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Performance Analysis of Particle Swarm Optimization based Training Algorithm for MIMO System

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Abstract—Multi Input Multi Output (MIMO) is the most commonly used technology in wireless systems because of its reliability and efficiency. The paper gives a brief introduction of MIMO Systems and Particle Swarm Optimization. It then discusses Multi Input Multi Output (MIMO) beam forming along with the use of Particle Swarm Optimization as a training algorithm for neural network based channel prediction system. The paper also gives an analysis of research work already done in this field of study.

Index Terms—Particle Swarm Optimization, PSO, Beamforming, MIMO, RNN, Evolutionary Algorithm.

I. INTRODUCTION

Adaptive Antenna has been a major development in the field of communication Engineering. These adaptive antennas perform the function of localization by performing direction estimation and capacity extension with MIMO procedures [1]. In addition to this, they also help in achieving optimal efficiency by eliminating interferer influences. The procedure of adaptive adjustment of the directional characteristic of the used array antenna systems [2] to achieve the above mentioned tasks of adaptive adjustment is known as beam forming.

In the context of a cellular network, both transmitters and intereferers are real world mobile devices. Any transmitter or mobile present in the same base station area, at the same time, transmitting at the same frequency and performing radio transmission can be categorized as an interferer. Therefore, adaptation or control of the antenna and its pattern has real time limitations and conditions to meet, failure of which might cause loss of connection. For the real time adaptation of patterns, multiple approaches have been identified.

The contemporary methods used direction estimation algorithms [3] like ESPRIT and MUSIC for determining the location of the transmitters and the interferers. Once the location was determined, parameter settings were deduced from a table which was pre-configured. The limitation of these methods was the expenses it involved. As a result of its expensive nature, the table had to be pre-configured and not dynamically configured. In addition to this, the number of scenarios that could be validated using this approach was very limited.

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The second approach that can be followed is using blind adaptive beam forming [4]. Blind Adaptive Beam Forming can be defined as the adjustment and continuous adaptation of the directional radio pattern of an electrically and/or electronically controllable array antenna without the need of measuring, simulating or elsewhere knowing the directional characteristic of the antenna system itself [2]. In this approach, the actual location of the mobile terminal is not determined. Instead, a parameter called fitness value is calculated using other parameters like field strength, SNR ratio etc. The strong point of this approach is that no re-computation of tables is required on occurrence of any changes in the environment.

The third approach makes use of neural networks to train the network, which acts as a link between locations of different transmitters and the preferred parameter setting. The efficacy of this approach depends on the algorithm used in the neural network. Multiple Input Multiple Output (MIMO) systems have shown significant improvements in spectral efficiency and reliability, when compared to its predecessors. These results are known to be possible only when the transmitters are aware of the channel coefficients.

These coefficients have to be either estimated or predicted. Channel estimation can be done by either using pilot symbols [7] or space time block codes (STBC) [8]. The usage of this method suffers from a serious limitation. In both these cases, the time that is invested in sending and receiving these entities could well be used for transmission of actual data. Therefore, it causes wastage of the most critical resource in the system. This limitation is overcome by channel prediction. Channel Prediction can be implemented using conventional methods or using neural networks. This scope of this paper is limited to channel prediction using recurrent neural network and the algorithm used for training this recurrent neural network is the Particle Swarm Optimization (PSO) Algorithm.

The paper describes the use of Particle Swarm Optimization (PSO) as a training algorithm for channel prediction in MIMO wireless systems. The next section gives a brief background on the basics of beam forming, MIMO systems and also introduces the concept of Particle Swarm Optimization, which are topics central to the theme of this paper. The sections to follow describe MIMO beam forming and Channel Estimation & Prediction. In the end, the paper concludes with an analysis and comparison of other algorithm that can be or have been used as training algorithms in a recurrent neural network for channel prediction.

II. BACKGROUND

This section provides a brief background on topics that form the foundation of the paper. It first discusses the concept of beam forming and then goes on to introduce and elaborate MIMO communication systems. The section ends with a brief overview of the Particle Swarm Optimization along with its implementation algorithm.

