered jammer, transmitting static on the GPS frequency band, can overpower legitimate GPS signals over a wide area — as much as a 100 kilometer circle at just 1 watt radiated power.

Smart antenna or Adaptive Array Antenna systems continually monitor their coverage areas and the system adapts to the user's motion providing an antenna pattern that tracks the user, achieving the maximum gain in the user's direction, and provide theoretically null and practically very low gain to any interference. For this purpose smart antenna base station combines an antenna array with a control unit that optimize reception and radiation patterns dynamically in response to the signal environment, i.e., mobile vehicle moving about

Table 1.

Anti-Jam Signal Processing Techniques	Jammer Rejection	Cost & Complexity	Implementation
Pre-correlation Adaptive Nulling Antenna (ANA) Processing	30-50 dB	High	Analog/Digital
Pre-correlation Temporal/Spectral Processing	20-30 dB	Very Low	Digital
Post-correlation Processing	10-15 dB	Low	Digital Hardware/ Software

the coverage area. In this paper we will discuss Smart Antenna Technology with the help of LMS as adaptation algorithm for creating null towards the interference and maximize gain towards the desired signal and also for detecting and collecting multipaths of desired signals (instead of rejecting) to improve jamming rejection performance with some simulation result carried out using MATLAB™ for a conventional GPS receiver on a moving platform like vehicle and or airborne system.

2. ADAPTIVE ARRAY ANTENNA

In a mobile communication system, the mobile is generally moving; therefore the DOAs (Direction of Arrival) of the received signals in the base station are time-varying. Also, due to the time-varying wireless channel between the mobile GPS receiver and the base station, and the existence of the co channel interference, multi path, and noise, the parameters of each impinging signal are varied with time. For a beam former with constant weights, the resulting beam pattern cannot track these time-varying factors. However, an adaptive array may change its patterns automatically in response to the signal environment. An adaptive array is an antenna system that can modify its beam pattern or other parameters, by means of internal feedback control while the antenna system is operating. Adaptive arrays are also known as adaptive beam formers or adaptive antennas [1–4]. A simple narrowband adaptive array is shown in Figure 1. In this paper we have also proposed a simple DOA estimation technique for all signals with

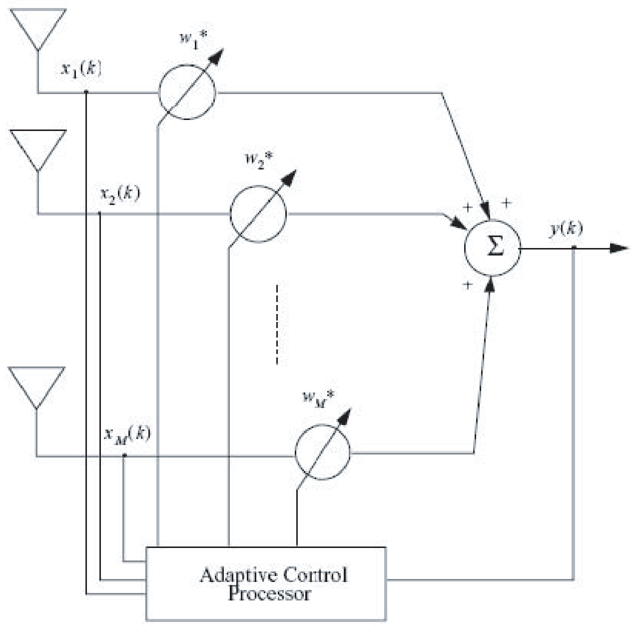


Figure 1. A simple narrowband adaptive array.

significant power level impinging on antenna array using the concept of rotating array plane with small angle. This small angle of rotation can be estimated for any airborne GPS receiver with the help of gyro. For a GPS receiver on a moving vehicle on earth this angular deviation can be calculated by the speed and distance covered by the vehicle.

In Figure 1, the complex weights $W_1, W_2, \ldots W_M$ are adjusted by the adaptive control processor. The method used by the adaptive control processor to change the weights is called the adaptive algorithm. Most adaptive algorithms are derived by first creating a performance criterion, and then generating a set of iterative equations to adjust the weights such that the performance criterion is met. Some of the most frequently used performance criteria include minimum mean squared error (MSE), maximum signal-to-interference and noise ratio (SINR), maximum likelihood (ML), minimum noise variance, minimum output power, maximum gain, etc. These criteria are often expressed as cost functions which are typically inversely associated with the quality of the signal at the array output. As the weights are iteratively adjusted, the cost function becomes smaller and smaller. When the cost function is minimized, the performance criterion is met and the algorithm is said to have converged.

For one adaptive array, there may bet several adaptive algorithms that could be used to adjust the weight vector. The choice of one algorithm over another is determined by various factors like **Rate of convergence, Tracking, Robustness and Computational requirements**.

Since there exists a mapping between the narrowband beam former and the FIR filter, most of the adaptive algorithms used by the adaptive filter may be applied to the adaptive beam former. However, some of the adaptive beams forming algorithms also have their unique aspects that an adaptive filter algorithm does not possess. Most of these algorithms may be categorized into two classes according to whether a training signal is used or not. One class of these algorithms is the non-blind adaptive algorithm in which a training signal is used to adjust the array weight vector. Another technique is to use a blind adaptive algorithm which does not require a training signal. A brief survey of LMS adaptive beam forming algorithms is given in next two sections.

