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Energy-based Localization by Enhanced Elephant Herding Optimization

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ABSTRACT The present work proposes a new approach to address the energy based acoustic localization problem. The proposed approach represents an enhanced version of evolutionary optimization based on Elephant Herding Optimization (EHO), where two major contributions are introduced. Firstly, instead of random initialization of *elephant* population, we exploit particularities of the problem at hand to develop an *intelligent* initialization scheme. More precisely, distance estimates obtained at each reference point are used to determine the regions in which a source is most likely to be located at. Secondly, rather than letting *elephants* to simply wander around in their search for an update in the source location, we base their motion on a local search scheme which is found on a discrete gradient method. Such a methodology significantly accelerates the convergence of the proposed algorithm, and comes at a very low computational cost, since discretization allows us to avoid the actual gradient computations. Our simulation results show that the enhanced algorithm significantly outperforms the standard EHO method for low noise and matches its performance for high noise, in terms of localization accuracy. Moreover, they show that the proposed enhanced version requires significantly less number of iterations to converge.

INDEX TERMS Acoustic Localization, Elephant Herding Optimization, Gradient Descent, Population Initialization, Swarm Intelligence.

I. INTRODUCTION

ACOUSTIC event detection, classification and localization has gained much attention in the signal processing community in recent years. Since the introduction of the acoustic decay model [1], [2] many studies have been proposed in several fields of applications, namely wildlife environments [3], assisted living [4], gunshot characterization [5], underwater sensors networks [6], smart cities [7], and localization [8], just to name a few examples.

The present work focuses on localization of an acoustic source, and more particularly, on the energy-based acoustic localization problem. This problem has been addressed by several authors, mostly using deterministic approaches. Ho and Sun [9] proposed an algebraic closed-form solution which offers a good performance for low noise power, but their solution presented considerable degradation for higher levels of noise. Two different weighted least squares methods were proposed in [10], [11] with low computational burden for energy-based localization. Even though these methods have low computational burden, both methods ignore second-order noise terms (although [11] adds a correction technique leading to further performance gains); hence, their performance is highly degraded when noise power becomes large. Wang [12] and Beko [13] proposed two semi-definite relaxation methodologies, both with good performance even in noisy environments, but their major drawback is their high computational complexity, which increases significantly with the size of the network. Beko showed in [14] that this issue can be alleviated to some extent by applying Second-Order Cone Programming (SOCP) relaxations instead. Nonetheless, although the SOCP offers relatively good accuracy even in noisy environments, its computational complexity is still not satisfactory for real-time applications.

Moreover, all above mentioned algorithms bypass the original localization problem by applying a set of approximations/relaxations to the problem in order to transform it into a form suitable for solving by the applied tools. Although the solutions obtained in this manner are reasonable in general, they are sub-optimal and their quality depends on the tightness of the applied relaxations. In huge contrast to the deterministic algorithms, here we take a different approach which tackles the original problem directly, without applying any approximations/relaxations.