A. Beam Forming

Beam forming is a technique that is extensively used in the field of signal processing for controlling the directionality of radiation pattern [13]. By effectively controlling the directionality of the radial pattern, it is possible to eliminate interference by making the antenna more sensitive to the direction of the desired signal and if not insensitive, at least lesser sensitive to the direction of unwanted signals. This can be achieved by spatial filtering of signals that are transmitted or received by the antenna array. For this purpose, elements of the antenna are allocated weights and this allocation is in accordance with the desired results for sensitivity. These weights produce interference that is constructive in some directions and destructive in some other directions [22]. These weights can be fixed or adaptive. In case of adaptive beam forming, information about location is used for identification of areas that should be given higher priority.

B. MIMO Systems

Multi Input Multi Output (MIMO) systems is a type of communication system that makes use of multiple antennas both at the receiver as well as the transmitter end thereby taking advantage of multipath propagation [14]. By properly handling the signals at the transmitter and the receiver end, a number of independent sub-channels are synthesized.

The history of MIMO systems can be dated back to the 1970's. The first mention of MIMO communication systems and their capacity was made by Kaye and George [15]. It was much later in 1998 that the demonstration of the first prototype was made. One of the reasons of such grave interest in MIMO communication systems has been the fact that it promised optimum usage of the spectrum by increasing the transfer rate linearly with the minimum of the number of antennas, at transmitting or receiving end. It is this feature of MIMO systems that makes it an essential component for many wireless systems like WiFi and WiMax.

The block diagram of a MIMO system is shown in the figure below.

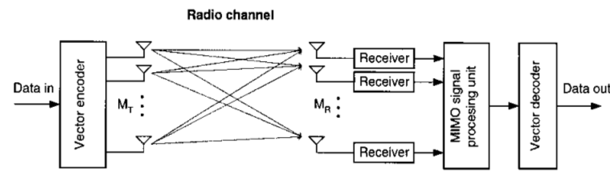

Figure1 – Block Diagram of a MIMO System [16]

As can be seen in the figure shown above, the stream of data is encoded using the vector encoder, shown in the figure. This encoded data is then transmitted using the transmitters M_T. The signal propagates via the radio channel, which also incorporates some noise in the signal. All the transmitted signals are received by each of the receiver antennas and then these signals are sent to the processing unit for the estimation of the actual stream of data that was sent.

In order to explain the basics of MIMO systems, let us consider a communication system consisting of a two element array at both the transmitting as well as the receiving end. Using the array theory, it is known that the best approach towards the establishment of communication between the transmitter and the receiver in free space is to synthesize two radio patterns. These patterns should maximally be in the direction of the other array. If the operating environment of the communication system changes to indoor, simple line of sight communication is not possible because of the presence of objects. The presence of objects results in phenomena like diffraction. Therefore, in an indoor environment, multipath propagation will take place [25].

Consider a simple communication system consisting of two scatterers and one blocking screen is considered, as shown in figure2 (a). The effects of polarization and mutual coupling

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are neglected. Moreover, the radiation pattern is also assumed to be isotropic in nature, for simplicity's sake.

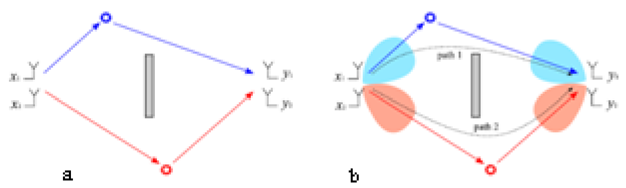

Figure2 – Multipath Propagation [14]

Figure (b) illustrates the independent sub-channels that are synthesized as a result of the synthesis of two orthogonal radio patterns both at the transmitter as well the receiver end. Each of these orthogonal pattern points towards the corresponding scatterer at the other end. This is how spatial multiplexing of information is performed in this case[26].

MIMO RECEIVED MODEL

A MIMO wireless flat fading communication system with Nr receiving antenna and Nt transmitting antenna can be written as,

$$y = Hx + n \text{ ---- } (1)$$

Here, y is Nr × 1 received symbol vector, x is Nt × 1 transmitted symbol vector and n is the white noise vector of size Nr ×1 with

$$n_i \overset{iid}{\sim} CN(0, No) \quad \text{---- } (2)$$

For a Nr ×Nt channel matrix, the complex channel gain is between the mth receiver antenna and the nth transmit antenna is given by,

$$H = \{hmn\}$$

MIMO CHANNEL MODEL

The sub-channels in MIMO are represented by [17] in the following manner,

$$g_{mn}(k) = f\left(\left(g^{I}_{mn}(k) + j g^{Q}_{mn}(k)\right)\right) \quad \text{---------------------- } (4)$$