In a non-blind adaptive algorithm, a training signal, $\mathbf{d(t)}$, which is known to both the transmitter and receiver, is sent from the transmitter to the receiver during the training period. The beam former in the receiver uses the information of the training signal to compute the optimal weight vector, W_{opt} After the training period, data is sent and the beam former uses the weight vector computed previously to process the received signal. If the radio channel and the interference characteristics remain constant from one training period until the next, the weight vector w_{opt} will contain the information of the channel and the interference, and their effect on the received signal will be compensated in the output of the array [5–7].

3. WIENER SOLUTION

Most of the non-blind algorithms try to minimize the mean-squared error between the desired signal $d(t)$ and the array output $y(t)$. Let $y(k)$ and $d(k)$ denote the sampled signal of $y(t)$ and $d(t)$ at time instant t_k, respectively. Then the error signal is given by

$$\mathbf{e(k)} = \mathbf{d(k)} - \mathbf{y(k)} \tag{1}$$

and the mean-squared error is defined by

$$J = E\left[|e(k)|^2\right], \tag{2}$$

We also derived previously

$$y(k) = w^H x(k) \tag{3}$$

Where $E[.]$ denotes the ensemble expectation operator. Substituting Equation (1) and (3) into Equation (2), we have

$$\begin{aligned} J &= E\left[|d(k)-y(k)|^2\right] \\ &= E\left[\{d(k)-y(k)\}\{d(k)-y(k)\}^*\right] \\ &= E\left[\left\{d(k)-\mathbf{w}^H\mathbf{x}(k)\right\}\left\{d(k)-\mathbf{w}^H\mathbf{x}(k)\right\}^2\right] \\ &= E\left[|d(k)|^2 - d(k)x^H(k)\mathbf{w} - \mathbf{w}^H\mathbf{x}(k)d^*(k) + \mathbf{w}^H\mathbf{x}(k)\mathbf{x}^H(k)\mathbf{w}\right] \\ &= E\left[|d(k)|^2\right] - p^H\mathbf{w} - \mathbf{w}^H p + \mathbf{w}^H\mathbf{R}\mathbf{w}, \end{aligned} \tag{4}$$

Where

$$\mathbf{R} = E\left[\mathbf{x}(k)\mathbf{x}^H(k)\right]$$

And

$$\mathbf{p} = E\left[\mathbf{x}(k)d^*(k)\right]$$

In the above equations, $\mathbf{R}$ is the $M \times M$ correlation matrix of the input data vector $\mathbf{x}(k)$, and ρ is the $M \times 1$ cross-correlation vector between the input data vector and the desired signal $d(k)$.

The gradient vector of J, $\nabla(\mathbf{J})$, is defined by

$$\nabla(J) = 2\frac{\partial J}{\partial \mathbf{w}^*}$$

Where $\delta j/\delta w^*$ denotes the conjugate derivative with respect to the complex vector w^*. When the mean-squared error of J is minimized, the gradient vector will be equal to an $M \times 1$ null vector.

$$\nabla(J)|_{\mathbf{w}_{opt}} = \mathbf{0} \tag{5}$$

Substituting Equation (4) into Equation (5), we have

$$-2\mathbf{p} + 2\mathbf{R}\mathbf{w}_{opt} = \mathbf{0} \tag{6}$$

or equivalently

$$\mathbf{R}\mathbf{w}_{opt} = \mathbf{p} \tag{7}$$

Equation (7) is called the **Wiener-Hopf equation**. Multiplying both sides of Equation (7) by R^{-1}, the inverse of the correlation matrix, we obtain -

$$\mathbf{w}_{opt} = \mathbf{R}^{-1}\mathbf{p} \tag{8}$$

The optimum weight vector W_{opt} in Equation (8) is called the Wiener solution. From Equation (8), we see that the computation of the optimum weight vector W_{opt} requires knowledge of two quantities:

(1) The correlation matrix R of the input data vector $x(k)$, and
(2) The cross-correlation vector p between the input data vector $x(k)$ and the desired signal $d(k)$.

4. METHOD OF STEEPEST-DESCENT

Although the Wiener-Hopf equation may be solved directly by calculating the product of the inverse of the correlation matrix $\mathbf{R}$ and the cross-correlation vector $\mathbf{p}$, nevertheless, this procedure presents serious computational difficulties since calculating the inverse of the correlation matrix results in a high computational complexity. An alternative procedure is to use the method of steepest-descent. To find the optimum weight vector W_{opt} by the steepest-descent method we proceed as follows:

1. Begin with an initial value $w(0)$ for the weight vector, which is chosen arbitrarily. Typically, $w(0)$ is set equal to a column vector of an $M \times M$ identity matrix.
2. Using this initial or present guess, compute the gradient vector $\nabla J(k)$ at time k (i.e., the k-th iteration).
3. Compute the next guess at the weight vector by making a change in the initial or present guess in a direction opposite to that of the gradient vector.
4. Go back to step 2 and repeat the process. It is intuitively reasonable that successive corrections to the weight vector in the direction of the negative of the gradient vector should eventually lead to the minimum mean-squared error $\mathbf{J_{min_n}}$, at which the weight vector assumes its optimum value W_{opt}.