Evolutionary optimization falls within the set of metaheuristics algorithms for global optimization inspired by biological evolution. In general, it works as follows. An initial group of candidate solutions is generated and iteratively updated based on a predetermined behaviour. Each new generation is produced by removing less desired solutions, and introducing small random changes based on the behavior of interest (biological, swarm, or physical) [15]. Due to the simplicity of the computational models adopted, this kind of algorithms have low computational complexity and consequently, low processing time. To overcome the limitations of deterministic methods, a swarm intelligence algorithm based on Elephant Herding Optimization (EHO) proposed by Wang [16], was applied to the acoustic energy-based problem [17], [18]. It showed promising results, in both simulation environment and field experiments. The method was also applied to other engineering problems, namely for proportional integral derivative control [19], networks quality of service [20] and drone placement control [21]. Other swarm algorithms are also worth mentioning, namely, Monarch Butterfly optimization algorithm [22], Grey Wolf Optimization [23], Chicken Swarm Optimization Algorithm [24], among several others that are used in a variety of fields nowadays. It is worth mentioning that none of the above methods take into account information coming from the observations (i.e., the model itself) for initialization (it is considered random in general), which represents a serious overlook. Intuitively, it is clear that additional information about the problem at hand could offer us an upper hand. Still, to the best of our knowledge, there is no existing metaheuristic method which accounts for this additional information; thus, the present work is the first one to show one way of how measurements acquired within a network could be exploited to better the performance of a metaheuristic algorithm. All of the mentioned algorithms, based on particle swarms, namely EHO, are proposed as generic methods, usually tested on generic fitness functions, with the purpose of being applied afterwards in all kind of scientific areas where the main goal is achieving global optima. Hence, although the authors in [17] study the same problem as the current work, the proposed EHO presents some shortcomings that can be avoided. It disregards any specification or internal information about the model that serves as a base to derive a cost function. The same issue is applied concerning population initialization, where randomization is most frequently employed. Nevertheless, the proposal of new initialization methods and their improvement have been the subject of several studies over the years [25]. Randomization, being the most widely used method, aims to generate evenly distributed populations [26]. Population initialization is crucial since poor initial guesses might prevent an algorithm to find optimal solutions. Besides generic methods like pseudo-random number generator [27] or chaotic number generator [28], application specific initialization methods have also been considered for a particular set of problems, namely for antenna design [29] or image segmentation [30].

Firstly, a new strategy based on theoretical foundations through distance estimation is proposed for the initialization of population. The second major contribution concerns the acceleration of the method's convergence by integrating discrete gradient search methodologies in the EHO algorithm [31]. With this procedure, it will be shown that the modified algorithm obtains up to 1 m of reduction in the localization error for lower values of noise, requiring considerably less iterations. For higher values of the noise, it replicates the performance of the original EHO. The increase in computational effort is compensated by the reduction of the number of iterations, due to substantial increase of the convergence rate.

The paper is organized as follows. Section II formulates the mathematical approach in terms of the acoustic model and the optimization algorithm. Section III present the novel methodology for the population initialization. Section IV defines the new methodology for accelerating EHO convergence rate. Section V presents and discusses simulations results of the proposed enhanced algorithm and Section VI concludes the paper and presents future lines of research.

II. PROBLEM FORMULATION

Consider a 2-dimensional sensor network, composed of N sensors and one acoustic source node. The sensors are uniformly distributed on a circle, centered at the middle point of the search space, deployed over a 100m $\times$ 100m square region. The unknown location of the source is denoted by $\mathbf{x}$ and the known location of the i_{th} sensor by $\mathbf{s}_i$, where $i = 1, \ldots, N$. The goal of this work is to determine the unknown location of the source by exploiting acoustic energy measurements acquired by sensors. The relation between the acoustic signal and other model parameters is correlated with the decay model of an acoustic signal [1], [2].

To obtain the energy observations at the i_{th} sensor, we average the readings over M signals obtaining the following decay model equation:

$$y_i = \frac{g_i P}{||\mathbf{x} - \mathbf{s}_i||^\beta} + \nu_i, \qquad \text{for } i = 1, \ldots, N, \tag{1}$$

where P is the transmitted power, ν_i represents the measurement noise, assumed as a Gaussian distribution with zero mean, $\nu_i \sim \mathcal{N}(0, \sigma^2_{\nu_i})$, and β is the path loss exponent. The value of β typically falls within the interval $[2, 4]$ (2 in free space and 4 in adverse indoor environments) [1], [2]. In this work we consider $\beta = 2$, since we consider signal propagation in free space, without reflections or reverberations. By employing the noisy observations defined in (1), the maximum likelihood (ML) estimator of $\mathbf{x}$ can be formulated as [1], [2]:

$$\widehat{\mathbf{x}} = \arg\min_{x} \sum_{i=1}^{N} \left(y_i - \frac{g_i P}{||\mathbf{x} - \mathbf{s}_i||^2} \right)^2 \tag{2}$$

