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Deep Learning and Smart Antennas for Beamforming Strategies

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Abstract

With the advent of the 5G and future 6G, base stations will be used as station controllers. The antenna systems are networked and equipped with a processor to optimize the detection of signal arrival, beamforming, and computing time. The present work aims to improve the antenna radiation pattern by using neural networks and CDRs (Call Detail Records) according to the spatial occupation of the area by the users. It focuses on the computation time of synthesis algorithms by Deep learning and proposes an optimal management strategy. The tests carried out show that Despite the diversity of the quality of the results provided, the computation times remain comparable for the classical DoA estimation methods, the slowest being the PRONY approach (linear prediction). The neural network approach has the advantage of being a global optimum search technique requiring the shortest computational time, which is about 10 times the time required for a local optimum approach. Neural network and spectral methods reduce the influence of noise on communication to zero. It has proposed a new approach based on mathematical modeling to exploit blocked TRX to cancel the radiation on this channel.

Keywords

Beamforming, Deep Learning, Neural Networks, Smart Antennas

1. Introduction

Nowadays, most wireless communication systems use omnidirectional antennas or sectorial antennas whose radiation pattern is static. This has the disadvantage of transmitting the signal in directions where no user is present. In addition to this waste of electromagnetic energy, interference from adjacent channels is increasing.

It is also noted the problem of multiple paths which causes the phenomenon of signal fading on reception. To avoid these problems, wireless communication systems are increasingly using antenna arrays and associated synthesis algorithms. It is also used to obtain a dynamic or variable radiation pattern. An optimal combination of one of the parameters of this network makes it possible to obtain an optimized radiation pattern with the characteristics required by the designer (very low secondary lobe levels, the desired directivity, a very narrow half-power aperture, and a main lobe of specific shape: cosine shape).

Several synthesis methods have been used, such as the invasive weeds method (Invasive weeds optimization), which was developed in order to determine the directions of the arrival of the waves. Each method has its specificities: resolution and calculation time of the algorithms. In synthetic electromagnetic problems, stochastic methods are more robust than deterministic algorithms. Among the most popular stochastic methods in electromagnetism are the invasive weeds method (Invasive weeds optimization), the genetic algorithm [1]-[4], and the particle swarm… calculation of the order of 0.1345 s [1]-[7]. By combining genetic algorithms with analytical methods, the average computing time of the genetic algorithm increases to around 2.7 s.

However, this method, inspired by the work of Marc Darwin [7] [8] in the 19th century, therefore arouses little enthusiasm and is less and less integrated into the system of antennas and electronic devices because of its latency. It is in this sense that we can legitimately ask the question: How can we improve the execution time of the synthesis algorithms of smart antennas by using deep learning specific to neural networks and the traffic management data recorded in operators' databases?

In this article, we propose a study on the computation time of synthesis algorithms by Deep learning and propose an optimal management strategy.

In the first paragraph devoted to the literature review, we will start by presenting what has been done in the synthesis process of the antenna array in general and, in particular, stochastic methods. At the same time, we will present the problems related to genetic algorithms in the context of antenna processing so far.

The second paragraph will then present the tools and methods used to solve the latency problem observed in the different synthesis algorithms. Finally, the last paragraph will be devoted to the presentation of the results and prospects.

2. Basic Concepts and Literature Review

Synthesis algorithms are grouped into two main categories:

- Spectral estimation methods;
- Structural methods with eigenvalues (or methods of subspaces).

2.1. Deterministic Algorithms

Deterministic algorithms belong to two large groups of algorithms for synthesizing radiation patterns with heuristic algorithms [9]. We can classify the deterministic algorithms for the detection of directions of arrival according to several criteria that may relate either to the approach used, to the information to which they are used, or to the implementation approach. What interests us in this section is their computation time during the synthesis of the antenna arrays.

However, we generally retain the following three main classes:

- Spectral methods: Qualified as low-resolution approaches, estimating the direction of arrival angles consists of using lane formation (or spatial filtering) by scanning the space for all possible DoAs. This amounts to finding the maxima of a function called pseudo-spectrum. We find there the approaches of BARLETT [6] [9], CAPON [6] [10], PRONY (linear prediction) [6] [10], etc.
- The techniques of subspaces also called high-resolution methods, are based on the analysis of the eigenvalues and eigenvectors of the correlation matrix of the observation vector. We can cite, among others, PISARENKO, MUSIC, Minimum standard, ESPRIT [6]-[10], etc.
- Maximum likelihood methods.

Spectral Methods		
BARLETT	$P=\frac{1}{M^2}A^H R_{xx} A$	(1)
CAPON	$P=\frac{1}{A^H R_{xx}^{-1} A}$	(2)
PRONY	$P=\frac{\mathcal{U}_m^H R_{xx}^{-1}\mathcal{U}_m}{\left\lvert \mathcal{U}_m^H R_{xx}^{-1} A\right\rvert^2}$ $\mathcal{U}_m$ is the m[th] column of the identity matrix I_M	(3)
SUBSPACE TECHNIQUES		
PISARENKO	$P=\frac{1}{\left\lvert A^H e_1\right\rvert}$ where e_1 is the eigenvector associated with the eigenvalue λ_1	(4)
MUSIC	$P=\frac{1}{\left\lvert A^H E_b E_b^H e_1\right\rvert}$	(5)
MAXIMUM LIKELIHOOD METHOD	$P=\frac{1}{A^H C_m C_m^H A}$ where C_m is the m[th] column of the inverse of the correlation matrix R_{xx}	(6)

2.1.1. Spectral Methods

In [5]-[7], the BARLETT method, known as the spatial Fourier transform, is among the first known techniques for estimating the direction of arrival. This relationship means that in order to increase the resolution, it is necessary to increase the number of elements of the antenna array or the inter-element distance factor. The average computing time is 0.17566 s. After using the genetic algorithm on BARLETT, the average time increases, and we get 0.265775 s.

