SIGNAL
&
IMAGE PROCESSING
An International Journal

Full Paper

SIPAIJ, 1(1), 2016 [001-006]

Controlling the element excitations of the smart antenna arrays using genetic algorithms

J.R.Mohammed
Department of Communication and Computer Engineering, Cihan University, Erbil, Kurdistan region, (IRAQ)
E-mail: jafarram@yahoo.com

ABSTRACT

Traditionally, the excitation coefficients of elements in smart antenna has been determined and controlled by using least mean square (LMS) algorithm. It is well-known that the LMS performs poorly in very noisy environment such as in a mobile communication systems. In this paper, a Genetic Algorithm (GA) is utilized for optimizing the excitation coefficients of smart antenna. The performance of the smart antenna based on GA has been evaluated and has been compared with its LMS based counter part. Simulation results showed that the GA has nearly optimal interference cancellation. Other advantages of the GA is its simplicity and fast convergence provided that the parameters are appropriately chosen, which makes it a practical algorithm for determining the excitation coefficients of smart antenna.

KEYWORDS

Excitation cofficients;
*Smart A*ntennas;
Genetic algorithm optimization.

INTRODUCTION

Mobile and wireless communication systems are becoming increasingly more complex in an effort to cope with the growing demand for more supporting peak data rates, coverage requirements, and capacity objectives, as well as exciting new applications such as wireless multimedia and anywhere-anytime mobile Internet access. Although new access technologies such as code division multiple access (CDMA) are promise to meet these requirements, this is often achievable only under ideal channel conditions[1]. Smart antennas have great potential in overcoming the impairments caused by the channel in real systems. Its radiation pattern is controlled via adaptive algorithms based upon certain criteria. These criteria could be maximizing the signal-to-interference ratio (SIR), or minimizing the total output power. Since the output power consists of both the desired signal and interferences, some constraints are needed to insure that the output contains minimal contributions due to noise and interference signals arriving from directions other than the desired signal direction[2]. However, adaptive algorithms such as least mean square (LMS), which is widely used in practical due to its simplicity, depends on steepest descent (gradient) and other known signal properties in order to provide feedback to control the excitation coefficients (weights) of antenna elements. These algorithms are quite sensitive to the starting values of the amplitude weights and may quickly fall into a local minimum because their theoretical development is based on finding the minimum of a bowl-shaped objective function[3]. Moreover, the convergence of these algorithms is depended upon the eignvalue spread such that larger spreads require longer convergence rates. In addition, the performance of the conventional smart antenna based LMS algorithm is known to degrade substantially under high noise condition[4]. This undesired behavior results in a reduction of the array output signal-to-interference-plus-noise ratio (SINR). Furthermore, the radiation pattern of the smart antenna based LMS algorithm can present irregular and unacceptable high sidelobes, which further reduce its performance in the presence of unexpected interferences.

In this paper, a GA is used for updating the excitation coefficients of an array. The advantageous of the GA such as fast convergence provided that the GA parameters are appropriately chosen[5,6], global optimization, and independently on the eignvalue spread makes it a practical algorithm for determining the excitation coefficients of smart antenna.

Controlling the excitation cofficients by LMS

Figure 1 shows a block diagram of an array antenna controlled by LMS algorithm. The output of such array which consists of N antennas at a time sample k is given by

$$y(k) = \mathbf{w^H x}(k) \tag{1}$$

where k is the time

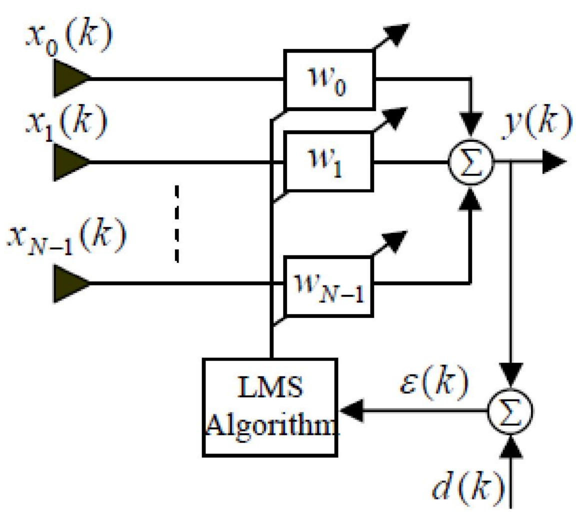

Figure 1 : Smart antenna using LMS

index, $\mathbf{x}(k) = [x_0(k) \quad x_1(k) \ldots x_{N-1}(k)]^T$ is the complex vector of received signal, $\mathbf{w} = [w_0 \quad w_1 \ldots w_{N-1}]^T$ is the excitation coefficients vector, T and H denote transpose and conjugate transpose, respectively.