The problem in (2) is non-convex and has singularities, thus, it is well suited for application of a metaheuristic optimization method. EHO algorithm [16], which models herding behavior of elephants in nature, can be summarized as follows: the population of elephants contains a number of clans, which comprise a number of elephants. Each clan moves under the leadership of a matriarch, while a number of male elephants that reached adulthood leave the clan they belong to and live alone in nature. EHO models these behaviors with two operators: clan update (which updates the elephants and matriarch current positions in each clan) and a separation operator (which enhances the population diversity at the later search phase) [16]. In terms of population initialization, each clan and its respective elephants, are randomly distributed in the search space. For those not familiar with the biological terminology used here, what the presented methodology represents is essentially an *intelligent* Monte Carlo search, in which a set of points (called elephants) is evaluated through a cost function (the objective function in (2)) in search for the best one. Mathematically, the algorithm can be resumed by eq. (3) to (6). Eq. (3) is the clan updating operator, that controls the movement of the clan according to the elephant matriarch c_i

$$\mathbf{x}_{new,c_i,j} = \mathbf{x}_{c_i,j} + \alpha(\mathbf{x}_{best,c_i} - \mathbf{x}_{c_i,j})r \tag{3}$$

where $\mathbf{x}_{new,c_i,j}$ and $\mathbf{x}_{c_i,j}$ are the updated and previous positions of the j_{th} elephant in the i_{th} clan respectively, $\alpha \in [0,1]$ is a tuning parameter and $r \sim \mathcal{U}\ [0,1]$ is a randomly generated number, with a uniform distribution and $\mathbf{x}_{best,c_i}$ represents the fittest elephant individual in clan c_i. Eq. (4) and (5) update the position of the fittest elephant in the clan where $\xi \sim \mathcal{U}\ [0,1]$

$$\mathbf{x}_{new,c_i} = \xi\, \mathbf{x}_{center,c_i} \tag{4}$$

$$\mathbf{x}_{center,c_i,d} = \frac{1}{n_{c_i}} \sum_{j=1}^{n_{c_i}} \mathbf{x}_{c_i,j,d} \tag{5}$$

while α determines the influence of the i_{th} matriarch on $x_{new,c_i,j}$, ξ determines the influence of $\mathbf{x}_{center,c_i}$ on $\mathbf{x}_{new,c_i}$, where $\mathbf{x}_{center,c_i}$ is the centre of clan c_i. Index d is a reference to the d_{th} dimension, where $1 \leq d \leq D$ and D being the dimension of the considered problem, n_{c_i} is the number of elephants in the i_{th} clan. Eq. (6)

$$\mathbf{x}_{worst,c_i} = \mathbf{x}_{min} + (\mathbf{x}_{max} - \mathbf{x}_{min} + 1)\,\psi, \tag{6}$$

corresponds to the separating operator that moves the elephants with the worst fitness to their new position, where $\mathbf{x}_{max}$ and $\mathbf{x}_{min}$ are respectively the upper and lower bound of the position of elephant individual, and $\psi \sim \mathcal{U}\ [0,1]$. More details can be found in [16].

III. POPULATION INITIALIZATION METHOD

As seen in Section II, the original EHO algorithm initializes elephants in clans, the matriarchs and male elephants randomly, without considering any prior knowledge of the problem itself. When applying the algorithm to a specific problem, we can take the advantage of knowing the observation model employed. If we consider the acoustic decay model presented in eq. (1), we can obtain an estimate of the distance between sensor $\mathbf{s_i}$ and the source, from the noisy observations $\mathbf{y_i}$ as

$$\widehat{\mathbf{d_i}} = \sqrt{\frac{\mathbf{g_i} P}{\mathbf{y_i}}}, \qquad i = 1, \ldots, N \tag{7}$$

Eq. (7) provides an ML estimate of the distance from each sensor to the source, meaning that the source is within a circle centered at each one of the sensors with a *known* radius equal to $\widehat{\mathbf{d_i}}$. If the measurements were noise-free, the true source coordinates would be at the intersection point of all radii. Nevertheless, in practice, there will not exist a single intersection point of the circles, due to noise. In order to study the most likely region of intersections, we consider groups of 3 sensors. The extrapolation to different number of sensor is straightforward.

