Research Article
Joint Estimation of Amplitude and Direction of Arrival for Far Field Sources using Intelligent Hybrid Computing

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Abstract: In this study, an intelligent hybrid computing technique is presented to estimate jointly the amplitude and Direction of Arrival (Elevation angle) of far field sources. In this intelligent hybrid scheme, Genetic Algorithm (GA) is hybridized with Pattern Search (PS), in which GA is working as a global optimizer while PS is used as local optimizer for further improvement of the results. GA and PS techniques are also applied independently to compare with GA hybridized with pattern search. The fitness evaluation function is formed by the Mean Square Error (MSE) of the desired response with the estimated one. This function is simple and requires a single snapshot to reach the optimum solution. A sufficient number of Monte-Carlo Simulations is used to evaluate the convergence rate, MSE and estimation accuracy of each scheme.

Keywords: Direction of arrival, genetic algorithm, intelligent hybrid computing, pattern search

INTRODUCTION

Efficient estimation of DOA is one of the most challenging and important concern in the field of array signal processing and wireless communication. It has applications in sonar, radar, seismic exploration and biomedical engineering, etc., Gavan and Ishay (2001) and Khan et al. (2012). Heaps of work has been done in this area by using classical methods as well as heuristic computational approaches (Krim and Viberg, 1996).

The importance and applicability of meta-heuristic techniques is growing rapidly with the passage of time among the researchers because these techniques can be coped easily and performs well even in the presence of local minima and low Signal to Noise Ration (SNR). These techniques include Genetic Algorithm (GA), Differential Evolution (DE), Ant Colony Optimization (ACO), Bee Colony Optimization (BCO) and Particle Swarm Optimization (PSO), etc. It has been observed that the reliability and applicability of meta-heuristic techniques increases drastically if these are combined with any other capable approaches such as Interior Point Algorithm (IPA), Active Set (AS), Pattern Search (PS), etc., Junaid et al. (2011a, b), Fawad et al. (2012a, b, c and d). In Fawad et al. (2012a), PSO is combined with PS while in Fawad et al. (2012b), DE and PSO are hybridized with PS to jointly estimate the parameters (DOA, range, amplitude) of far field sources and near field sources respectively which are impinging on

Uniform Linear Array (ULA). In Fawad et al. (2012c); GA and Simulated Annealing (SA) techniques have been used in combination with PS to estimate the 3-D parameter (DOA, elevation angle and Azimuth angle) of far field sources using L shape array. Similarly GA and SA are hybridized with IPA in Fawad et al. (2012d) to estimate the 3-D parameters (range, amplitude and elevation angle) of near field sources. In Fawad et al. (2012a, b, c and d), MSE is used as an objective function and it has been proved that whenever the hybrid approach is used it performed well as compared to GA, PS, DE, PSO, IPA and SA alone. The same fitness function has been used in Fawad et al. (2012e).

In this study, Intelligent Hybrid Computational (IHC) approach based on (GA-PS) is presented for joint estimation of amplitude and DOA for far field sources. The results of hybrid GA-PS technique are compared with GA and PS alone. Different cases are discussed on the basis of various numbers of sources, different values of SNR and MSE. The objective evaluation function is formed by the Mean Square Error (MSE) of the desired response with the estimated one. This function is simple and requires a single snapshot to reach the optimum solution. The applicability as well as the reliability of the given scheme is tested on the basis of large number of Monte-Carlo simulations. Moreover, the robustness of given schemes are examined in the presence of Low Signal to Noise Ratio (SNR) methodology.

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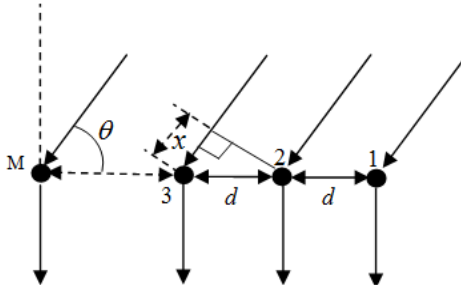
Fig. 1: ULA having M elements

Problem formulation for far field sources: In this section, a data model is developed for L sources lying in the far field and impinging on ULA from different directions. The ULA is composed of M elements having same spacing ″d″ between two consecutive elements as shown in Fig. 1 (Khan *et al.*, 2011). All sources are considered to be narrow band and having known frequency ω_o where each source has different elevation angle (α) and amplitude (s). For L≤M, the output at m-th element for l-th source can be written as:

$$y_m = \sum_{l=1}^{L} s_l (\exp(-jkd(m-1)\cos(\theta_l) + n_m) \tag{1}$$

where,
m = 1, 2,… M
n_m = The additive white Gaussian noise added at the output of m-th element in the ULA