The received signal at time instantis given by

$$\mathbf{x}(k) = \mathbf{s}(\mathrm{k}) + \mathbf{i}(\mathrm{k}) + \mathbf{n}(\mathrm{k})$$
$$= s(k)\mathbf{a}(\theta_s) + \sum_{j=1}^{I} i_j(k)\mathbf{a}(\theta_j) + n(k) \tag{2}$$

where I is the number of interference signals. Here, $s(k)$ and $i_j(k)$ are the signal and interference symbol samples. The signal and interference directions of arrival are θ_s and θ_j, $j = 1,\ldots,I$, respectively, with corresponding steering vectors $\mathbf{a}(\theta_s)$ and $\mathbf{a}(\theta_j)$.

The error signal $\varepsilon(k)$, as indicated in Figure 1, is

$$\varepsilon(k) = d(k) - \mathbf{w^H}(k)\mathbf{x}(k) \tag{3}$$

where $d(k)$ is the desired output at sample. Minimizing the mean square error of (3) and by taking the instantaneous estimates of correlation matrix of the received signal, the LMS solution for excitation coefficients is given by[3]

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu\varepsilon^H(k)\mathbf{x}(k) \tag{4}$$

where μ is the step size parameter. Choosing the excitation coefficients to minimize output power can cause cancellation of the desired signal, since it also contributes to total output power. The desired signal cancellation can be overcome through the application of linear constraints to the excitation coefficient vector. A linearly constrained minimum variance based LMS algorithm performs the minimization of the output signal's variance with respect to unit gain constraint. The cost function of the linearly constrained minimum variance can be formulated as

$$\min_{\mathbf{w}} \ \mathbf{w^H \hat{R}_{xx}^{-1} w} \quad \text{subject to} \quad \mathbf{w^H a(\theta_s)} = 1 \tag{5}$$

where $\hat{\mathbf{R}}_{xx}$ represents the covariance matrix of the received signal. The LMS algorithm is canonical adaptive signal processing algorithm. It is based on the steepest descent algorithm, which is easy to implement but can get stuck in a local minimum. In other words it can not find the optimal values for excitation coefficients. In the following section, a GA-based smart antenna is developed to overcome these

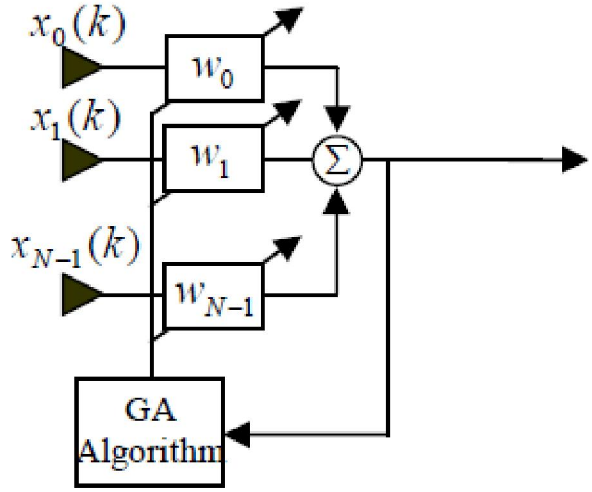

Figure 2 : Smart antenna using GA

limitations (stuck in a local minimum, not optimality of the excitation coefficients, and desired signal attenuation).

CONTROLLING THE EXCITATION COFFICIENTS BY GA

The excitation coefficients of the smart antenna controlled by a GA are shown in Figure 2.