To demonstrate two extreme configurations, we considered a setup of $N = 9$ sensors with simulated observation readings between $\mathbf{s_1}$, $\mathbf{s_4}$, $\mathbf{s_7}$ and one source (blue square). Fig. 1a corresponds to a consistent case, where all circumferences intersect, forming a convex hull. On the opposite, in Fig. 1b, we obtained three external circumferences without intersections. In the following two subsections, both cases will be treated separately in terms of concerning the proposed strategy for initialization of the clans.

A. SECANT CIRCUMFERENCES

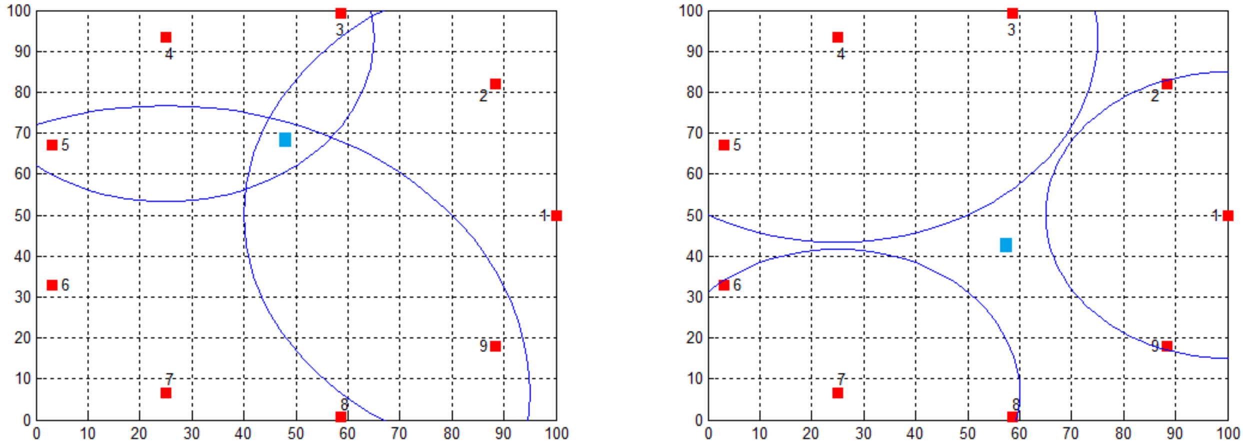
In this case, we are interested in calculating the center of the convex hull formed by the intersection of the three circumferences that will be the center of the clan.

Consider 3 circumferences with center at coordinates $s_i \in \mathbb{R}^2$ and radius $R_i \in \mathbb{R}, i = 1, ..., N$, where the circumferences intersect themselves at at least two points, which means that the expression (8) is logically true (Fig. 1a).

$$(\mathbf{d}_{14} < R_1 + R_4) \wedge (\mathbf{d}_{17} < R_1 + R_7) \wedge (\mathbf{d}_{47} < R_4 + R_7) \tag{8}$$

In eq. (8), $\mathbf{d}_{ij}$ refers to the true Euclidean distance between sensors $\mathbf{s}_i$ and $\mathbf{s}_j$.

Considering Fig. 2, the points delimiting the convex hull common to the intersection of the three circumferences, $\mathbf{P_{C1}}$, $\mathbf{P_{C2}}$ and $\mathbf{P_{C3}}$, will be defined by the following



(a)

(b)