In the above equations, f is arbitrary and bounded by e, m and n are such that,

$$1 \le m \le Nr$$
$$1 \le n \le Nt$$

The in phase component (g^{I}_{mn} (k)) is given by,

$$g^{I}_{mn}(k) = \sqrt{\frac{2}{M}}\sum_{n=1}^{m} \cos\ (2\pi f_d k T_s \cos(\alpha_n) + \emptyset_n) \quad \text{------ } (5)$$

And, the quadrature component (g^{Q}_{mn}(k) is given by,

$$g^{Q}_{mn}(k) = \sqrt{\frac{2}{M}}\sum_{n=1}^{m} \cos\ (2\pi f_d k T_s \cos(\alpha_n) + \psi_n) \quad \text{------ } (6)$$

Where, T_s is the sampling period and f_d *is* the maximum Doppler frequency.

The parameters ψ_n, $\emptyset_n$ and θ, are Uniform random variables represented by U(-π, π) and α_n is given by,

$$\alpha_n = \frac{2\pi n - \pi + \theta}{4M} \quad \text{---------------------- } (7)$$

Since spatial correlation may exist between the transmitting and the receiving antenna therefore, the channel is represented as follows,

$$H(k) = \emptyset_{Rx} k^{\frac{1}{2}} G(k) \emptyset_{Tx} k^{1/2} \quad \text{---------------------- } (8)$$

Here,

$$\emptyset_{Tx} \triangleq \frac{1}{N_r}\sum_{n=1}^{N_r} E\{h_r(k)^H h_r(k) \quad \text{----------------- } (9)$$

$$\emptyset_{Rx} \triangleq \frac{1}{N_r}\sum_{n=1}^{N_r} E\{h_r(k) h_r^H(k) \quad \text{--------------- } (10)$$

And h_r represents the rth row of H(k) and H is The Hermitian Operator. $\emptyset_{Tx}$ and $\emptyset_{Rx}$ are correlation matrices which are dependent on factors like distance between the transmitting and receiving antenna, angular spread etc [25].

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C. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart in 1995 [9] [10]. This algorithm has originated from the social system and is based on the social makeup of a bird flock. Initial modifications to the algorithm included the introduction of nearest neighbor velocity matching [9] and multidimensional search [9]. As this algorithm was evolving, it became clear that it was in entirety an optimizer. Once, this became clear, some relevant changes like elimination of unwanted variables were performed and an implementation was developed [11].

Particle Swarm Optimization (PSO) algorithm is generally compared to the Genetic Algorithm (GA). Although, Particle Swarm Optimization (PSO) Algorithm, like Genetic Algorithm (GA) initializes the system using a population of random solutions [24], it differs from Genetic Algorithm (GA) in the sense that each of these random solutions is assigned a random velocity. These random solutions, in Particle Swarm Optimization (PSO) are also known as particles. Since a dense population of particles is used, hence the name "Particle Swarm".

III. CHANNEL ESTIMATION AND PREDICTION

Narrow band channel prediction can be performed using a Recurrent Neural Network (RNN) [6]. The advantage that recurrent neural networks have over other neural networks is that they have the ability to perform extraction of data from the outputs collected from the network. A Recurrent Neural Network [18] can be trained online or offline. The online method of training a neural network is using the Kalman filter. A downside of this approach is that accurate estimation of the channel prediction error is required [23]. In contrast to this, is the offline mode of training which uses PSO or PSO modified algorithms for training the recurrent neural network. The block diagram of the recurrent neural network is shown in the figure below,

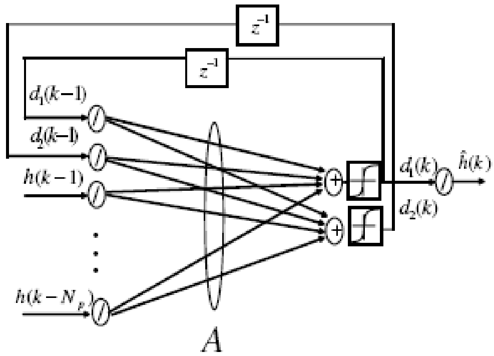

Figure 3– Block Diagram of RNN [18]