The GA performs the adaptation by manipulating the excitation coefficients vector of the cost function until the total output power is minimized. In this case, the cost function is a linear array with variable amplitude weights. Controlling the weights modifies the main beam peak and nulls. Since the GA reduces the total output power of the smart antenna, constraints are used to prevent desired signal attenuation in the main beam. In this paper, the constraints take the form of using only a few of the edge elements of the array. Because only few of the edge elements are adaptive, the main beam receives limited perturbation. This idea was first used in[7]. As an example, consider an array of 20 elements that are spaced 0.5λ apart. Three edge elements on both ends of the array have continues variable amplitude settings. A continues variable GA is used to perform the adaptation. The array is assumed to start with a uniform amplitude distribution.

The GA uses the following steps for determining the excitation coefficients of smart antenna elements:

An initial population of chromosomes is randomly generated. By this way, the first generation of chromosome is created. The weights of those three edge elements is described by a chromosome, i.e. each chromosome contains three variables (the amplitude weights of the array are assumed symmetric).

The weights of those edge elements are examined and the output power is measured. In this way, a fitness (cost) value is assigned to each chromosome in the population in order to expressing how well the chromosome meets requirements to the optimized system.

Members of the population with high costs are discarded and a new population of chromosome (offspring) is generated by selecting the best existing chromosomes (parents). The parents are combined by crossover and mutation to produce offspring. The offspring replace the discarded chromosomes. This step is iterated *K* times. This means thatgenerations of chromosome are created in order to find as good chromosome as possible.

The result of the genetic optimization is obtained as the best chromosome at the *K* iteration. The resulting adapted amplitude weights are given by

$$\mathbf{w} = [0.1685 \;\; 0.8188 \;\; 0.0949 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1$$

$$1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 1 \;\; 0.0949 \;\; 0.8188 \;\; 0.1685].$$

GA is described by the size of population, by number of generation and by mutation probability. With regard to convergence rate, it is worth to mention that the GA with small population size and high mutation rates can find a good solutions fast[8,9].

SIMULATION RESULTS

To evaluate the performance of the GA-based smart antenna, some computer simulations have been carried out in various scenarios. In the following, we assume a uniform linear array with 20 elements and half-wavelength element spacing. The desired signal with SNR=10dB is assumed to impinge on the array from the direction $\theta_s = 0^o$. Two interferers are assumed to impinge on the array from the directions $\theta_1 = -20^o$ and $\theta_2 = 20^o$, both with interference-to-noise ratio (INR) equal to 30dB. The noise, $n(k)$, is spatially and temporally white and it has a complex Gaussian zero mean distribution with variance $\sigma_n^2 = 1$. In our first example, we study the convergence rate of the smart antenna based on GA compared to smart antenna based on LMS for interference cancellation. In this case, each run of Monte Carlo simulation consisting of $K = 500$ samples of $\mathbf{x}(k)$, i.e. 500 iterations or generations are used. The step size parameter of the LMS algorithm is chosen as $\mu = 1/4trace[\hat{\mathbf{R}}_{\mathbf{xx}}]$. Under this condition, the convergence of the weight vector in (6) to the optimum values in the mean-square sense is guaranteed. The convergence rate of the LMS for interference cancellation is governed by the eignvalue spread of $\hat{\mathbf{R}}_{\mathbf{xx}}$. While GA parameters include a population size of 8, a 50% selection rate, roulette wheel selection, uniform crossover, and a 10% mutation rate. The quiescent and resulting adapted patterns for both LMS and GA techniques appears in Figure 3(a). From Figure 3(a), we observe that both patterns have nulls at the DOAs of the interferences. However, the deep nulls in the GA pattern come at a cost of increased average sidelobe levels. When we does not apply the constraints observe the reduction in the main beam peaks of both GA and LMS patterns. The sum of both interference powers as a function of iteration/generation (K) is shown in Figure 3(b). It is quite clear from Figure 3(b) that the GA quickly converge to optimal interference cancellation. In the

