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Research Article

3-D Near Field Source Localization by using Hybrid Genetic Algorithm

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Abstract: In this study, a method based on hybrid Genetic Algorithm is used to jointly estimate 3-D (range, amplitude, elevation angle) parameters of near field sources arriving on uniform linear array. In this approach, Genetic Algorithm is hybridized with pattern Search. In this hybridization, Genetic Algorithm acts as a global search optimizer while Pattern Search is used as a rapid local search optimizer. The performance of Genetic algorithm and pattern search alone is also evaluated. The fitness function used in this study is based on Mean Square Error. This fitness function acted well even in the presence of low signal to noise ratio and requires only single snap-shot to achieve the goal. The validity and efficiency of the proposed approach is checked through a large number of Monte Carlo Simulations.

Keywords: Direction of arrival, genetic algorithm, near field sources, pattern search, uniform linear array

INTRODUCTION

Direction of Arrival (DOA) estimation of sources is one of the hot areas of research since last few decades. It has wide range of application in radar, sonar, communication and array signal processing (Zhang *et al*., 2012; Bencheikh and Wang, 2011). Most of the researchers have proposed various techniques to estimate DOA offar field sources in which the impinging signals on antenna array are assumed to be plane waves and we need to estimate single DOA for a particular source (Zhang and Xu, 2008; Sun and Zhou, 2009). The problem of estimating DOA becomes more complicated when we deal with near field sources because along with DOA, we also need to estimate theirrange (Yuntao *et al*., 2004). In this case, the wave frontimpinging on aperture array is spherical as plane wave is no more applicable. Hence, the algorithms designed for estimating the DOA of far field sources cannot be applied directly to estimate the DOA of near field sources.

Many techniques have been developed for the estimation of DOA and range of near field sources such as the higher order ESPRIT method (Challa and Shamsunder, 1995), Maximum Likelihood method (Swindlelhurst and Kailath, 1988) and the weighted linear prediction method (Emmanuele *et al*., 2005). Most of these techniques suffer from heavy computational burden, iteration process and computation of cumulants. Moreover, these techniques need more sensors in the array and thus their hardware becomes expensive.

In recent development, no one can deny the importance of meta-heuristic techniques such as Genetic Algorithm (GA), Particle swarm optimization (PSO), Differential Evolution (DE) etc. Among these techniques, GA got extra attention due to its simplicity in understanding, ease in implementation and less probability of getting stuck in local minima. GA is being widely applied to a mixture of fields ranging from handy applications in industry and commerce to leading-edge scientific research. In many problems the significance of GA increases more when it is hybridized with any other efficient technique such as Pattern Search (PS), Active Set (AS) and Interior Point Algorithm (IPA) (Zaman *et al*., 2012a, b, c, d, e). In Zaman *et al*. (2012a), the hybrid approach GA-PS is used for the joint estimation of amplitude and DOA of far field sources impinging on uniform linear array and it has been shown that the hybrid GA-PS performs well as compare to GA and PS alone. In Zaman *et al*. (2012b), GA and Simulated Annealing (SA) are hybridized with PS to jointly estimate the 3-D (amplitude, elevation angle, azimuth angle) while in Zaman *et al*. (2012c) GA and SA are hybridized with IPA to estimate jointly the range, amplitude and elevation angle of near field sources. In Zaman *et al*. (2012d), PSO is hybridized with PS for joint estimation of amplitude and elevation angle of far field sources impinging on ULA and it has been shown that the hybrid PSO-PS produced better result as compare to PSO alone (Zaman *et al*., 2012e).