Limited by its low resolution, more advanced techniques quickly had to be used.

The CAPON or MVDR (Minimum Variance Distorsionless Response) estimation method. This exploited method [4]-[7] consists of estimating, by the criterion of maximum likelihood, the power received in a given direction by considering the other sources as interferents. CAPON has reached an average computation time very close to 0.178447 s. After using the genetic algorithm on CAPON, the average time is 2.274417 s.

In order to minimize the prediction error on the response of any element of the network [6] [7], PRONY has implemented a method of finding weighting coefficients of the network, which will minimize the average value of this error. [7] The latency of PRONY is 0.190271 s, and the application of the genetic algorithm on PRONY rather worsens, and they reach 0.263529 s.

This is attributable to BURG, Maximum entropy estimation, whose goal is to find the directions that maximize the directions of arrival [6]. MEM's latency time is 0.177403 s, and the application of the genetic algorithm on MEM gets worse, reaching 0.269666 s.

2.1.2. Subspace Techniques

The methods of subspaces are based on the decomposition of space into a noise space and a signal space by searching for the eigenvectors of the correlation matrix of the observation vector [7]-[13]. It was PISARENKO who had the idea in 1973 by showing that its lowest eigenvalues corresponded to noise, which made it possible to divide the space in two and to deduce the directions of arrival.

This method displays a calculation time per lap of 0.172794 s, and by applying this, we obtain 0.264251 s.

The goal of PISARENKO's harmonic decomposition technique is to minimize the root mean square error of the network output under the constraint that the norm of the weight vector is equal to unity. The eigenvector of the correlation matrix, which minimizes this mean square error and minimizes the execution time, is associated with the smallest eigenvalue [2] [7]. Its latency time is 1.173082 s, and with the genetic algorithms on PISARENKO, we obtain 0.272009 s.

The Minimum Standard Method was developed by REDDI, KUMARESAN, and TUFS, which optimizes the weighting vector by solving the equations. Minimum standards run in 0.172794 s, and with Genetic Algorithms, we reach 0.264251 s.

The MUSIC approach, offered in its basic version by SCHMIDT, is one of the most popular techniques used for estimating directions of arrival. It has a high angular resolution and also makes it possible to determine, in addition, the number of sources and the power of the incident signals.

The pseudo-spectrum then gives:

On the other hand, the MUSIC algorithm does not work if the noise and the incident signals are strongly correlated. [6] [7] [11], its latency time is similar to others, around 0.17947 s, and in combination with Genetic Algorithms, we have 0.268659 s. This confirms that MUSIC is better because it improves resolution at the same execution times.

The ESPRIT method exploits the rotational invariance of the signal subspace and the translational invariance of the structure of the array of elements by breaking it down into two identical antenna sub-arrays, one of which can be obtained by translation of the other. [7]

The algorithm uses the same signal model as the MUSIC algorithm, but it has the advantage of drastically reducing the computing power and memory required for storage.

Besides all these methods, the maximum likelihood method is considered to be asymptotically efficient and without distortion [7]-[13].

They are often preferred over other methods when they have simple analytical solutions.

Unfortunately, the analytical resolution of this problem is cumbersome and difficult to implement [6]. Hence, there is a need to rely on other optimization methods, in particular global optimum approaches, to resolve them [7]-[13].

Several techniques for estimating directions of arrival have been studied in this section. They all have limitations, among others: complexity and computation time, which are not always favorable to real-time applications, accuracy, and antenna size.

2.2. Stochastics Algorithms

Two types of heuristics are mainly used: construction heuristics (for example, greedy methods), which iteratively build a solution, and descent heuristics, which from a given solution seek a local optimum.

More advanced heuristics have been developed and have given rise to a new family of algorithms: meta-heuristics.

The goal of a meta-heuristic is to succeed in finding a global optimum. To do this, the idea is both to browse the search space and to explore areas that appear promising.

2.2.1. Neural Networks

In [14]-[16] artificial neural networks are characterized by their efficiency and performance in terms of the speed of convergences. Tools made it possible to test and compare analytical and neuronal methods. The learning base was produced using the analytical synthesis method. Measurements were carried out on several lobe configurations in order to prove the effectiveness of the neural network approach. The results obtained show a good agreement between the simulation and the measurements.

2.2.2. Genetic Algorithms

Genetic algorithms are programming techniques that mimic biological evolution as a resolution strategy. It is initialized by a set of probable or randomly chosen candidate solutions, and then this set is coded in a certain way. A metric called the cost or adaptation function (fitness in English) allows each candidate to be quantified. A selection criterion is then applied in order to retain some of these candidate parents, who will be used to produce other candidate sons by random mutation and crossing operations. The stop criterion allows either to resume operations from the metric calculation or to retain a final solution close to the global optimum [1] [8].