Let $w(k)$ denote the value of the weight vector at time k. According to the method of Steepest-descent, the update value of the weight vector at time $k+1$ is computed by using the simple recursive relation [9]

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \frac{1}{2}\boldsymbol{\mu}\left[-\nabla\left(J(k)\right)\right], \tag{9}$$

Where $\boldsymbol{\mu}$ is a positive real-valued constant. The factor 1/2 is used merely for convenience. From Equation (4) we have

$$\nabla\left(J(k)\right) = -2\mathbf{p} + 2\mathbf{R}\mathbf{w}(k)$$

Hence, substituting it into the Equation (9) we obtain

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \boldsymbol{\mu}\left[\mathbf{p} - \mathbf{R}w(k)\right] \text{ where } k = 0, 1, 2, \ldots\ldots \tag{10}$$

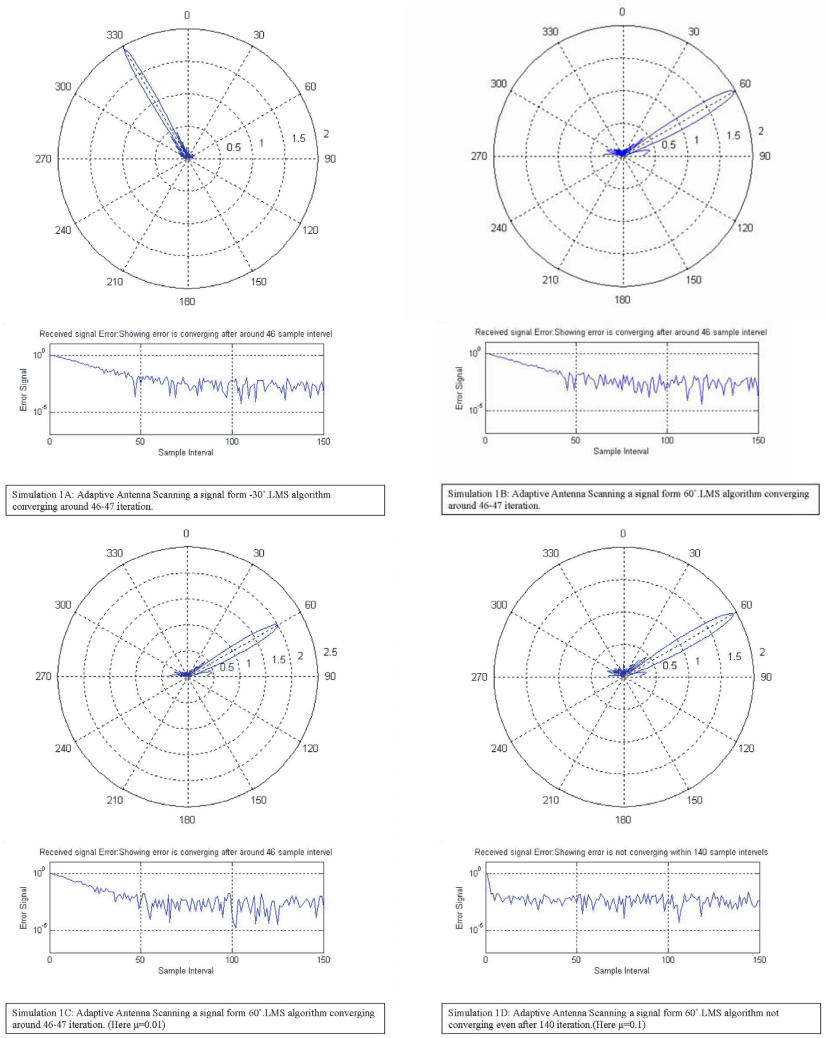


Figure 2. Simulation 1A, 1B, 1C, 1D (tracking of single signal).

We can also write

$$\begin{aligned}\nabla\left(J(k)\right) &= -2E\left[\mathbf{x}(k)d^*(k)-\mathbf{x}(k)\mathbf{x}^H(k)\mathbf{w}(k)\right]\\ &= -2E\left[\mathbf{x}(k)\left\{d(k)-y(k)\right\}^*\right]\\ &= -2E\left[\mathbf{x}(k)e^*(k)\right].\end{aligned}\tag{11}$$