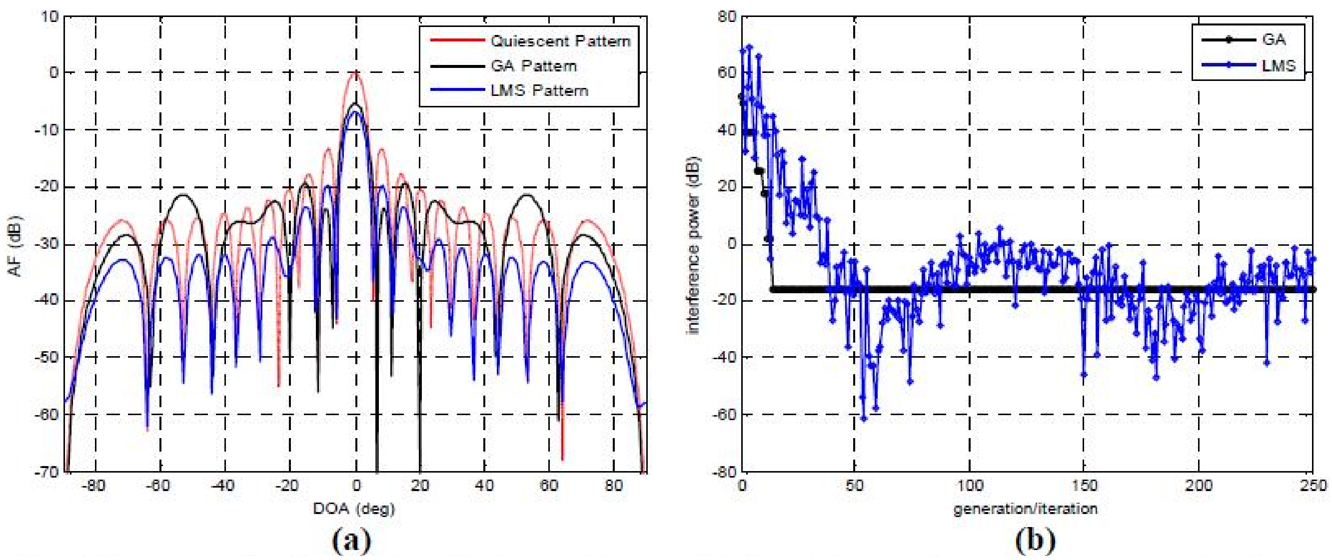

Figure 3 : Unconstraint scenario: (a) Comparison of patterns, (b) Interference cancellation versus number of iteration/ or generation.

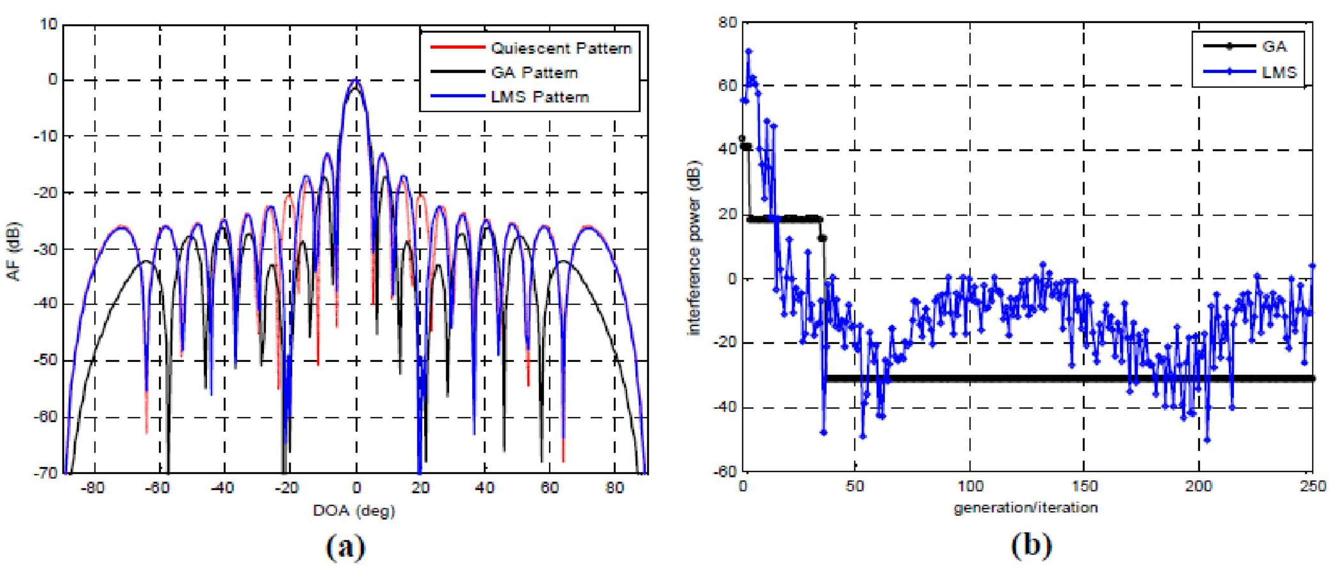

Figure 4 : Constraint scenario: (a) Comparison of patterns, (b) Interference cancellation versus number of iteration/ or generation