The output of complete array in matrix-vector form can be written as:

$$\mathbf{y} = \mathbf{C}(\alpha)\mathbf{s} + \mathbf{n} \tag{2}$$

where in Eq. (2):

$$\mathbf{y} = [y_1, y_2, y_3 ..., y_M]^T \tag{3}$$

$$\mathbf{s} = [s_1, s_2, s_3 ..., s_L]^T \tag{4}$$

$$\mathbf{n} = [n_1, n_2, n_3, ..., n_M]^T \tag{5}$$

$$\mathbf{C}(\alpha) = [\mathbf{c}(\alpha_1)\mathbf{c}(\alpha_2)...\mathbf{c}(\alpha_L)]^T \tag{6}$$

$$\mathbf{c}(\alpha_l) = [\exp(-j\psi_l)]^T \tag{7}$$

where, $\Psi_l = kd (m-1) \cos\alpha_l$ for l = 1, 2, …, L. In Eq. (2), C (α) is called steering matrix composed of steering vectors for sources as defined in Eq. (6). It is obvious from Eq. (1), the unknown parameters are the amplitudes S_l and the angle of Arrival α_l Hence, the problem which has to be solved is they jointly estimation of amplitudes i.e., $S_1, S_2, …, S_L$ and DOA of sources i.e., $\alpha_1, \alpha_2, …, \alpha_L$ at the output of ULA.

PROPOSED METHODOLOGY

In this section, we discussed the proposed methodology structure for the estimation of amplitude and DOA of far field sources. The flow diagram of proposed structure is shown in Fig. 2, in which the solution is initiated with GA and ended up with PS. A MATLAB built-in optimization tool box is used for GA and PS for which the parameters settings are shown in Table 1. PS method is gradient free technique and can be used as global and local optimizers. It plays very important rule for optimization problems like "Bound constrained minimization" and "Globaly Convergent Augmented Lagrangian algorithm" Torczon (1997). PS method is more effective especially in the presence of fewer minima and become more effective when it is hybridized with DE, GA and PSO (Fawad *et al.*, 2012a, b and c). Hence to take advantage of PS, in present study it is not only applied independently but also used as a local search optimizer with GA i.e., the best individual results got through GA is given as an input to PS for further improvement.

Genetic algorithm was first introduced by Holland (1975) and is one of the famous and powerful tools for optimization. GA has already shown its brilliance not only in the presence of local minima but also in the presence of Low Signal to Noise Ratio (SNR). GA has got application almost in every field which includes commerce, engineering etc., (Addad *et al.*, 2011). The Steps of GA in the form of pseudo-code is given as:

Table 1: Parameter settings for GA and PS

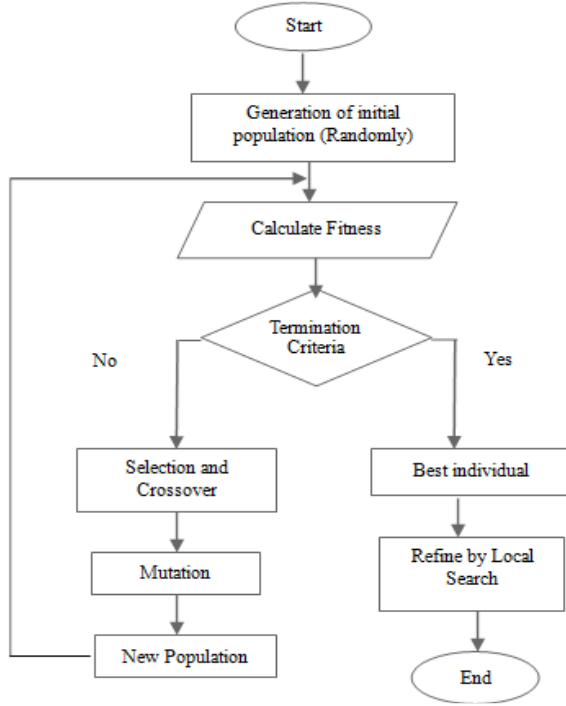| GA		PS	
Parameters	Settings	Parameters	Setting
Population size	240	Maximum iteration	1500
No of generation	1000	Polling order	Consecutive
Crossover fraction	0.3	Poll method	GPS positive basis 2 N
Migration direction	Both way	Function evaluation	16000
Crossover	Heuristic	Mesh size	01
Mutation function	Adaptive feasible	Expansion factor	2.0
Initial range	[0-1]	Contraction factor	0.6
Scaling function	Rank	Penalty factor	100
Selection	Stochastic uniform	Bind tolerance	10^{-04}
Elite count	2	Mesh tolerance	10^{-07}
Function tolerance	10^{-15}	X tolerance	10^{-07}