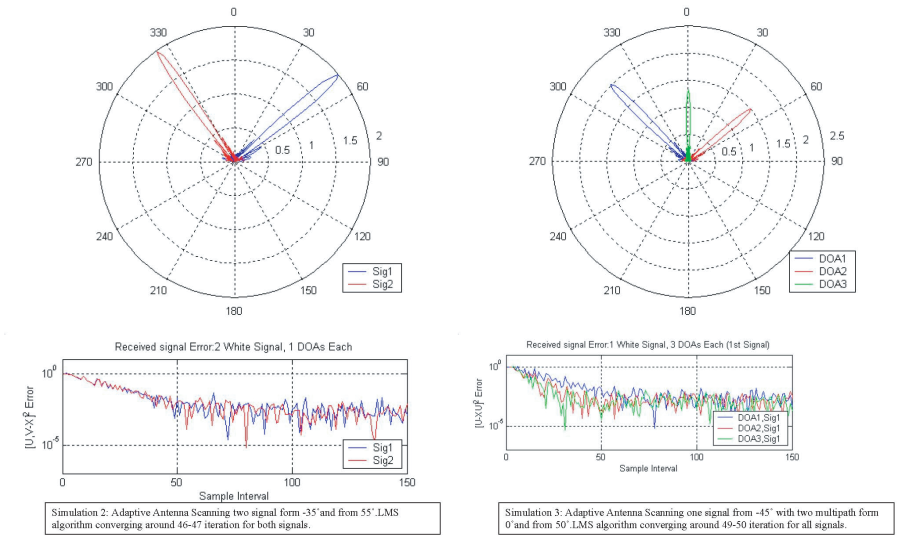


Figure 3. Simulation 2, 3 (Signals with Multipaths).

Eq. (10) also can be written as

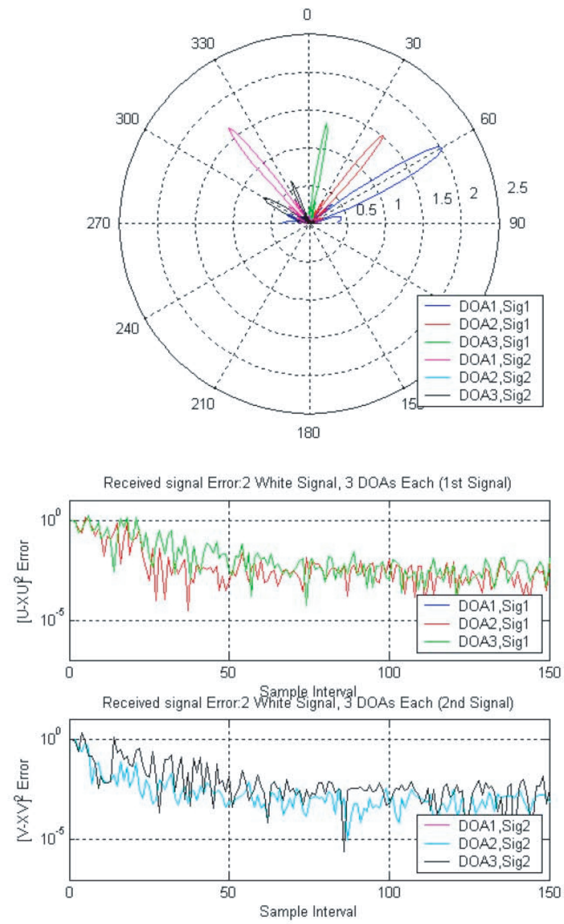
$$\mathbf{w}(k+1) = \mathbf{w}(k) + \boldsymbol{\mu} E\left[\mathbf{x}(k)e^*(k)\right]. \tag{12}$$

We observe that the parameter $\boldsymbol{\mu}$ controls the size of the incremental correction applied to the weight vector as we proceed from one iteration cycle to the next. We therefore refer to $\boldsymbol{\mu}$ **as the step-size parameter or weighting constant**. Equations (10) and (12) describe the mathematical formulation of the steepest-descent method.

5. LEAST-MEAN-SQUARES (LMS) ALGORITHM

If it were possible to make exact measurements of the gradient vector $\nabla\mathbf{J}(\mathbf{k})$ at each iteration, and if the step-size parameter μ is suitably chosen, then the weight vector computed by using the steepest-descent method would indeed converge to the optimum Wiener solution. In reality, however, exact measurements of the gradient vector are not possible since this would require prior knowledge of both the correlation matrix $\mathbf{R}$ of the input data vector and the cross-correlation vector $\mathbf{p}$ between the input data vector and the desired signal.

Consequently, the gradient vector must be estimated from the available data. In other words, the weight vector is updated in accordance with an algorithm that adapts to the incoming data.



Simulation 4

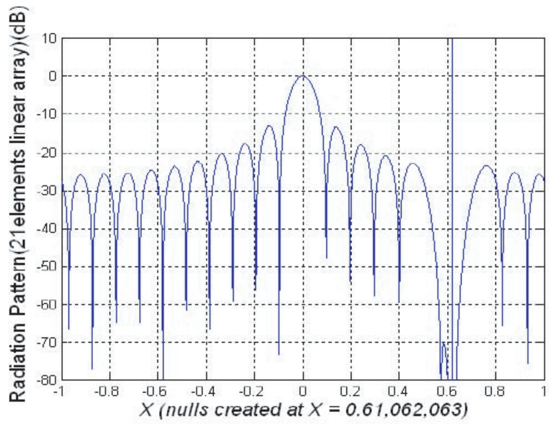
Figure 4. Simulation 4 (signals with multipaths).

One such algorithm is the least-mean-squares (LMS) algorithm. A significant feature of the LMS algorithm is its simplicity; it does not require measurements of the pertinent correlation functions, nor does it require matrix inversion.