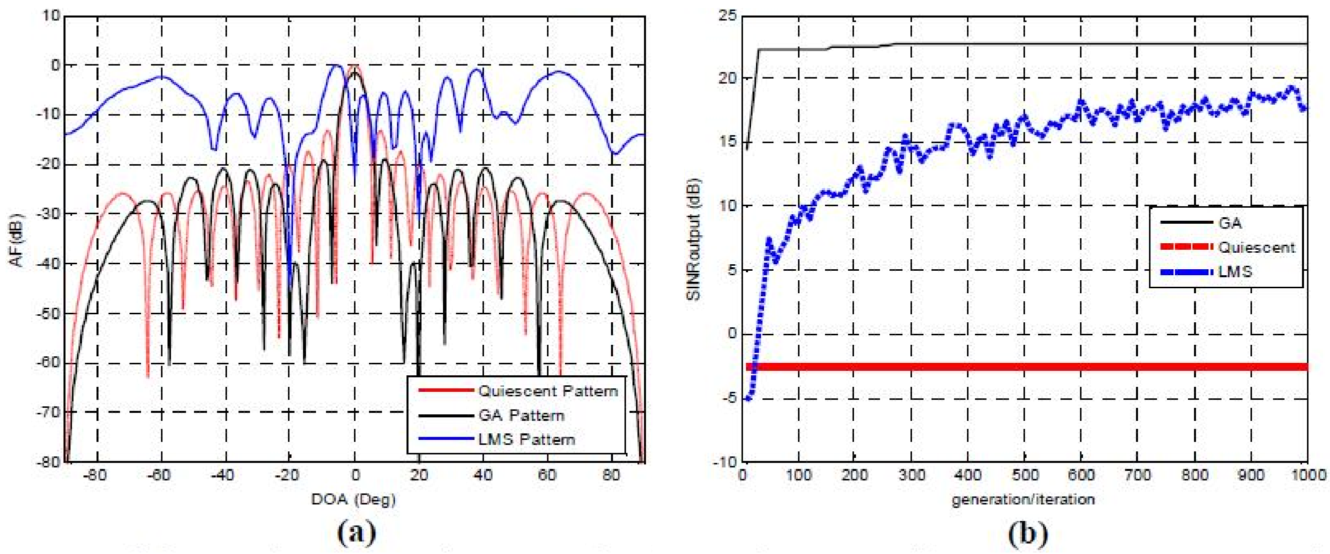

Figure 5 : Finite number of iteration scenario: (a) Comparison of patterns, (b) Output SINR versus number of iteration/ or generation