FIGURE 1: Distances Configurations. (a) Consistent Case (Secant circumferences) (b) Non-Consistent Case (External Circumferences)

generalized expressions:

$$\mathbf{P_{ck}} = \begin{cases} x_{ck} = P'(x) - h\frac{s_j(y)-s_i(y)}{||\mathbf{s_i}-\mathbf{s_j}||} \\ y_{ck} = P'(y) + h\frac{s_j(x)-s_i(x)}{||\mathbf{s_i}-\mathbf{s_j}||} \end{cases}, ||\mathbf{P_k} - \mathbf{P_{ck}}|| < R_k$$

$$\mathbf{P_{ck}} = \begin{cases} x_{ck} = P'(x) + h\frac{s_j(y)-s_i(y)}{||\mathbf{S_i}-\mathbf{S_j}||} \\ y_{ck} = P'(y) - h\frac{s_j(x)-s_i(x)}{||\mathbf{s_i}-\mathbf{s_j}||} \end{cases}, ||\mathbf{P_k} - \mathbf{P_{ck}}|| > R_k$$

where $\mathbf{P'}$ is the intersection point between $\overline{\mathbf{P_a P_{c_1}}}$ and $\overline{\mathbf{s_1 s_4}}$, x_{ck} and y_{ck} are the coordinates of the point $\mathbf{P_{ck}}$, and
$\mathbf{P'} = \mathbf{s_i} + a\frac{\mathbf{s_j}-\mathbf{s_i}}{||\mathbf{s_i}-\mathbf{s_j}||}$
$a = R_i^2 - R_j^2 + ||\mathbf{s_i} - \mathbf{s_j}||^2$
$h^2 = R_i^2 - a^2$.
The calculated clan center will correspond to the center of mass of $\mathbf{P_{C1}}$, $\mathbf{P_{C2}}$ and $\mathbf{P_{C3}}$, thus

$$\mathbf{P_x} = \frac{\mathbf{P_{C_1}} + \mathbf{P_{C_2}} + \mathbf{P_{C_3}}}{3} \tag{9}$$

B. EXTERNAL CIRCUMFERENCES

Consider 3 circumferences with center in coordinates $\mathbf{s_i} \in \mathbb{R}^2$ and radius $R_i \in \mathbb{R}, i = 1, ..., N$, where the circumferences do not intersect themselves (Fig. 1b), meaning that eq. (10) is logically false:

$$(\mathbf{d_{14}} < R_1 + R_4) \vee (\mathbf{d_{17}} < R_1 + R_7) \vee (\mathbf{d_{47}} < R_4 + R_7) \tag{10}$$

In the case of external circumferences not having any point of intersection, we consider the straight-line segment between $\mathbf{s_7}$ and $\mathbf{s_1}$, $\overline{\mathbf{s_7 s_1}}$, that will intersect the circumferences radii in two points, $\mathbf{P_A}$ and $\mathbf{P_B}$ (Fig. 3). Our point of interest will be the middle point $\mathbf{P_{17}}$, obtained with the following expressions:

$$\mathbf{P_{17}} = \frac{\mathbf{P_A} + \mathbf{P_B}}{2} \tag{11}$$

$$\mathbf{P_A}(x,y) = \begin{cases} P_A(x) = s_7(x) + \cos(\alpha)R_7 \\ P_A(y) = s_7(y) + \sin(\alpha)R_7 \end{cases} \tag{12}$$

$$\mathbf{P_B}(x,y) = \begin{cases} P_B(x) = S_1(x) - \cos(\alpha)R_1 \\ P_B(y) = S_1(y) - \sin(\alpha)R_1 \end{cases} \tag{13}$$

where:

$$\alpha = \arccos\left(\frac{|s_1(x) - s_7(x)|}{||\mathbf{s_7} - \mathbf{s_1}||}\right)$$

The center of the clan will correspond to the center of the triangle formed by $\triangle\mathbf{P_{17}P_{47}P_{14}}$, thus

$$\mathbf{P_x} = \frac{\mathbf{P_{17}} + \mathbf{P_{47}} + \mathbf{P_{14}}}{3} \tag{14}$$

The application to other set of points is straightforward. The next sets to consider would be $(\mathbf{s_2 s_5 s_8})$ and $(\mathbf{s_3 s_6 s_9})$. In our study, we did some approximations for calculating the center of mass considering straight-line segments. A more precise approach would be to consider the semicircles that delimit the space, but the computational effort would not justify their use, since they might bring only a marginal gain.