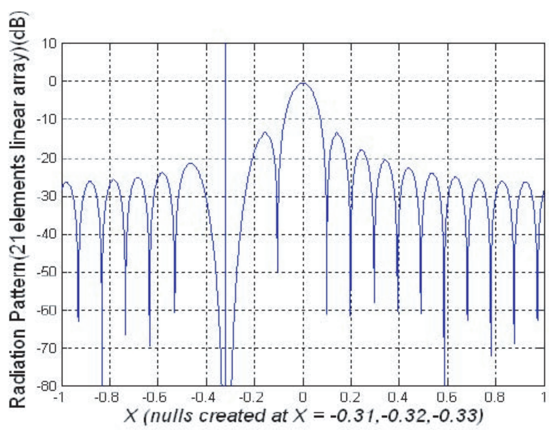
To develop an estimate of the gradient vector $\nabla J(k)$, the most obvious strategy is to substitute the expected value in Equation (11) with the instantaneous estimate-

$$\hat{\nabla}\left(J(k)\right) = -2\mathbf{x}(k)e^{*}(k) \tag{13}$$

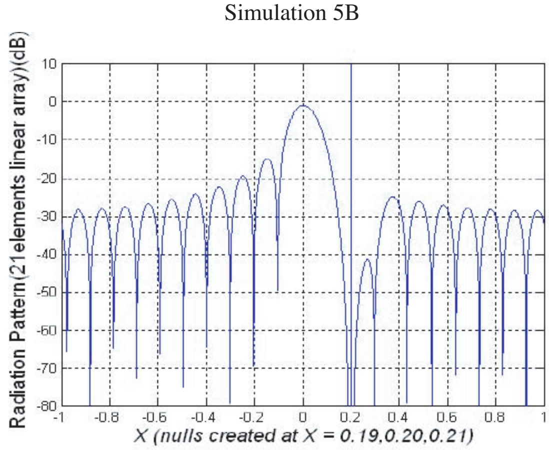
Substituting this instantaneous estimate of the gradient vector into



Simulation 5A



Simulation 5B



Simulation 5C

Figure 5. Simulation 5A, 5B & 5C (NULL towards single jammer).

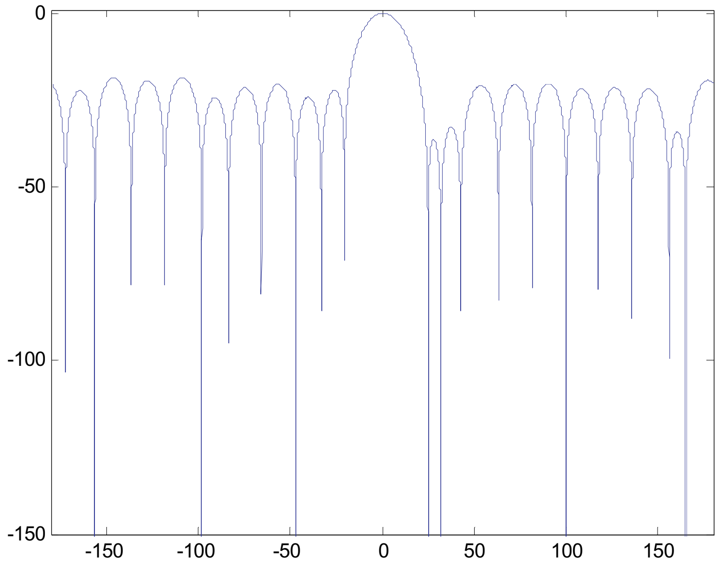


Figure 6a. Creating NULLS towards the jammer directions of $25°, -98°, 32°, 165°, -156°, 100°$ and $47°$, where desired signal coming thorough mainlobe.

Equation (9), we have

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu\mathbf{x}(k)e^*(k). \tag{14}$$

Now, we can describe the LMS algorithm by the following three equations

$$\begin{aligned} y(k) &= \mathbf{w}^H(k)\mathbf{x}(k) \\ e(k) &= d(k) - y(k) \\ \mathbf{w}(k+1) &= \mathbf{w}(k) + \mu\mathbf{x}(k)e^*(k). \end{aligned} \tag{15}$$

The LMS algorithm is a member of a family of stochastic gradient algorithms since the instantaneous estimate of the gradient vector is a random vector that depends on the input data vector $x(k)$. **The LMS algorithm requires about 2M complex multiplications per iteration, where M is the number of weights (elements)** used in the adaptive array [12]. The response of the LMS algorithm is determined by three principal factors: (1) the step-size parameter, (2) the number of weights, and (3) the eigen-value of the correlation matrix of the input data vector [9–11].