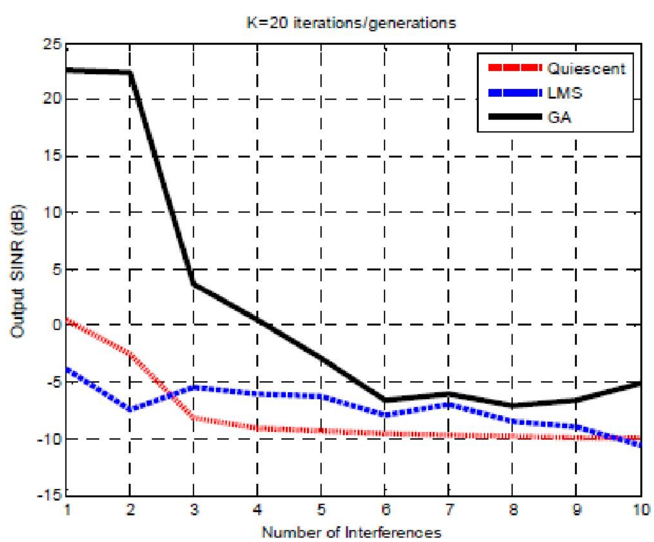

Figure 6 : Output SINR versus number of interferences

second simulation example, we study the impact of constraints, using (5) with LMS and subset of only 3 edge elements with GA, on the mainbeam reduction and sidelobe level. Figure 4(a) shows the patterns of the tested antennas. Convergences of the LMS and GA algorithms for interference cancellation is shown in Figure 4(b). Deep nulls are created in the tested patterns with little perturbation to the mainbeam of GA pattern. This perturbation depends on the number of edge elements that used for constraint. In our simulation we find out that the best result is obtained when 3 elements on each end of the array are used. In the next example, we investigate the effect of the small number of iteration/generation. In this scenario, the smart antenna based on GA demonstrates an appropriate operation under this situation. On the other hand, as illustrated in Figure 5(a), the pattern of the smart antenna based on LMS allocates a deep null for the desired signal since it is interpreted as an interference signal. This inadequate operation of the smart antenna based on LMS is highly depends on the iteration number (). In Figure 5(b) we show the output SINR of the antennas tested versus the iteration number . It is clearly demonstrate that the smart antenna based on GA shows better capabilities against the effect of low number of iteration. The smart antenna based on LMS requires a large number of. However, the smart antenna based on GA works well even whenis as small asgenerations. It is worth mentioning that in all previous examples only two interferences were considered. In our last example, we simulate multiple interference signals impinging into the array from DOAs

$\theta_j = [-20^o, 20^o, -8^o, 14^o, -40^o, 33^o, -48^o, 60^o, -70^o, 80^o]$. According to our simulation result, the operation of the smart antenna based on GA depends on the number of subset elements that used for constraints, and on the number of available degrees of freedom to perform the nulling. For instance, Figure 6 shows that the smart antenna based on GA breaks down when more than three interference signals impinges into the array. With three subset elements and for less than three strong interferences, we have enough adaptive nulling to reject the interferences. When more interferences are included $(I > 3)$, the number of subset elements must be increased. In this case, a trade-off between the mainbeam perturbation and the number of subset elements should be carefully taken into consideration. Finally, it can be seen from Figure 6 that the operation of the smart antenna based on LMS is unsatisfactory even at small number of interference signals.

CONCLUSION

For the conventional smart antenna based on LMS, a low number of iteration results in adapted antenna patterns with high sidelobes and distorted mainbeams. The smart antenna based on GA have been proposed as an alternative to the smart antenna based on LMS. The design of the corresponding GA was highlighted and its achievable performance was characterized in terms of both the optimal interferences cancellation and the SINR. It was demonstrated that a potentially more attractive SINR is achievable by the proposed smart antenna based on GA. Moreover, fast convergence to optimal solution is achieved by using a small population size and high mutation rate.

REFERENCES

[1] A.El Zooghby; Smart antenna engineering, Artech House, INC, Norwood, MA, **(2005)**.

[2] 0.L.Frostl “An algorithm for linearly constrained adaptive array processing”, Proc. IEEE, 926-935, Aug **60**, **(1972).**

[3] S.Haykin, T.Kailath; “Adaptive filter theory”, 4^{th} Edition, Person education (singapore), Indian Branch, India, **(2002)**.

[4] M.Wax,Y.Anu, “Performance Analysis of the Minimum Variance Beamformer in the Presence of Steering Vector Errors,” IEEE Trans. Signal Process., 938–947, Apr. 1996.

[5] R.L.Haupt; “Phase-only adaptive nulling with genetic algorithm,” IEEE Trans, On antennas and propagation, **45 (5)**, 1009-1015, June, **(1997)**.

[6] C.Florens, Z.Raida; “Adaptive beamforming using genetic algorithm”, Radio Engineering, **7(3)**, 1-6, September, **(1998)**.

[7] R.L. Haupt and H.L. Southall, “Experimental adaptive nulling with a genetic algorithm,” Microwave Journal, Vol. **42(1)**, 78-89, Jan., **(1999)**.

[8] R.L. Haupt and S.E. Haupt, “Optimum population size and mutation rate for a simple real genetic algorithm that optimizes array factors,” Applied Computational Electromagnetic Society Journal, **15(2)**, 94-102, July, **(2000)**.

[9] R.L. Haupt, S.E.Haupt, Practical genetic algorithms, 2^{nd} Edition, New York: Wiley, (**2004)**.