Fig. 2: Flow diagram for hybrid GA-PS

Table 2: Estimation accuracy of two sources

Scheme	S_1	S_2	α_1	α_2
Desired values	7.0000	9.0000	0.5236	1.9199
GA	7.0006	9.0006	0.5242	1.9205
PS	7.0022	9.0021	0.5256	1.9221
GA-PS	7.0000	9.0000	0.5235	1.9198

Table 3: Estimation accuracy for three sources

Scheme	S_1	S_2	S_3	α_1	α_2	α_3
Desired values	3.0000	8.0000	4.0000	0.6109	1.1345	1.6581
GA	3.0024	8.0024	4.0023	0.6133	1.1368	1.6605
PS	3.0092	8.0091	4.0092	0.6201	1.1437	1.6673
GS-PS	3.0009	8.0009	4.0009	0.6118	1.1354	1.6590

Step 3: Terminate, if any of the following condition is satisfied and go to step 5 else go to step 4:

- The fitness value has been achieved i.e., $\xi_j \leq 10^{-15}$
- The total number of iteration has been completed
- Predefined value of the TolFun has been achieved

Step 4: By using the parameters of elitism, mutation and crossover as shown in Table 1, reproduces the new population and go to step 2.

Step 5: Give the best individual results of GA as an input to PS for further improvement.

Step 6: Store all the values for later discussion and comparison.

RESULTS AND DISCUSSION

In this section, comparison between GA, PS and GA-IPA is made on the basis of convergence rate, MSE and estimation accuracy and proximity effect. All the values of DOA are taken in radians while the enter element spacing between two consecutive elements in the array is same i.e., $\lambda/2$. Initially no noise is added from case 1 to case 3. All the results are carried out for 100 independent runs and for a threshold value of MSE is 10^{-2}.

Case 1: In this case, the convergence rate, MSE and estimation accuracy are evaluated for two far field sources. The ULA is composed of five elements and the desired values of amplitudes and DOA are $\{(s_1 = 7, \alpha_1 = 0.5236$ rad), $(s_2 = 5, \alpha_2 = 1.9199)\}$. As shown in Table 2, all the three techniques produced fairly good results. However, it is quite obvious that GA becomes more accurate when it is combined with PS and hence, it produces better results as compared to GA and PS alone. The second best scheme in this archive is GA alone.

In Fig. 3 and 4, the percentage convergence and MSE of each scheme is shown respectively. One can see that the convergence arte and MSE of each scheme improves with the increase of elements in the array. In this case also, the hybrid GA-PS approach converges more times and maintains a minimum MSE as compared to PS and GA alone for each number of elements in the ULA.

Step 1: Like other meta-heuristic technique, the first step is to initialize GA i.e., produced randomly Q number of chromosomes. The length of each chromosome differs from problem to problem. In the current problem the length of each chromosome is 2*L where L is the total number of sources. The first L genes in each chromosome represent the elevation angles while the next L genes show amplitudes of sources. The i-th chromosome can be written as:

$$\mathbf{d}_i = [\alpha_{i1}, \alpha_{i2}, \ldots \alpha_{iL}, s_{iL+1}, s_{i,L+2}, \ldots s_{i,2L}] \quad (8)$$

$\alpha_{ij} \in$ R: $0 \leq \alpha_{ij} \leq \pi \forall i = 1, 2, \ldots, k, j = L + 1, L + 2, \ldots, 2L$ and $s_{ij} \in$ R: $L_s \leq s_{ij} \leq U_s$ where L_s and U_s are the lower and upper bound of signals amplitude for i = 1, 2, …, k, j = 1, 2, …, L.