Article [1] [8] makes it possible to notice that for the arrival directions, the times elapsed by GA are 4 times greater than those previously obtained by analytical methods. However, they hover around 1 s, which is just as acceptable.

At the end of this work, they were able to observe that for the arrival directions, the times elapsed by GA are 4 times greater than those obtained previously by analytical methods.

2.3. Summary

To meet the demands in terms of speed and quality of service, which could be triggered by big data and the Internet of Things, how can we use antenna networks and neural networks to reduce their computing time?

3. Methodology

3.1. Materials and Methods

In order to improve the execution time of smart antenna synthesis algorithms by:

- Implementing a strategy to perform neural networks and to reduce the execution time of synthesis algorithms for smart antennas.
- Proposing a method aiming to use the quality of service data recorded in the databases of the BSS/RAN in the beamforming process.

We used the powerful $MATLAB\ R2016a$ programming environment with its various toolboxes:

- Bioinformatic Toolbox
- Fuzzy Logic Toolbox
- Global Optimization Toolbox
- Neural Network Toolbox
- Optimization Toolbox

The tic and toc functions are the tools provided by Matlab to measure the program performance. They start the timer to access the execution time of the function. The tic function starts the stopwatch, and toc reads the time elapsed since the start of the tic function.

For the observations, we used RFS sector antennas of the 1700 - 2200 MHZ frequency range with the following characteristics:

Optimizer® Dual Polarized Antenna, 1710 - 2200, 65 deg, 18.0 dBi, 1.3 m, VET, 4 - 14 deg.

The implementation of smart antennas goes through two successive stages: the determination of the directions of arrival and the consequent steering of beams.

Design:

- We will use a planar array antenna because, in a MIMO environment, the antenna provides more input and output possibilities than linear or circular antenna arrays.
- We will create the conditions for an efficient use of neural networks.
- Choice of the training function.
- Choice of the different parameters of the neural networks.
- Choice of the antenna network shutdown function.

Build a Matlab code to visualize the different algorithms and compare them.

3.2. Mathematical Formalization of MIMO System

Figure 1 summarizes the work covered by this power.

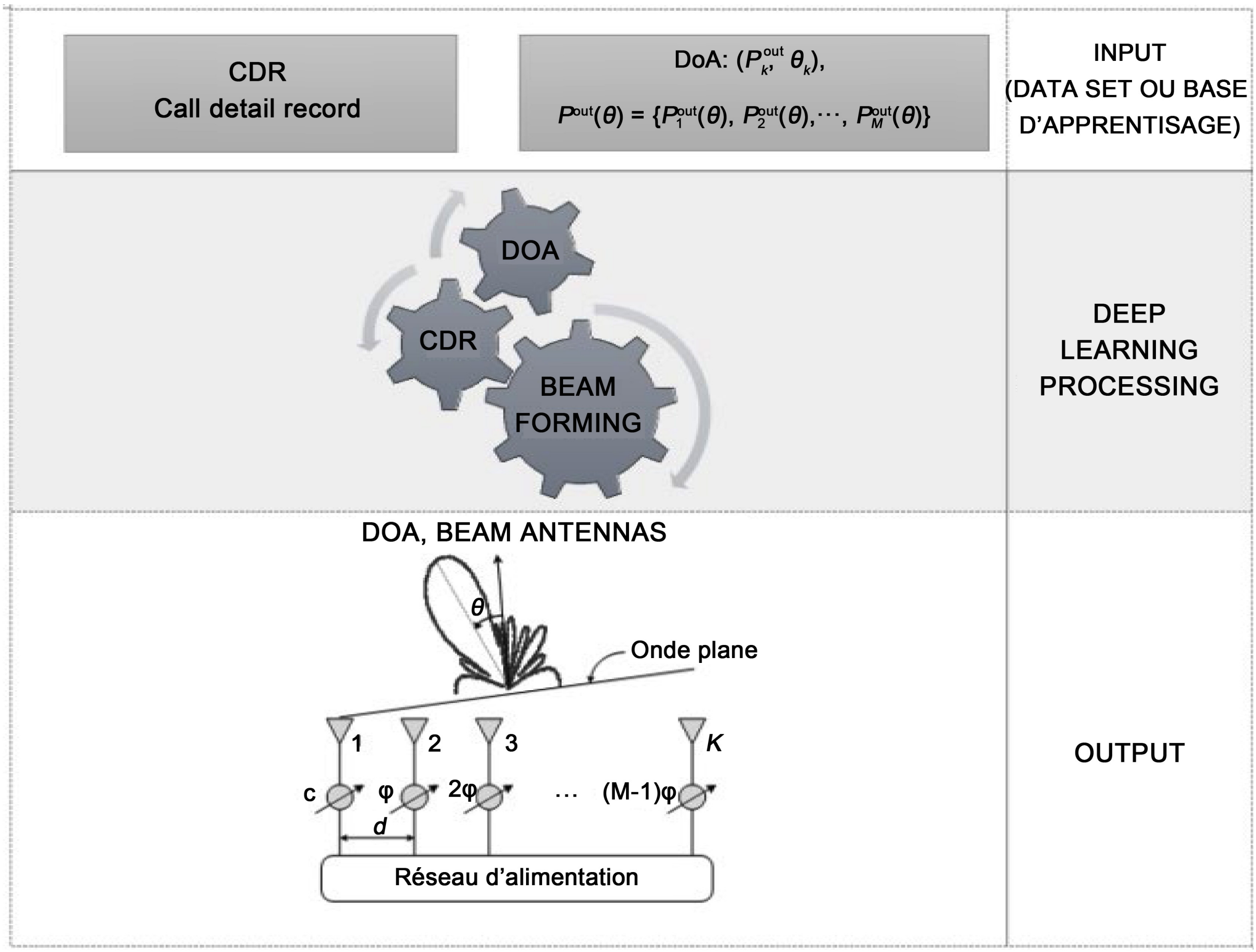

Figure 1. Sumary of the activities.