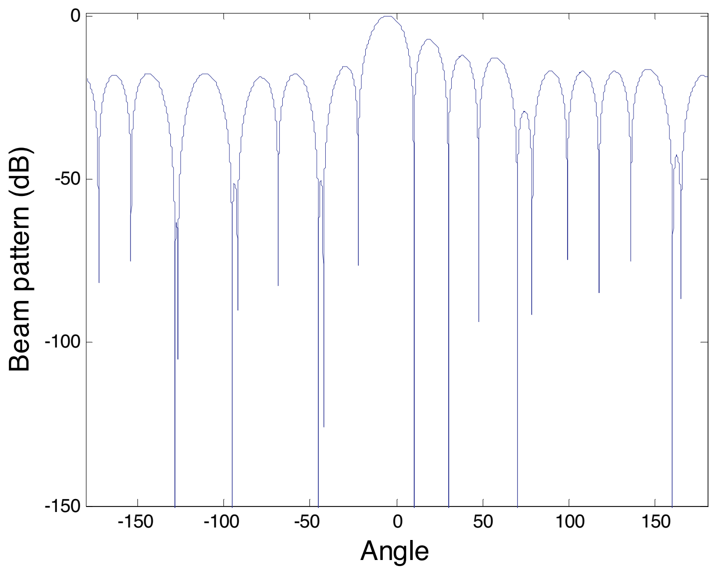


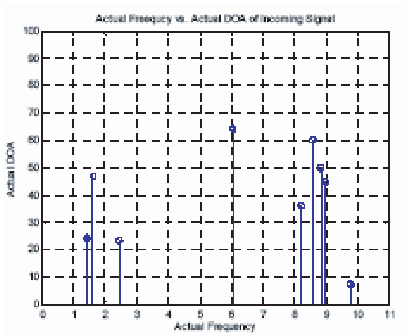
Figure 6b. Creating NULLS towards the jammer directions of $10°, 30°, 70°, -45°, -95°, 128°$ and $160°$, where desired signal coming thorough mainlobe.

Simulation 6A & 6B (NULL towards Multiple Jammer).

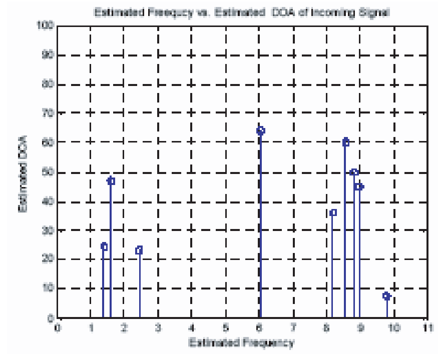
From the stability analysis of LMS algorithm we can prove that if, $0 < \mu < \frac{2}{\sum_{i=k-n+1}^{k} d^2(i)}$ then $e(k)$ indeed converging. If we choose μ too small then algorithm will adopt the change very slowly, and if we chose μ too big, then error will not converge [13, 14].

6. DOA ESTIMATION BY ROTATING ARRAY PLANE

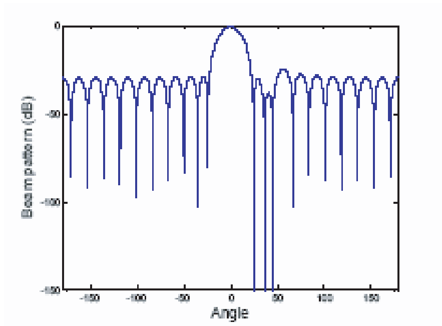
Adaptive Array Antenna or Space Time Adaptive Processing techniques is the best suitable method for jamming resistance GPS receiver to counter spatially separated but in band frequency jammer. Suitably designed algorithm can collect the main signals' multipaths and add them constructively with main signal with very low side lobe level in all other directions, hence eliminating the jamming signal form other directions. A new technique for DOA estimation of signals impinging on the array, using mechanical rotation of the array plane by small angle also has been proposed for further analysis and discussions.



simulation 7A
Actual DOAs vs. actual frequencies of all incoming sigmals



Simulation 7B
Estimated DOAs vs. estimated frequencies



Simulation 7C
Creating nulls towards three undesired signals

Actual Frequency (MHz) = 8.5710 8.1940[J1]
2.4570 8.9760[J2] 6.0410 1.3970[J3]
1.6130 8.8320 9.7860
Estimated FREQUENCY (MHz) = 1.6135
1.3966[J3] 2.4571 6.0406 8.5678 8.8321
8.9767[J2] 8.1928[J1] 9.7861
Actual DOA (Degree) = 60.1300 36.1800[J1]
23.1400 44.9700[J2] 64.3100 24.5200[J3]
46.8000 49.7400 7.5000
Estimated DOA (Degree) = 46.8144
24.4964[J3] 23.1461 64.3081 60.1187
49.7416 44.9763[J2] 36.1727[J1] 7.5100

Data Results of Simulation 7A & 7B

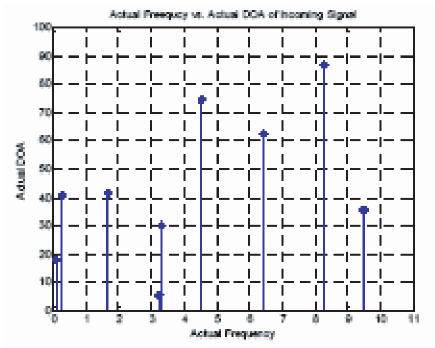
Figure 7. Simulation 7 (DOA estimation by array plane rotation).