Step 2: In step 2, the error is minimized between desired response and estimated response using the following relation:

$$D(i) = 1/M \sum_{m=1}^{M} \left| y_m - \hat{y}_m^i \right|^2 \quad (9)$$

where, i represents i-th chromosome. In Eq. (9), y_m is defined in Eq. (1) while:

$$\hat{y}_m^i = \sum_{l=1}^{L} \hat{d}_l \exp(-j(m-1)\pi \cos(\hat{d}_{L+l})) \quad (10)$$
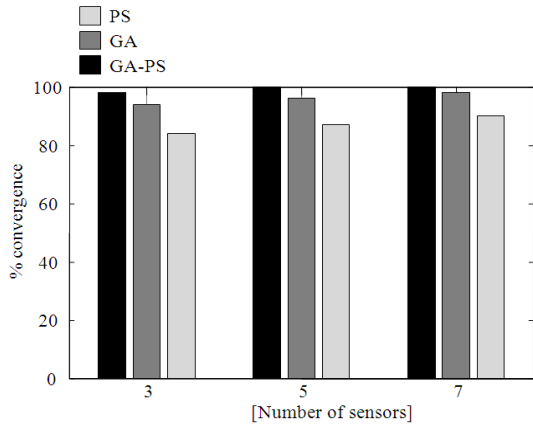
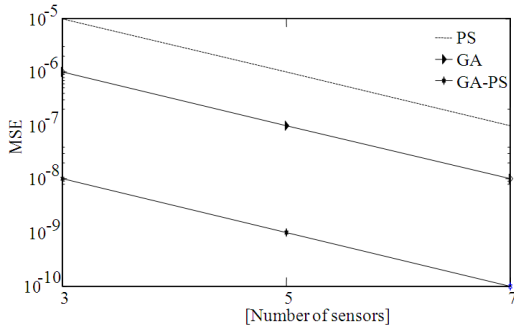Fig. 3: % Convergence vs number of elements

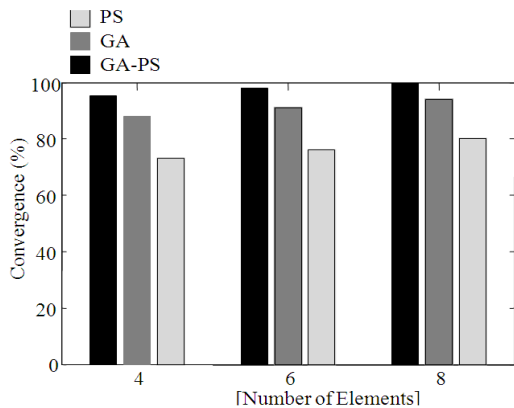
Fig. 4: MSE vs number of sensors

Fig. 5: Convergence rate vs number of elements

Case 2: In this case, the estimation accuracy, convergence rate and MSE are discussed for 3 sources. For estimation accuracy, we used 6 elements in the ULA and the desired values of amplitudes and DOA are $\{(s_1 = 3, \alpha_1 = 0.6109), (s_2 = 8, \alpha_2 = 1.1345), (s_3 = 4, \alpha_3 = 0.6109)\}$. As shown in Table 3, the performance of all three schemes despoiled a bit due to increase of sources. However, once again the hybrid GA-PS technique proves to be the finest technique as compared to PS and GA alone. The second best is once again GA alone.
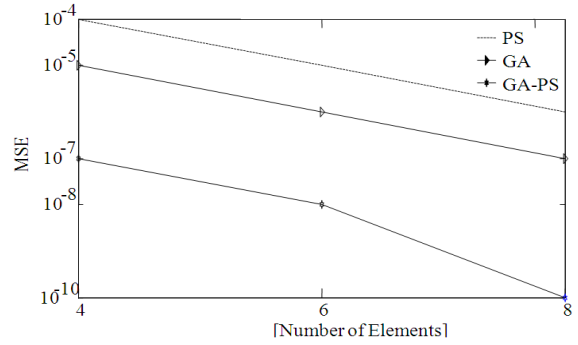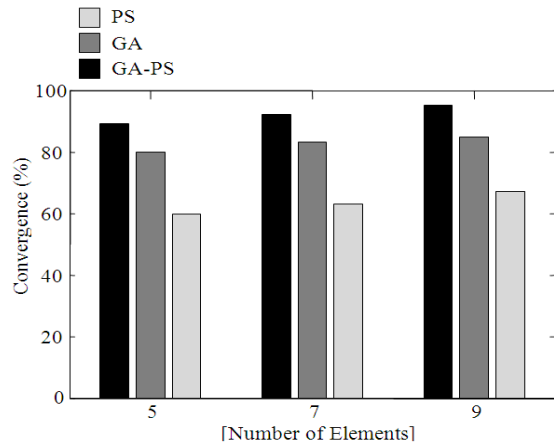

Fig. 6: MSE vs number of elements

Fig. 7: Convergence rate vs number of elements

In Fig. 5 and 6, the convergence rate and MSE are shown respectively for each scheme. Both the convergence and MSE of each scheme improves with the increase of elements in the ULA. One can clearly deduce that among all three techniques, the GA-PS technique has better convergence rate and MSE. GA alone is the second best in this scenario.