In this study, GA is hybridized with PS to jointly estimate the range, elevation angle and amplitude of near field sources. In this hybrid approach GA is treated

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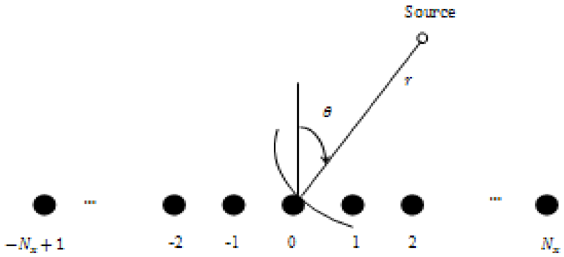

Fig. 1: Array geometry

as a global optimizer while PS as local search optimizer. MSE which is derived from Maximum likelihood principle (Zaman *et al*., 2012c) is used as an objective function. The main issue in multiple targets tracking system is the association of new estimates of DOAs with old estimated DOAs which requires large computations. By using MSE, the new DOA is automatically linked with the old DOA estimated in the previous snapshot (Sastry *et al*., 1991). Moreover, this fitness function is easy to implement, avoids any ambiguity between the angles that are supplement to each other and requires single snapshot to converge. The results of the proposed scheme are tested on the basis of inclusive Monte-Carlo simulation.

PROBLEM FORMULATION

We assumed narrow band signal model of near field sources, where a uniform linear array having elements $N = 2N_x$ with same inter-element spacing, receives P sources from different directions as shown in Fig. 1. For $N \geq P$, our appropriate signal model at lth sensor in the array is given as:

$$x_l = \sum_{i=1}^{P} s_i \exp(j(\omega_i l + \phi_i l^2)) + \mu_l \tag{1}$$

for $l = -N_x + 1, \ldots, 0, 1, \ldots, N_x$, where we assumed that $l = 0$ be the reference point of our co-ordinate system. In (1) s_i are the amplitudes of sources while ω_i and ϕ_i are defined as follows:

$$\omega_i = \frac{-2\pi d}{\lambda} \sin(\theta_i)$$

And,

$$\phi_i = \frac{\pi d^2}{\lambda r_i} \cos^2(\theta_i)$$

where, θ_i and r_i are the elevation angle and range respectively of ith source and μ_l is additive white noise added at the output of l^{th} sensor in the array. In matrix, vector form, the output of the array can be written as:

$$\mathbf{x} = \mathbf{As} + \boldsymbol{\mu} \tag{2}$$

where,

$$\mathbf{x} = [x_{-N_x+1}, \ldots x_o \ldots xN_x]^T$$

$$\mathbf{s} = [s_1, s_2, s_3, \ldots s_P]^T$$

$$\boldsymbol{\mu} = [\mu_{-N_x+1}, \ldots, \mu_o, \ldots \mu_{N_x}]^T,$$

$$\mathbf{A} = [\mathbf{a_1 a_2 \ldots a_P}]^T,$$

where,

$$\mathbf{a}_i(\theta_i, r_i) = [e^{j(-N_x+1)\omega_i + j(-N_x+1)^2\phi_i} \ldots e^{j(-\omega_i+\phi_i)}{}_1 e^{j(\omega_i+\phi_i)} \ldots e^{jN_x\omega_i + jN_x^2\phi_i}]^T.$$

Here, clearly, the problem in hand is to estimate correctly the unknown parameters i.e. amplitude (s_i), DOA (θ_i) and range r_i from the received data for $i = 1, 2, \ldots P$.

PROPOSED METHODOLOGIES

In this section, we discussed a brief introduction, parameter setting and flow diagram of GA, PS, SA, GA-PS and SA-PS.

Pattern Search (PS) is a stochastic base algorithm and can be used for local and global optimization problems. It belongs to a class of direct search method which does not require the gradient of the problem (Zhang and Ma, 2010). To find the optimum value, PS uses stochastic searching technology based on translated and scaled integer and is quite capable to reach the local optimistic value (Taddy *et al*., 2009).

GA inspired by natural phenomena is more valuable and well-organized algorithm than any other evolutionary technique. Due to ease in implementation and its strong ability to avoid getting stuck in the presence of local minima, it has found frequent applications in the field of array signal processing, soft computing and medical imaging (Addad *et al*., 2011; Maulik, 2011).