For an adaptive antenna system, if p users transmit signals from different locations, and each user's signal arrives at the array through multiple paths. Let L_{Mi} denote the number of multipath components of i-th user. We have $\sum_{i=1}^{p} LM_i = p$. Let's further assume that all of the multi path components for a particular user arrive within a time window which is much less than the channel symbol period for that user, then the input data vector could be expressed as

$$x(t) = \sum_{i=1}^{p} \sum_{k=1}^{L_{M_i}} \alpha_{i,k} a(\theta_{i,k}) s_i(t) + n(t) \tag{16}$$

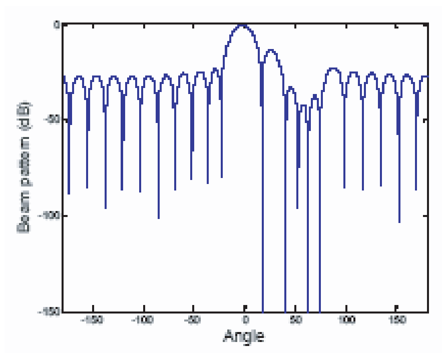
Or we can write

$$x(t) = \sum_{i=1}^{p} G_i s_i(t) + n(t) \tag{17}$$



simulation 8A

Actual DOAs vs. actual frequencies of all incoming sigmals



Simulation 8C
Creating nulls towards four undesired signals

Actual Frequency (MHz) = 9.4850 4.5170(J1) 3.3170 0.0780(J2) 1.6580 8.2820 6.4340(J3) 3.2230 0.2640(J4)
Estimated FREQUENCY (MHz) =0.0774(J2) 0.2633(J4) 8.2833 4.5165(J1) 1.6591 3.3177 6.4368(J3) 3.2228 9.4849
Actual DOA (Degree) =35.5400 74.3900(J1) 29.8700 18.1200(J2) 41.5200 86.7300 62.4900(J3) 5.5200 40.4100(J4)
Estimated DOA (Degree) =16.7296(J2) 40.2472(J4) 86.7306 74.3877(J1) 41.5637 29.8979 62.5029(J3) 5.5211 35.5417

Data Results of Simulation 8A & 8B

Figure 8. Simulation 8 (DOA estimation by array plane rotation).

where $\theta_{i;k}$ is the DOA of the k-th multi path component for the i-th user, $a(\theta_{i;k})$ is the steering vector corresponding to $\theta_{i;k}, \alpha_{i;k}$ is the complex amplitude of the k-th multipath component for the i-th user, and G_i is the spatial signature for the i-th user and is given by

$$G_i = \sum_{k=1}^{L_{M_i}} \alpha_{i,k} a(\theta_{i,k}) \tag{18}$$

Direction of Arrival Estimation by Rotating Adaptive Array Antenna Plane Mechanically:

The signal component arriving on nth antenna element at a particular instance of time is given by [13]

$$X_n = A \exp\left(j2\pi nd \cos\varphi/\lambda\right) \tag{19}$$

Where $A =$ complex amplitude of the signal, $\varphi =$ Direction of Arrival (DOA) of the signal (unknown), $d =$ spacing between antenna elements and $\lambda =$ wavelength.

Now one can view (19) as

$$X_n = A \exp\left[j2\pi f(nd\cos\varphi/c)\right] \tag{20}$$

Where $f =$ frequency of the signal and $c =$ velocity of wave.

Now if we mechanically steer the antenna plane by $\delta\varphi$, then (20) becomes

$$X'_n = A \exp\left(j2\pi f(nd\cos(\varphi + \delta\varphi)/c)\right) \tag{21}$$

Now taking the frequencies (which can be known by seeing the spectra of the signal) of the signal form (20) and (21), and taking their ratio one could get

Frequency of X_n/Frequency of $X'_n = \cos\varphi/\cos(\varphi + \delta\varphi) = 1/K$ (K is Known)

Hence,

$$\boldsymbol{\varphi = \tan^{-1}\left[(\cos(\delta\varphi) - K)/\sin(\delta\varphi)\right]} \tag{22}$$

Now using the simple relation given in (22) one can determine the unknown DOA (i.e., $\boldsymbol{\varphi}$) of all incoming signal impinging on the array with suitable algorithm based on (20), (21) and (22). (Refer simulation 7A, 7B, 8A and 8B).

7. PRINCIPLE JAMMING TECHNIQUES

A brief summary of the main categories of jamming applicable to GPS receivers will be given prior to describing the AJ techniques that are designed to counter these jammers.

There seems to be a broad consensus among the experts, that wideband noise jamming represents the most affordable, tactically feasible, effective jamming technique that is likely to be encountered by GPS receivers in the near term. With numerous sources of information available (many on the internet), a competent electronics technician should be easily able to build a noise jammer with an effective range of tens of kilometers for \$1 K to \$10 K. Wideband jamming was the electronic countermeasure (ECM) used in the example calculations of the previous section of this report.

The power in wideband jamming is diluted over a broad frequency interval (usually matched to the spread spectrum bandwidth of the targeted signal/receiver). However, even though wideband jamming is characterized by low power spectral density, it is virtually impossible to filter out with embedded receiver signal processing techniques. The fraction of the jamming signal that makes it through a GPS receiver (and into base band processing functions) becomes additive to the noise floor, degrading the output signal-to-interference power ratio (SIR) and corresponding receiver operation.