C. POPULATION INITIALIZATION ALGORITHM

Notice that, in real life applications, Fig. 1a would correspond to additive noise in all sensors, while Fig. 1b would reflect subtractive noise in all sensors readings. Nevertheless, in practice it is likely that a combination of the two extreme cases occurs. In such a case, one should consider the expressions of Subsections (III-A) and (III-B) separately, for each pair of sensors combination. The purpose of determining the center points of the convex hull limited by the intersections, or the middle points when facing external circumferences, lays in the fact that the solution of the ML problem that will be applied to EHO algorithm is likely to be located in the regions of intersection. One of the goals of our enhanced methodology is to initialize EHO clans at the center of the intersection points presented in Subsections III-A and III-B. With that purpose, the matriarch will be initialized at the center and elephants belonging to the same clan, will be initialized in a circumference with the biggest radius that covers all intersection points. Notice that, since we are dealing with three sensors for each intersection set, the total number of sensors must be a multiple of three, and the number of clans (N_{Clans}) that will be generated is directly related with the number of sensors

$$N_{Clans} = N/3 \tag{15}$$

where N is the total number of sensors. Male elephants will be generated outside the clan radius, but sufficiently close to it, catching possible local minima that could fall outside the radius.

As we shall see, this simple procedure enables a substantial improvement of the original EHO algorithm in terms of convergence. This can be explained to some extent by the fact that the population is initialized *near* the optimal solution. It should be noticed that the number of function evaluations is directly proportional to the number of new clans generations (eq. 16); thus, with a lower number of generations it is expected to obtain similar results

$$NF_{Eval} = N_{Clans} * N_{C_i} * N_{Gen} \tag{16}$$

where NF_{Eval} is the number of function evaluations, N_{Clans} is the number of generated clans, N_{C_i} is the number of elephants in each clan and N_{Gen} the number of generations.

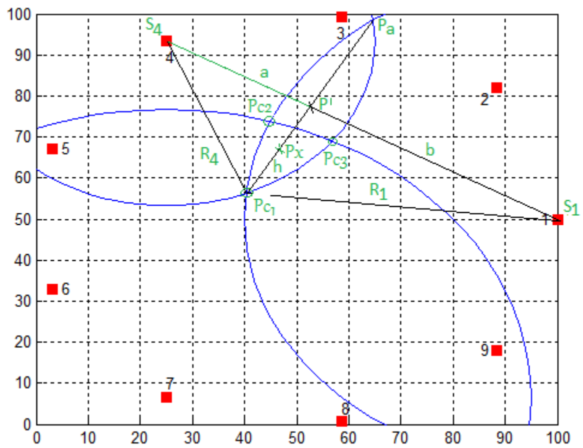


FIGURE 2: Secant Circumferences Center Calculation

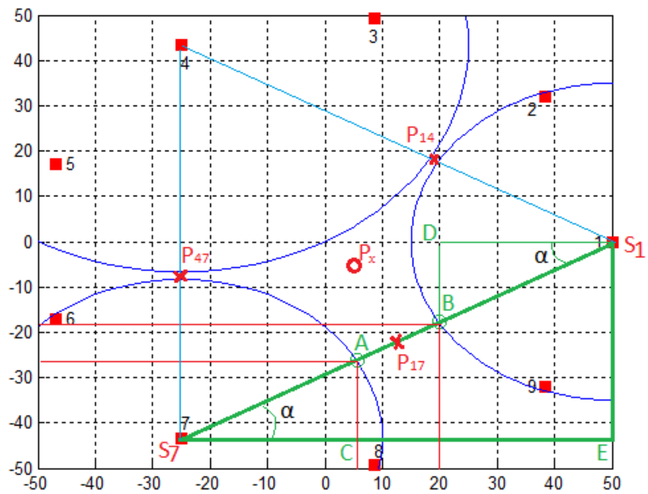


FIGURE 3: External Circumferences Center Calculation

A pseudo code of the proposed procedure to generate the initial population is summarized in Algorithm 1.