GA becomes more efficient and reliable when it is hybridized with any other efficient evolutionary computation technique e.g., with PS, IPA etc. The general steps for GA and GA-PS are given as,

Step 1: Initialization: As shown in "Eq. (1-2)", the unknowns variables are $[s_k]_{k=1}^{P}$, $[\theta_i]_{i=1}^{P}$ and $[r_j]_{j=1}^{P}$. Hence, we generate randomly M number of particles (chromosomes) as shown in Table 1.

$$\mathbf{b}_i = [s_{i,1}, \ldots s_{i,P}, \theta_{i,P+1}, \ldots \theta_{i,2P}, r_{i,2P+1}, \ldots r_{i,3P}]$$
$$= [b_{i1}, \ldots b_{iP}, b_{i,P+1}, \ldots, b_{i,2P}, b_{i,2P+1}, \ldots b_{i,3P}]$$

Table 1: Randomly generated M number of particles

Amplitudes	Elevation angles	Ranges	
$s_{11} s_{12}$ . . .	$s_{1P} \theta_{1,P+1} \theta_{1,P+2}$ . . .	$\theta_{1,2P} r_{1,2P+1} r_{1,2P+2}$ . . .	$r_{1,3P}$
$s_{21} s_{22}$ . . .	$s_{2P} \theta_{2,P+1} \theta_{2,P+2}$ . . .	$\theta_{2,2P} r_{2,2P+1} r_{2,2P+2}$ . . .	$r_{2,3P}$
$s_{31} s_{32}$ . . .	$s_{3P} \theta_{3,P+1} \theta_{3,P+2}$ . . .	$\theta_{3,2P} r_{3,2P+1} r_{3,2P+2}$ . . .	$r_{3,3P}$
. .	. . .	. . .	.
. .	. . .	. . .	.
. .	. . .	. . .	.
$s_{M1} s_{M2}$ . . .	$s_{MP} \theta_{M,P+1} \theta_{M,P+2}$ . . .	$\theta_{M,2P} r_{M,2P+1} r_{M,2P+2}$ . . .	$r_{M,3P}$

Table 2: Parameters settings for GA and PS

GA		PS	
Parameters	Settings	Parameters	Setting
Population size	240	Poll method	GPS Positive basis 2 N
No of generation	1000	Polling order	Consecutive
Migration direction	Both way	Maximum iteration	800
Crossover fraction	0.2	Function evaluation	16000
Crossover	Heuristic	Mesh size	01
Function tolerance	10-12	Expansion factor	2.0
Initial range	[0-1]	Contraction factor	0.5
Scaling function	Rank	Penalty factor	100
Selection	Stochastic uniform	Bind tolerance	10-03
Elite count	2	Mesh tolerance	10-06
Mutation function	Adaptive feasible	X Tolerance	10-06

Table 3: DOA, Range and amplitude estimation of two sources

Scheme	θ_1	θ_2	r_1	r_2	s_1	s_2
Actual values	0.5981	1.2216	1.0000	2.0000	3.0000	5.0000
GA	0.6002	1.2238	1.0022	2.0021	3.0021	5.0022
PS	0.6026	1.2261	1.0045	2.0043	3.0044	5.0045
GA-PS	0.5981	1.2216	1.0000	2.0000	3.0000	5.0000

where,

$$s_{ij} \in R : L_s \le s_{ij} \le H_s, \forall i = 1,2,..,M,\ j = 1,2,...P,$$

where L_S and H_S are the lowest and highest possible limits of the signal amplitudes. Similarly,

$$\theta_{ij} \in R : 0 \le \theta_{ij} \le \pi, \forall i = 1,2,...,M,\ j = P+1, P+2,...,2P,$$

And

$$r_{ij} \in R : L_r \le r_{ij} \le H_r, \forall i = 1,2,...,M,\ j = 2P+1, 2P+2,...,3P,$$

where L_r and H_r are the lowest and highest possible limits of the source ranges.

Step 2: Fitness evaluation: The fitness function given below is used to findout the fitness of each particle:

$$FF(i) = 1/(1 + D(i)) \tag{3}$$

where, D(i) can be written as:

$$D(i) = 1/M \sum_{l=1}^{M} \left| x_l - x_l^i \right|^2 \tag{4}$$

where, x_l is given by Eq. (1) and x_l^i is written as follow:

$$x_l^i = \sum_{i=1}^{P} b_i \exp(j(\omega_i l + \hat{\phi}_i l^2)$$

where,

$$\omega_i = \frac{-2\pi d}{\lambda} \sin(\hat{b}_{P+i})$$

$$\phi_i = \frac{\pi d^2}{\lambda r_{b,2P+i}} \cos^2(\hat{b}_{P+i})$$

For i = 1, 2, …, P

Step 3: Termination criteria: The stopping criteria is made on the following results achieved:

- If the fitness value is reached which is pre-defined i.e., $\varepsilon_j \le 10^{-12}$
- If the total number of iterations have completed.