Narrowband (or spot) noise and continuous wave (CW) tone jammers can cause degradation to receiver SIR and degradation/denial of GPS navigation similar to wideband noise. In fact, the effectiveness of these jamming techniques is potentially greater than wideband noise since they result in higher power spectral densities at receiver outputs, being more concentrated signals in the frequency domain. However, unlike wideband noise, spot noise and CW tone jamming signals can be located in frequency and filtered out of the GPS signals with practical (and low cost) embedded signal processing techniques that result in only minor degradation in receiver signal-to-noise power ratio (SNR) and navigation function.

Wideband pulse jammers deliver high peak power interference signals at low duty cycles to damage or saturate receiver front ends. Since GPS receivers typically employ PIN (microwave) diode-based limiters in the RF front end, pulse jamming represents a minimal threat. The limiter passes normal signal levels without distortion but clips the amplitude of high peak power jamming signals or interference (e.g., a radar transmitter). Even with the limiter in place, the receiver is still inhibited while the pulse jamming signal is high; however, this represents a small percentage of time in accordance with the low duty cycles typical of pulse jammers. Meanwhile, the limiter protects the RF front end from damage and prevents amplifiers from being driven into saturation such that the receiver can recover and function between pulses.

Accordingly, pulse jamming effectively represents degradation in receiver SNR that is directly proportional to the complement of jammer duty cycle (e.g., 10% duty cycle results in an effective SNR degradation by a factor of 0.9 or 0.5 dB).

Finally, spoofing is a deception jamming technique wherein a hostile entity transmits a replica of an actual GPS satellite signal, complete with a valid pseudo-random noise (PRN) binary code sequence modulated onto the L1 and/or L2 GPS carrier frequencies. The goal of the spoofer is to cause a receiver channel to lock onto the deception signal instead of the actual satellite signal. This denies the receiver access to valid range measurements from that satellite and substitutes false or meaningless range measurements in their place. The false range measurements will, in turn, degrade, disrupt, or deny the GPS receiver's navigation function.

The use of actual GPS signals makes spoofing a potentially devastating deception jamming technique; accordingly, an inherent anti-spoofing (AS) feature was designed into GPS at its inception. This feature is the encryption of the P-code, which converts it to the $P(Y)$-code. Without the keys to properly seed the P-code generator, an adversary cannot transmit a valid encrypted $P(Y)$-code.

8. SIMULATION RESULTS AND DISCUSSION

Simulation 1A, 1B and 1C: Adaptive antenna algorithm (i.e., LMS here with $\mu = 0.008$) successfully scanning a single signal with a very narrow mainloab beam width and very low side low level) from different direction. Error signal converging satisfactorily after 46–47 samples of time intervals. For the simulation 1C we have chosen $\mu = 0.01$, and for this we can observer same type of scanning as in 1B or 1A, but mainloab power has been reduced somewhat, which shows the effect of parameter μ on the rate and tracking efficiency of the LMS algorithm.

Simulation 1D: In this simulation we have arbitrarily chosen the value of $\mu = 0.1$ and solution is not converging at all as the chosen value of μ falling outside of it's stability range (0 to 0.075 approx).

Simulation 2: It shows that Adaptive processor can scan more than one signal simultaneously if we use LMS algorithm in parallel mode for both DOAs.

Simulation 3 and 4: These shows the perhaps most important result among all simulations. They exhibit that LMS algorithm can scan multipath component of single or more then one signal. We have introduced those multipaths with 1 or 2 symbol delay which are the practical cases, and the results obtained from those simulations clearly encourage any one to implement a RAKE RECEIVER which can compensate the multipath delay and add up the signal constructively to obtain high SNR.

Simulation 5A, 5B, 5C and 6A, 6B: We are applying null constraint in these simulations and obtained null for different interference directions, although with increased side lobe level, we can encounter single or multiple jammers by crating nulls towards their directions.

Simulation 4: Adaptive Antenna Scanning two signals from 60° (with two multipath form 40° and from 10°) and −40° (with two multipath form −60° and from −20°). LMS algorithm converging around 49–50 iteration for all signals.

After determining the frequencies and DOAs of all impinging signals on the array by using Fourier transform and using (20), (21), (22) as shown in simulation results. 7A, 7B and 8A, 8B and if desired signal directions are known to adaptive array (which is common for GPS receiver) as priori, then other signals' direction can be fed into a simple null creating algorithm [8] to produce nulls towards the undesired signals' directions [9] to reduce the jammer power (see simulation result 7C & 8C). In the simulation data, jammers are indicated as with superscript $(J1), (J2) \ldots$ etc., which stands for First Jammer Signal, Second Jamming Signal and so on. In these simulations $\boldsymbol{\delta\varphi} = \mathbf{1}^\circ$. Estimated Frequencies and Estimated DOAs are not with the same order as signals are sensed by the array, but after estimating the entire signal space, their plots almost identical as exhibited between 7A & 7B and between 8A & 8B.Maximum estimation error observed in DOA of second jammer signal of simulation 8, with an order of 1.5° only (see the estimated DOAs data results for 8A & 8B).

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