We consider a MIMO system made up of m_t antennas on transmission and m_r antenna on reception. We denote by x the vector of size m_t containing the symbols received. The relation which connects x and y is then written:

$$y = Hx + n \tag{7}$$

where H is the matrix of channel of size $m_t \times m_r$ and n is the noise vector. The capacity of the MIMO channel:

$$C = \log\left(\det\left(I_{m_r} + \rho HQH^*\right)\right) \tag{8}$$

In this formula I_{m_r} is the identity matrix, ρ is the signal-to-noise ratio, and Q is the correlation matrix of the emitted symbols.

To overcome these problems, the solution is to design a system in which the diagram would be dynamic, with "radiation holes" and privileged listening directions. This is the principle of smart antenna systems: transmit or receive in the directions of interest and remain "deaf" or "mute" in others, depending on the position of users and sources of interference. It is illustrated in Figure 2.

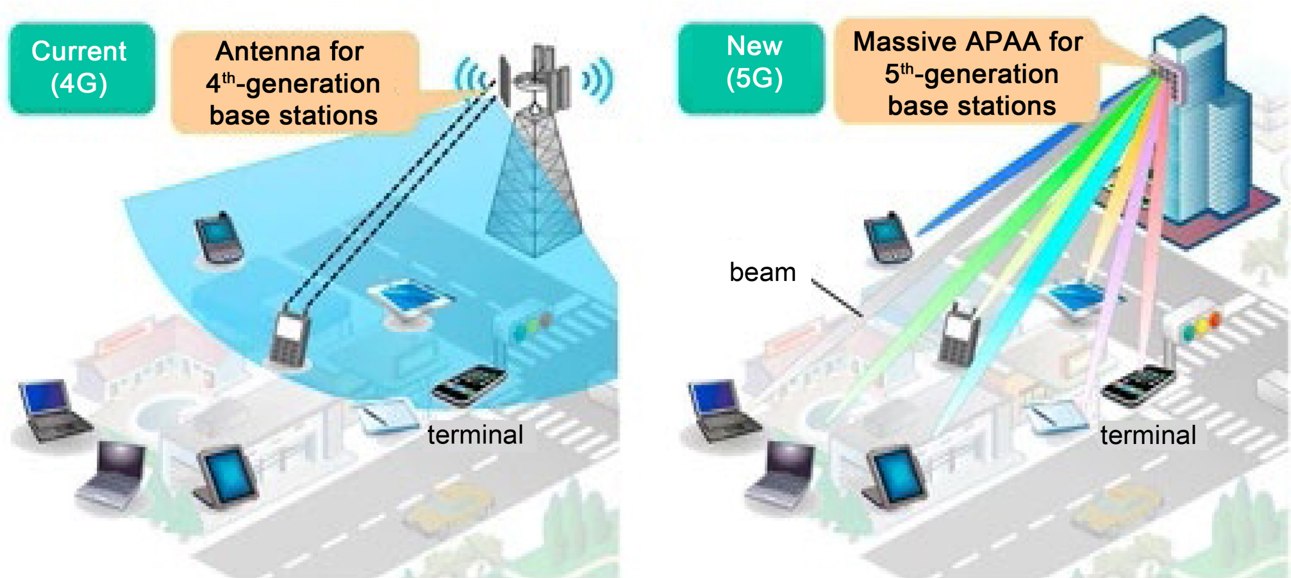

Figure 2. Evolution of multiantenna technology from 4G MIMO to 5G massive MIMO [17].

It promises very significant capacity gains and is the ultimate solution that will significantly increase throughput.

3.3. Antenna Network

3.3.1. Geometries of Network Antennas

Array antennas come in several geometries [3], the most common of which are linear, circular, or planar. They are called uniform if the antenna elements are evenly spaced.

3.3.2. Electronically Scanned Antenna

Consider a uniform linear network of elements regularly spaced apart by a distance (see Figure 3). These sources are supplied with the same amplitude and with a phase gradient. For a point P located in the far radiation zone, the total field is the summation of the field radiated by each of the sources, namely:

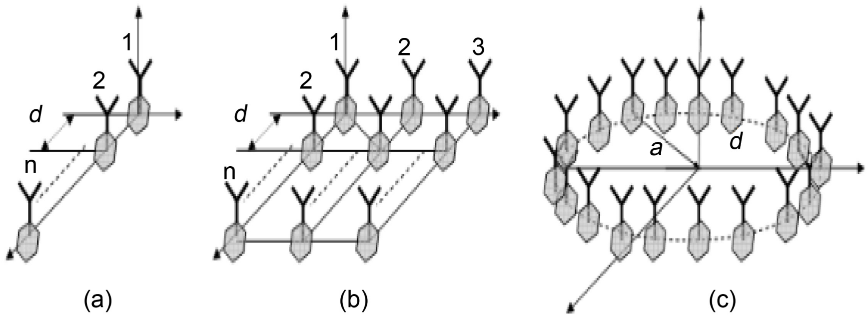

Figure 3. Network antenna geometries: (a) linear, (b) planar, (c) circular [2].

$$E(\vartheta) = E_0(\vartheta)\sum_{k=0}^{K-1}\exp\left[jk\left(2\pi\frac{d}{\lambda}\sin\vartheta+\varphi\right)\right] \tag{9}$$

where $E_0(\vartheta)$ is the radiation of an isolated element.