Step 4: Reproduction: Use the Mutation, crossover and Elitismas shown in Table 2 and 3 for generating new populations.

Step 5: Refinement: The PS technique is used for further tuning of results. The best result got through GA alone is given as a starting point to PS. In the same way, the best individual result of SA is given as a starting point to PS.

Step 6: Storage: For better statistical analysis, repeat the steps 2 to 5 and store the global best of each cycle.

RESULTS AND SIMULATIONS

In this section, we discussed the accuracy of GA, PS, GA-PS, for the joint estimation of amplitude, DOA and range of near field sources. We have used Uniform Linear Array (ULA) which consists of $N = 2N_x$ sensors. The inter-element spacing between two consecutive elements is kept fourth the wavelength of the signal i.e., $\mathrm{d} = \lambda/4$. The validity and efficiency of these schemes are tested on the basis of large number of Monte-Carlo simulations by using MATLAB version 7.8.0.347. The Mean Square Error (MSE) is used as a fitness evaluation function which is defined in "Eq. (4)". Throughout the simulations only a single snapshot is used and a MATLAB built-in tool box "optimization of population" based algorithm is used with the setting shown in Table 2. All the values of the DOA of sources are taken in radians and each result is averaged over 100 independent runs.

Case I: In this sub-section, we compared the accuracy of all three techniques. We assumed two sources arriving on which consists of six elements. The amplitude, DOA and range of these two sources are denoted by s_1, s_2, θ_1, θ_2 and r_1 , r_2 respectively. The s_1, θ_1, r_1 correspond to the first source while s_2, θ_2, r_2 correspond to the second source. Initially the performances of these techniques are discussed in the absence of any noise. We used$s_1 = 3, s_2 = 5, \theta_1 = 0.5981\ (rad), \theta_2 = 1.2216(rad), r_1 = 1\lambda, r_2 = 2\lambda$ as shown in Table 3. In this case, all the five techniques produce fairly good results. However, as one can observe that among all these techniques, the hybrid approach GA-PS produce better result as compared to the other two techniques. The second best results are given by GA alone.

Case II: In this case, we discussed the accuracy of all three techniques for three sources. The ULA consists of ten elements. We take $\mathrm{s}_1 = 7, \mathrm{s}_2 = 9, \mathrm{s}_3 = 5, \theta_1 = 0.6728, \theta_2 = 2.3962, \theta_3 = 1.9398$ and $\mathrm{r}_1 = 3, \mathrm{r}_2 = 2, \mathrm{r}_3 = 1$. In this case, with the increase of unknowns (number of sources), we faced few local minima due to which the performance of all schemes are degraded as compared to case.1. Table 4 shows that even in the presence of local minima, the hybrid approach GA-PS produces much accurate results as compared to the other four schemes. The second best result is given by GA.

Case III: In this case, the performance of all three algorithms is discussed for four near field sources. The array is composed of twelve elements. We take $\mathrm{s}_1 = 2, \mathrm{s}_2 = 4, \mathrm{s}_3 = 6, \mathrm{s}_4 = 8, \theta_1 = 0.5981, \theta_2 = 2.4090, \theta_3 = 2.0944, \theta_4 = 1.7925$ and $\mathrm{r}_1 = 3, \mathrm{r}_2 = 5, \mathrm{r}_3 = 7, \mathrm{r}_4 = 9$ as shown in Table 5. In this case, we have more strong local minima due to which the performance of all the techniques is degraded more as compare to previous case. Again, one can see from Table 5, that the hybrid approach (GA-PS) produces fairly good results even in the presence of strong local minima.