Case 3: This case explains the estimation accuracy, convergence rate and MSE for 4 sources. For estimation accuracy, the ULA consist of 8 elements. The desired values of amplitudes and DOA are $\{(s_1 = 2, \alpha_1 = 0.6981), (s_2 = 6, \alpha_2 = 1.3963), (s_3 = 3, \alpha_3 = 2.2689), (s_4 = 1, \alpha_4 = 2.7925)\}$. In this case, due to more sources we faced more local minima which have affected the PS a lot. The second effected technique due to more local minima is GA while the hybrid GA-PS technique performed well and stuck very few times in local minima. So, once again GA-PS made a good estimate of the desired response as shown in Table 4.

In Fig. 7 and 8, the convergence rate and MSE are evaluated for four sources respectively. Once again, it is quite evident that GA-PS not only converges more times but also maintained minimum MSE as compared to PS and GA alone. The Second best is again GA.

Table 4: Estimation accuracy for four sources

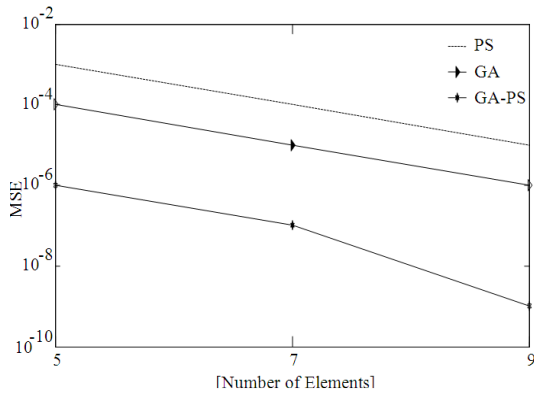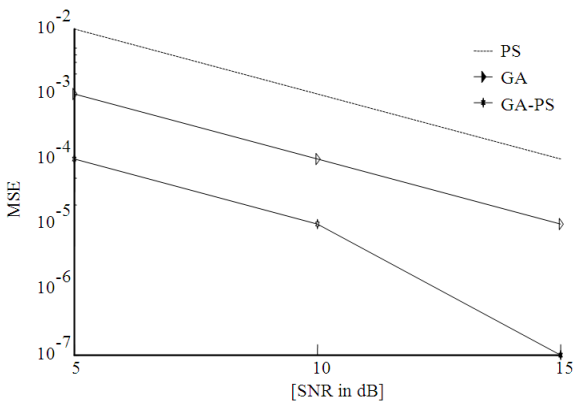| Scheme	S_1	S_2	S_3	S_4	α_1	α_2	α_3	α_4
Assumed	2.0000	6.0000	3.0000	1.0000	0.6891	1.3963	2.2689	2.7925
GA	2.0052	6.0052	3.0053	1.0052	0.6943	1.4016	2.2741	2.7977
PS	2.0160	6.0161	3.0162	1.0161	0.7051	1.4123	2.2849	2.8085
GS-PS	2.0019	6.0019	3.0018	1.0019	0.6910	1.3982	2.2708	2.7943

Fig. 8: MSE vs number of elements

Fig. 9: MSE vs SNR

Case 4: In this case, the MSE of all mentioned three schemes is evaluated against noise values. All values of SNR are taken in dB. For this we took two sources and 6 elements. As shown in Fig. 9, even in the presence of low SNR, the GA-PS technique performs well as compared to PS and GA alone. The GA-PS is fairly robust against all the values of SNR.

CONCLUSION AND RECOMMENDATIONS

In this study, intelligent hybrid approach is used for joint estimation of amplitudes and DOA of far field sources. The proposed hybrid scheme produced better results as compare to GA and PS alone. MSE has been used as fitness function which is optimal in nature and only single snapshot is required to attain the optimum solution. A major advantage of the given scheme is its simplicity in concept, ease in implementation and a fewer budgets is required for hardware implementation. All the three schemes fail when the number of sensors in the array is kept less than the number of sources. In future, we will use the same intelligent hybrid approach for null steering and side lobes in the field of adaptive beam forming.

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