For better prediction, it is necessary to have some knowledge of the fading process by supplying the recurrent neural network with previously estimated statistics. Therefore, by applying the same procedure used in [9], the minimum mean square estimate is calculated to determine the channel estimation error which is given in [6] as,

$$\sigma_w^2(k) = |\sigma_h^2(k) - \sigma_{\hat{h}}^2(k)|$$

TRAINING ALGORITHM FOR RNN CHANNEL PREDICTION –

The algorithm proposed for training of Recurrent Neural Network is Particle Swarm Optimization Algorithm that has been introduced in the previous sections. Two parameters are of high importance in Particle Swarm Optimization (PSO) algorithm, pBest and gBest. The parameter pBest is also known as the fitness value or particle best value and corresponds to the best solution coordinates of a particle in the problem space. The parameter gBest or global best value is an array that corresponds to the best solution coordinates overall and is computed at the optimizer level.

This algorithm involves changing the velocity of each particle in correspondence with the pBest and gBest values[24].

A step by step approach for implementing of Particle Swarm Optimization (PSO) Algorithm is as follows –

1. A population of particles is initialized with random values of the location and velocity within the boundaries of the problem space of d dimensions.
2. The Fitness function is evaluated for d parameters.
3. This Fitness function is compared with pBest. If this evaluated value is better than pBest, change pBest value and location to the evaluated value and location.
4. Further, this fitness function is compared with gBest. If this function is found to be better than gBest, the array index and value is changed in accordance with the current particle.
5. Next, the location and velocity of the particle are modified according to the following equations [12] –
   Equation (1) –
   v_{id} = v_{id} + c_1 * rand ( ) * (p_{id}- x_{id}) + c_2 * rand( ) * (p_{gd} - x_{id})
   Where, c_1 and c_2 are acceleration constants. These values control the movement of particles in the problem space in terms of their freedom to move towards and away from the locations of the target. And, rand( ) provides a pseudo-random number between 0 and 1.
   Equation (2) –
   $$x_{id} = (x_{id} + v_{id})$$
6. The steps from Step 2 to Step 5 are repeated until a particular condition is met. This condition can be for example, the maximum number of iterations that have to take place is set to n. Then, once the number of iterations performed for the algorithm reaches the number n, the execution is brought to a halt.

IV. Discussion

Algorithms like Particle Swarm Algorithm – Evolutionary Algorithm (PSO-EA) [19] and a hybrid PSO-EA-DEPSO [18] algorithm has also been used for training RNN for channel prediction. This section will give an analysis and comparison of the different algorithms mentioned above, their applicability as a training algorithm for recurrent neural network and a comparison of the results they produce.

Evolutionary Algorithm (EA) considered each parent or offspring as a chromosome that is made of a number of genes. If a population of N chromosomes is considered, each parent chromosome is characterized by two parameters, which are genes represented by $w_i$and a self adaptive parameter, which is represented by β_i. Each parent generates an offspring with updated $w_i$and β_i [19]. The parents that are present in the population of chromosomes are put through a selection process in which the parents are declared to be either winners or losers. The ones that are declared to be losers are replaced by the winners.

The PSO-EA Algorithm is a hybrid algorithm that incorporates features of both PSO or Particle Swarm Algorithm and EA or Evolutionary Algorithm. It amalgamates the PSO specific particle swarm behavior with the EA specific behavior of discarding particles that are not fit. The particles are declared unfit on the basis of their fitness value. Once the unfit particles are discarded, the fit particles generate offsprings with calculated values of position and velocity.

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The PSO-EA-DEPSO algorithm is a hybrid algorithm of PSO, EA and DEPSO algorithms. PSO and EA algorithms have been discussed above. The DEPSO algorithm is also a hybrid algorithm that incorporates in itself the characteristics of PSO and DE algorithm. It provides diversity on the population while keeping the swarm searching capabilities intact [20]. The PSO-EA-DEPSO algorithm makes use of these three algorithms alternatively. One-fourth of the iterations are made to work on PSO algorithm. This is done to ensure that the algorithm converges to an apt solution. The rest of the iteration alternate between EA and DEPSO. This done to prevent convergence before a potential solution is found.