Now, we look at the reliability of all three schemes for four sources. The threshold value of MSE is set

Table 4: Amplitude, DOA and range of two sources

Scheme	θ_1	θ_2	θ_3	r_1	r_2	r_3	s_1	s_2	s_3
Assumed	0.6728	2.3962	1.9398	3.0000	2.0000	1.0000	7.0000	9.0000	5.0000
GA	0.6822	2.4057	1.9492	3.0093	2.0094	1.0093	7.0094	9.0093	5.0093
PS	0.7056	2.4291	1.9726	3.0327	2.0328	1.0327	7.0328	9.0327	5.0327
GA-PS	0.6743	2.3979	1.9413	3.0015	2.0016	1.0015	7.0015	9.0014	5.0014

Table 5: Amplitude, DOA and range of three sources

Scheme	θ_1	θ_2	θ_3	θ_4	r_1	r_2	r_3	r_4	s_1	s_2	s_3	s_4
Assumed	0.5981	2.9040	2.0944	1.7925	3.0000	5.0000	7.0000	9.0000	2.0000	4.0000	6.0000	8.0000
GA	0.6165	2.4274	2.1127	1.8107	3.0184	5.0182	7.0183	9.0183	2.0183	4.0184	6.0183	4.0183
PS	0.6427	2.4537	2.1391	1.8371	3.0446	5.0444	7.0445	9.0445	2.0445	4.0.446	6.0445	4.0444
GA-PS	0.6073	2.4184	2.1037	1.8071	3.0094	5.0092	7.0093	9.0091	2.0093	4.0094	6.0092	4.0092

Table 6: MSE and %convergence of two sources for different number of sensors

No of elements	Scheme	MSE	%Convergence	No of elements	Scheme	MSE	%Convergence
8	GA	10^{-4}	60	12	GA	10^{-6}	65
	PS	10^{-3}	8		PS	10^{-4}	12
	GA-PS	10^{-5}	75		GA-PS	10^{-7}	82
10	GA	10^{-5}	62	14	GA	10^{-7}	72
	PS	10^{-3}	10		PS	10^{-4}	14
	GA-PS	10^{-6}	78		GA-PS	10^{-8}	85

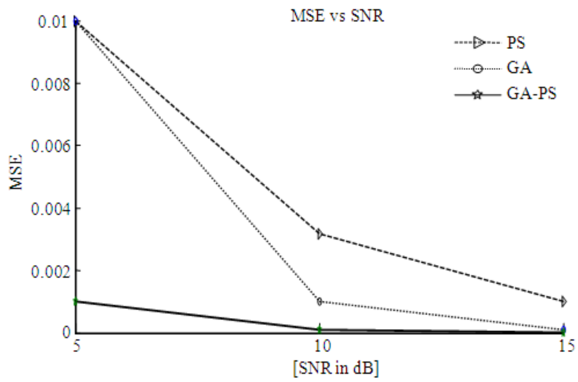

Fig. 2: MSE vs SNR

10^{-2}. Even in the presence of strong local minima the reliability of hybrid GA-PS technique is much better than the other four techniques which is 75% with MSE is 10^{-5}. The reliability of GA and PS are60% and 8% respectively. With the increase of elements in the array, the reliability and MSE of all schemes improves especially of GA-PS as shown in Table 6.

In this section, we discussed the robustness of each scheme against noise. The MSE of each scheme is drawn against Signal-to-Noise Ratio (SNR). In this we used, two sources and six elements in the ULA. The SNR is ranging from 5 dB to 15 dB. As shown in Fig. 2, the hybrid technique GA-PS has maintained minimum MSE against all the values of SNR. The second best technique is GA which is fairly good against all the values of SNR.

CONCLUSION AND RECOMMENDATIONS

In this study, five techniques, GA, PS and GA-PS have been discussed for joint estimation of amplitude, DOA and range of near field sources impinging on ULA. Different cases have been considered for various numbers of sources. MSE was used as a fitness evaluation function which is optimum and requires single snapshot to converge. It has been shown that every time the hybrid approach GA-PS produces better results as compared to GA and PS alone. These entire schemes fails when the number of elements in the array are kept less than the number of sources as it becomes an under-determined case.

In future, we shall use these techniques for the null steering and sidelobes reductions.

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