The network factor, which depends on the law of excitation of the elements of the antenna and their arrangements, is defined by:

$$AF(\vartheta) = \sum_{k=0}^{K-1}\exp\left[jk\left(2\pi\frac{d}{\lambda}\sin\vartheta+\varphi\right)\right] \tag{10}$$

3.3.3. Estimation of Angles of Arrival by Neural Network

In this section, the general concept of the DoA estimation methodology using NNs is stated. Consider N uncorrelated signals with amplitudes h_i, $i=1,\cdots,N$ impinge at the Ne element antenna array of a SBS like in **Figure 4** and **Figure 5**.

Let the angles of arrival θ_i, $i=1,\cdots,N$ composed a vector $\theta=(\theta_1,\theta_2,\cdots,\theta_N)$. M beams are used to cover the desired sector. If beam switching takes place, the m_{th} beam gives the main output of the system's total received power $P_m^{out}(\theta)$, $m=1,2,\cdots,M$, or

$$\begin{aligned} P_1^{out}(\theta) &= h_1^2P_1(\theta_1)+h_2^2P_1(\theta_2)+\cdots+h_N^2P_1(\theta_N) \\ P_2^{out}(\theta) &= h_1^2P_2(\theta_1)+h_2^2P_2(\theta_2)+\cdots+h_N^2P_2(\theta_N) \\ &\vdots \\ P_M^{out}(\theta) &= h_1^2P_M(\theta_1)+h_2^2P_M(\theta_2)+\cdots+h_N^2P_M(\theta_N) \end{aligned} \tag{11}$$

It is assumed that the signals are subject to power control impinging on the base station at the same mean power level, which in the following [18] [19] procedure is considered to be unity.

$$h_1^2 = h_2^2 = \cdots = h_N^2 = 1$$

This became

$$\begin{aligned} P_1^{out}(\theta) &= P_1(\theta_1)+P_1(\theta_2)+\cdots+P_1(\theta_N) \\ P_2^{out}(\theta) &= P_2(\theta_1)+P_2(\theta_2)+\cdots+P_2(\theta_N) \\ &\vdots \\ P_M^{out}(\theta) &= P_M(\theta_1)+P_M(\theta_2)+\cdots+P_M(\theta_N) \end{aligned} \tag{12}$$

The system of Equation (11) shows that the contribution of each signal to the total received power depends on its angle of incidence and the power pattern of the receiving beam. A power vector mapped to the corresponding angle vector can be constructed

$$P^{out}(\theta)=\left\{P_1^{out}(\theta),P_2^{out}(\theta),\cdots,P_M^{out}(\theta)\right\} \tag{13}$$

A NN is a structure of interconnected information-processing units called neurons, organized in the form of layers [18] [19]. NNs are trained to model complex relationships between certain inputs that produce certain outputs, determined by the weight connections of the neurons. In our problem, NNs should be trained to accept as input the measured/calculated power for each beam, and give as output the signals DoA.

For the NN to work, the number of the output nodes must be equal to the number of the angles of arrival to be estimated.

Therefore, generally, the network should know the total number of incoming signals in order to perform DoA estimation for all of them.

Let K be made up of a vector of N θ_k random, it is generated initially in a random way. The index k indicates the k^{th} vector. The elements of the vectors θ_k are les θ_{ki}, k,i are the integers. [18] [19]

For each θ_k cooresponding P_k^{out} which is calculatate from (28) and (29). Randomly, verses (P_k^{out}, θ_k) are generated, which is the training set of our neural network.

The activation function of the hidden layers is the hyperbolic tangent function, and that of the output layer is the linear function.

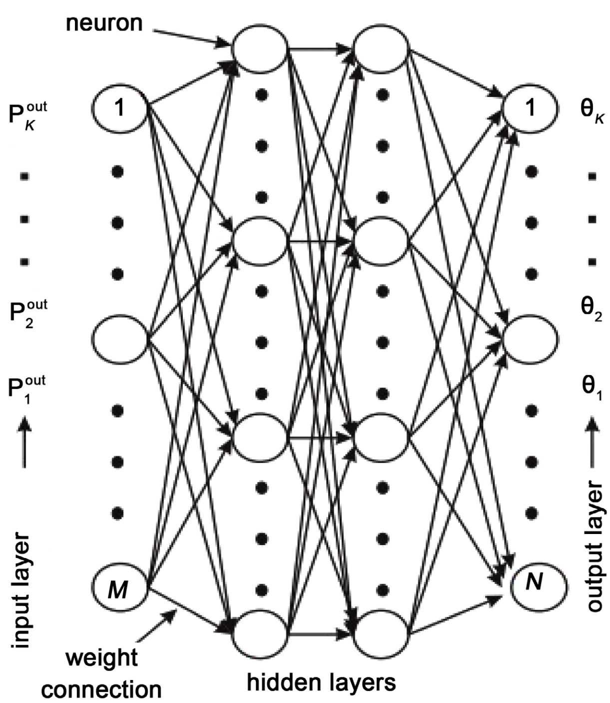

Figure 4. The MLP NN is used for the DoA estimation of N signals impinging [18] [19].