A comparison of these algorithms has been provided in [18]. For the comparison, a 2x2 spatially not correlated MIMO channel is used. The parameters chosen are as follows –

$$f(x) = x$$
$$N_{Train} = 100$$
$$\gamma_t = 0$$
$$\sigma_w^2(k) = 0.001$$
$$f_d T_s = 0.05$$

The fitness value is collected for multiple iterations. Other parameters are shown in the table below [18],

TABLE I. PARAMITERS SITTING FOR TRAINING ALGORHITM

Parameter	*Value*	*Description*
N_w	14	RNN Weights Number
V_{max}	2	PSO Velocity Max
X_{max}	4	PSO Position Max
W	0.8	PSO Inertia Weight
C_1	1	PSO Cognitive Weight
C_2	1.5	PSO Social Weight
P	40	Number of particles
P_c	0.5	Crossover probability for DEPSO
L	7	DEPSO Parameter
τ	0.3265	EA Parameter

The plot for average fitness values of the in phase and Quadrature components are plotted and can be seen in the figures shown below.

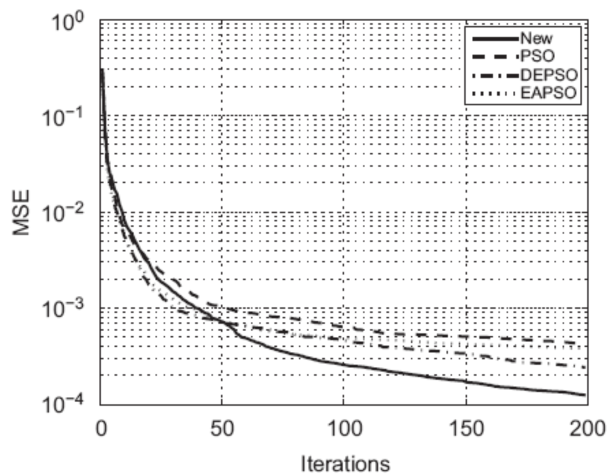

Figure 4– Mean Square Error Comparison for In Phase Component [18]

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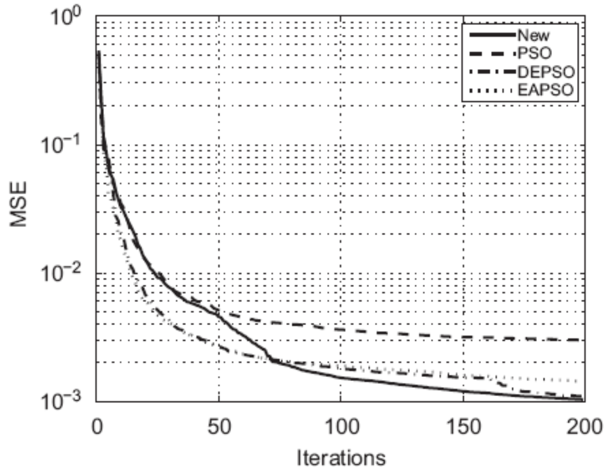

Figure 5 – Mean Square Error Comparison for Quadrature Component

The first 50 iterations for PSO and PSO-EA-DEPSO show similar results in both the graphs because PSO-EA-DEPSO also uses PSO for one-fourth of its iterations and hence the results are similar.

CONCLUSION

For the real time adaptation of radial patterns generated by an adaptive antenna, three main approaches have been identified.ESPRIT and MUSIC are contemporary methods that are used for direction estimation and determining the location of the transmitters and the interferers. The main limitation of these methods is that it is a very expensive implementation. The next approach that has been analyzed is the use of blind adaptive beam forming. The strong point of this approach is that no re-computation of tables is required on occurrence of any changes in the environment.

Finally, the third and the approach on which majority of this paper is based makes use of neural networks to train the network, which acts as a link between locations of different transmitters and the preferred parameter setting. The efficacy of this approach depends on the algorithm used in the neural network. Particle Swarm Optimization (PSO), Particle Swarm Algorithm – Evolutionary Algorithm (PSO-EA) [19] and a hybrid PSO-EA-DEPSO [18] algorithm can also be used for training RNN for channel prediction and an evaluation of the same has been provided in the paper. This approach is found to be not only effective but efficient.

Particle Swarm Optimization (PSO) algorithm can be used in artificial neural networks for not only controlling network weights but also for adapting and controlling the network structure. The methodology and implementation is also pretty simple and efficient which is a reason why it is seen as a good replacement for conventional methodologies like back propagation. Another strong point of this algorithm is that it can be used for any network architecture.

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