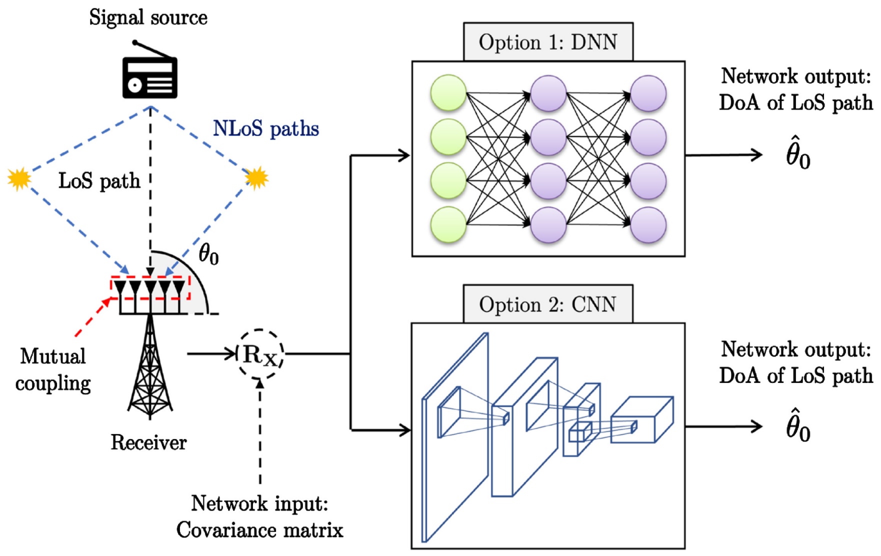

Figure 5. DoA process with NN architecture [18] [19].

$$AF(\vartheta) = \frac{\sin\left[\frac{K}{2}\left(2\pi\frac{d}{\lambda}\sin\vartheta + \varphi\right)\right]}{\frac{1}{2}\left(2\pi\frac{d}{\lambda}\sin\vartheta + \varphi\right)} \exp\left[j\frac{K-1}{2}\left(2\pi\frac{d}{\lambda}\sin\vartheta + \varphi\right)\right] \quad (14)$$

To obtain a maximum of radiation in a given direction, it is necessary to find the phase gradient that maximizes the modulus of the network factor in this direction, namely:

$$2\pi\frac{d}{\lambda}\sin\vartheta_0 + \varphi = 0 \quad (15)$$

In other words, the pointing direction of the network will be given by the relation:

$$\vartheta_0 = \sin^{-1}\left(\frac{\varphi}{2\pi}\frac{\lambda}{d}\right) = 0 \quad (16)$$

We can thus adjust the orientation of the radiation of an array antenna by playing on the phase gradient between its antenna elements: this is the principle of scanning antennas.

Another very important factor to consider when determining the direction of arrival is the availability of traffic cells or channels. The parameters that can influence the availability of cells are:

- A sudden loss of power to the site
- A crash or failure of the antenna processing unit

The above paragraph illustrates some blocked cells and the corresponding alarms. We can see in **Figure 6** and **Figure 7**. All blocked cells have zero user connections.

To model this situation, we will introduce the distribution of Paul Dirac.

It is not necessary to go over the details of this theory developed in mathematics

```
FlexiBSC  YABC01                     2021-05-12  17:50:18
RADIO NETWORK CONFIGURATION IN BSC:
                                                             E P  B
                                        F                    T R  C D-CHANNEL  BUSY
                        AD OP           R  ET- BCCH/CBCH/    R E  S O&M LINK   HR  FR
 LAC   CI          HOP  ST STATE   FREQ T  PCM ERACH         X F  U NAME  ST
                                                                                  /GP
==================== == ====== ==== == ==== =========== = = == ===== == === ===

BCF-0322  FLEXI MULTI  U WO                                      1  OM322 WO
 20501 13221 BTS-0964  U WO                                                  0   3
 CE03221         BB/-
                                                                                 3
             TRX-001   U WO       52  0    - MBCCH+CBCH     P  1
             TRX-002   U WO       67  0    -                   1
 20501 13222 BTS-0965  U WO                                                  1   4
 CE03222         BB/-
                                                                                 5
             TRX-005   U WO       49  0    - MBCCH+CBCH     P  1
             TRX-006   U WO       80  0    -                   1
 20501 13223 BTS-0966  U BL-BTS                                              0   0
 CE03223         BB/-
                                                                                 0
             TRX-009   U BL-BTS   46  0    - MBCCH+CBCH     P  1
             TRX-010   U BL-TRX   71  0    -                   1

COMMAND EXECUTED
```

Figure 6. Example of blocked cell.

```
EOL:322;
BTS ALARM LISTING
       YABC01       BCF-0322  BTS-0966   EQUIPM   2021-05-12  17:33:39.73
**  ALARM  TRX -010           CE03223
   <19340> 7606 TRX FAULTY
              RF Module has detected no TX power in internal filter block
              00 00 00 83 11 31

       YABC01       BCF-0322  BTS-0966   EQUIPM   2021-05-12  17:33:39.83
*** ALARM                     CE03223
   <19341> 7603 BTS FAULTY
              RF Module has detected no TX power in internal filter block
              00 00 00 83 11 31

       YABC01       BCF-0322  BTS-0966   COMM     2021-05-12  17:33:49.79
*   ALARM  TRX -009           CE03223
           LAPD-0991
   <19342> 7705 D-CHANNEL FAILURE

       YABC01       BCF-0322  BTS-0966   QUAL     2021-05-12  17:33:50.75
*** ALARM                     CE03223
   <19343> 7767 BCCH MISSING

       YABC01       BCF-0322  BTS-0966   COMM     2021-05-12  17:34:09.74
*   ALARM  TRX -010           CE03223
           LAPD-0992
   <19346> 7705 D-CHANNEL FAILURE

       YABC01       BCF-0322  BTS-0965   QUAL     2021-05-12  17:42:17.10
**  ALARM  TRX -005           CE03222
   <19423> 7745 CHANNEL FAILURE RATE ABOVE DEFINED THRESHOLD
              01 00 00 00 01 01 00 00 00 03 01 72d

       YABC01       BCF-0322  BTS-0965   QUAL     2021-05-12  17:42:17.10
**  ALARM  TRX -006           CE03222
   <19424> 7745 CHANNEL FAILURE RATE ABOVE DEFINED THRESHOLD
              01 00 01 01 01 01 01 01 01 04 01 87d

END OF BTS ALARM LISTING
COMMAND EXECUTED
```

Figure 7. The alarm indicates the unavailability of certain channels.

lessons but simply to remember the few elementary results that interest us in the case of the two fundamental signals that will be used:

- The distribution $\delta(t)$ or Dirac distribution.
- The Dirac comb.

The distribution of Dirac $\delta(t)$.

Product of a function, regular distribution, by the Dirac distribution on

$$P^{out}(\theta) = \left\{P_1^{out}(\theta), P_2^{out}(\theta), \cdots, P_M^{out}(\theta)\right\}$$

$$x(t)\delta(t-t_0) = x(t_0)\delta(t-t_0)$$

$$P^{out}(\theta)\delta(\theta-t_0) = P^{out}(t_0)\delta(t-t_0)$$

To introduce the blocked TX/RX of a BTS, we use the Dirac function:

$$\delta_x \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

The learning base becomes

$$\left(P_k^{out}\delta(\theta-t_0), \theta_k\right)$$

$\delta_x = 1$, if the TX/RX cell is functional.

$\delta_x = 0$, if the cell is blocked.

4. Results and Discussion

4.1. Procedure for Testing Results

Choose the configuration of the antenna network, which is either linear, planar, or circular. Enter the other parameters, such as:

The number of M elements:

However, the number of sources must be strictly less than the number of antenna elements ($L < M$ for linear and circular arrays or $L < (M \times M)$ for planar arrays). In other words, an array of K elements can only properly detect at most ($K - 1$) sources.

The inter-element distance in terms of lambda: d is set by default to 0.5, but the user can also modify it at will and observe the influence.

The number of samples N whose default maximum value has been set to 100.

The radius of the ring a (which is only taken into account for the circular network) is set by default to 0.25.

Enter the parameters of the sources to be detected, namely:

The frequency of use f0, the default value of which is set at 1.8 GHz, but the modification of which does not significantly affect the results. So you can try it at 2.4 GHz or 5 GHz.

The signal-to-noise ratio, the default value of which is fixed at 30 dB, is modifiable.

Directions of arrival ("DDA" in French and "DOA" in English) according to the number of lobes desired. We indicate where the source (s) we want to detect are located.

The analytical methods will serve as a reference. Synthesis using PMUC and RBFNN.

The synthesis is applied to each of the analytical methods developed previously:

MLP_sur_Barlett, MLP_ON_Prony, MLP_ON_Capon, MLP_ON_MEM, MLP_ON_MMSE, MLP_ON_MUSIC, MLP_ON_MinNorm. RBF_ON_Barlett, RBF_ON_Prony, RBF_ON_Capon, RBF_ON_MEM, RBF_ON_MinNorm,

RBF_ON_MMSE, RBF_ON_MUSIC.

For all these summaries, we must set:

The number of neurons in the input layer of the Artificial Neuron Network (ARN), ML for the case, by default set to 1;

The number of neurons in the output layer, which is automatically displayed equal to the number of rows of the vector/matrix P;

The learning rate, which determines how quickly the learning algorithm converges;

The learning algorithm, we have 11 choices possibles (traingdx, traingdm, traingd, trainlm, trainbfg, trainrp, trainbr, trainscg, traincgb, traincgf, traincgp). The value chosen by default is traingdx because of its acceptable results;

The momentum, or momentum constant, which is a value introduced to prevent the learning algorithm from getting stuck in a local minimum, also increases its speed of convergence;

MSE: Mean Square Error, or Mean Square Error (EQM), which is a tolerance threshold constituting one of the 2 criteria for stopping the learning phase;

Iter_max: the total number of samples in the learning base. Its value is generally set at 5000 but is modifiable to up to 10,000.

The transfer functions of the three layers of our ANN.

For each layer, we have the choice between 7 values: *purelin*, *tansig*, *logsig*, *hardlim*, *hardlim satlin* or *satlins*. A combination with purelin on all three coats gave us acceptable results. We have used it by default. However, the experimenter can modify them and observe the influence on the syntheses obtained. [20]-[23]

For the case of synthesis:

MATLAB automatically generates a small interface in the foreground that shows the evolution of the mean squared error as a function of the evolving number of examples already presented to the PMUC during the learning phase. The stop criterion can be either reaching the tolerance threshold (MSE) or reaching the maximum number of examples presented (iter_max).

4.2. Results (In Calculation Time) of Our Rbfnn Et Pmlnn Approach

To validate our approach, we simulated the classical approaches and the same methods coupled to NNs on the planar antenna under the following conditions 3 sources (50˚, 80˚, and 120˚).

- 10 elements with a distance factor of 0.5
- 100 samples
- Rapport Signal to noise ratio of 30 dB

The simulation gives us the following results (**Table 1**):

The results show a clear improvement for NNs with radial function in general. We can see it in **Figure 8**.

Table 2 shows directions of arrival from MUSIC and RBFNN, algorithm execution times, and errors.

Table 3 below shows the results obtained on 9 × 9 planar networks. The results are satisfactory. But the results are disappointing when it comes to a linear network.

Table 1. Simulation of the different algorithms on a planar antenna, 10 elements, 3 sources, and signal/noise ratio = 30 dB.

Analytics methods	Processing time	RN + Analytics methods	Processing time
BARLETT	0.17566	RBFNN-BARLETT	0.123
CAPON	0.178447	RBFNN-CAPON	0.132
PRONY	0.190271	RBFNN-PRONY	0.127
MEM	0.177403	RBFNN-MEM	0.12
PiSARENKO	0.173082	RBFNN-PiSARENKO	0.125
MUSIC	0.17947	RBFNN-MUSIC	0126
NORM-MIN	0.172794	RBFNN-NORM-MIN	0126

Table 2. Result of running the RBFNN algorithm compared to MUSIC.

DDA detected (˚)	50	80	120
DDA estimated (˚)	50	50	120
Error range (˚)	0	0	0

Table 3. Simulation of the different algorithms on a planar antenna, 10 elements, 3 sources, and S/N ratio = 30 Db on a planar antenna network.

Analytics methods	Processing time	RN + Analytics methods	Processing time
BARLETT	0.0716302	MLP-BARLETT	0.0573042
CAPON	1.23172	MLP-CAPON	0.0586535
PRONY	1.89522	MLP-PRONY	0.592257
MEM	0.111328	MLP-MEM	0.089063
PiSARENKO	0.086442	MLP-PiSARENKO	0.0691536
MUSIC	0.370532	MLP-MUSIC	0.0617553
NORM-MIN	0.101169	MLP-NORM-MIN	0.0578107

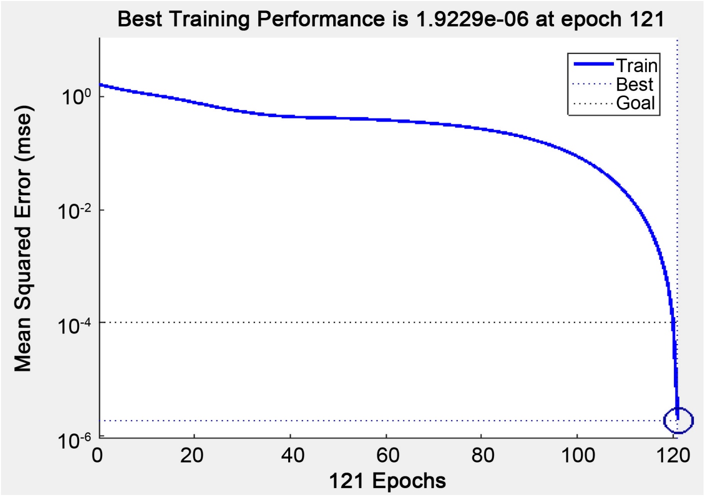

Figure 8. Training performance.

Table 4 shows directions of arrival from MUSIC and PMUC, algorithm execution times, and errors.

Table 4. Result of running the PMUC-NN algorithm compared to MUSIC.

DDA detected (˚)	50	80	120
DDA estimated (˚)	50	50	120
Error range (˚)	0	0	0

These results clearly show that the measures taken with the intention of reducing the computation time do have a significant positive effect on the computation time, since they allow it to be saved around 5%.

5. Conclusions

The implementation of the various algorithms allowed us to appreciate the effects of parameters on the precision of calculation of the angles of arrival and the conformation of associated beams. The tests carried out show that:

Despite the diversity of the quality of the results provided, the computation times remain comparable for the classical DoA estimation methods, the slowest being the PRONY approach (linear prediction).

The neural network approach has the advantage of being a global optimum search technique requiring a longer computational time, which is about 10 times the time required for a local optimum approach.

We also note that Neural Network and spectral methods reduce the influence of noise on communications to zero.

We have proposed a new approach based on mathematical modeling to exploit blocked TRXs to cancel the radiation from the concerned antenna element. This could lead to enormous energy savings and speed in antenna processing.

The advantages of antenna arrays and synthesis methods provide a fertile field for the exploitation and application of smart antenna. Their coupling to neural networks will make a bright future for the next generations of mobile communication.

Data Availability

The data used to support the findings of this study are included in the article. The code used to plot and process data can be provided on request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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