Algorithm 1 Clan Initialization Procedure

function CLANINIT($\mathbf{S}, \widehat{\mathbf{d}}$)
  $n = 1$
  $L = length(\mathbf{s})$ ▷ Number of Sensors
  $q = 0 : L/3 : L - L/3$ ▷ Select most distant sensors for each group
  for $k = 1 : L/3$ **do** ▷ Groups of 3 Sensors to create the clans
    $p = ||s_{kq_1} - s_{kq_2}||$
    if $D_k < D_{kq_2}$ **then** ▷ Check point positions
      $Rm = D_{kq_1}; RM = D_{kq_2}$
    else
      $Rm = D_{kq_2}; RM = D_{kq_1}$
    end if
    if $(D_k + Dk + q_2 > p)\&\&(p + Rm > RM)$ **then**
      $\mathbf{P_x} = ...$ ▷ Apply Eq. 9
    else
      $\mathbf{P_x} = ...$ ▷ Apply Eq. 14
    end if
    $\mathbf{P(k)} = \mathbf{P_x}$
    ... Repeat the procedure for remaining groups (q)
  end for
end function

IV. LOCAL SEARCH METHODOLOGY

Our proposed approach for local search is based on applying the Steepest Descent Gradient (SDG) method for each matriarch elephant [32], in each iteration, before applying the clan update operator. The simplest method, although not the most efficient one for determining the direction of search, the direction opposite to the function gradient. Therefore, a course in the set direction will imply the direction of maximum decay [33]. Thus, mathematically it corresponds to $\alpha^k \nabla f(\mathbf{x}^k)$. The determination of α^k, that corresponds to the search step, will be considered as an uni-dimensional search problem such as:

$$\alpha^k = \arg\min_{\alpha>0} f(\mathbf{x}^k - \alpha^k \nabla f(\mathbf{x}^k)) \tag{17}$$

A line search method as considered in (17), for choosing an appropriate step length, α^k, is considered. The solution presented in our present work, is the Backtracking Line Search (BLS). The BLS is a scheme based on the Armijo–Goldstein condition [34], where the method evolves from starting with a large estimate of the step size (α^k), and iteratively backtracks the step size until a decrease of the objective function is observed. The proposed local search procedure is summarized in Algorithm 2.

Algorithm 2 Local Search Procedure

```
function LOCALSEARCH
    k=0
    while Stopping Criterion is not reached do
        g_k = gradient(Model, x_k)          ▷ Finite Difference Approximation
        d_k = −g_k
        α_k = min(x_k + α_k.d_k)            ▷ A. G. condition
        x_{k+1} = x_k + α_k.d_k
        k = k + 1
    end while
end function
```

Notice that in the present work, a linear approximation of ∇f at the point $\mathbf{x_0}$ is obtained as a tangent line to the graph of f at $\mathbf{x_0}$. This is accomplished by using the forward finite difference method, where the truncation error is ignored [35]. In this way, we avoided tedious and burdensome gradient calculations, that would increase processing time, and take advantage of the fast convergence of the SDG for local search. The local search is performed at every generation, starting from the current best solution provided by the each clan matriarch, thus avoiding a high number of executions of Algorithm 2. The flow chart of Fig. 4 represents the integration of the presented features into the standard EHO algorithm, called here Enhanced EHO (EEHO), where new modifications are marked in red.

As it can be seen from Fig. 4, the present work proposes a new enhanced algorithm, based on the original EHO, with two major improvements represented. Firstly, expressions derived from Section III are used to initialize the clans instead of considering a random generation. Secondly, a local discrete gradient based method is used to improve convergence, before the original clan update operator is applied. However, in order to avoid a drastic increase of the number of function evaluations, the method is applied only to the matriarch elephant of each clan. Since the procedure is done before the updating operator, the eventual benefit obtained will propagate to all other elephants through eq. (3). Based on the presented improvements, it is expected to obtain a faster convergence. This hypothesis will be tested in the following section by changing the stopping criteria to a condition monitoring the evolution of the algorithm, expressed as

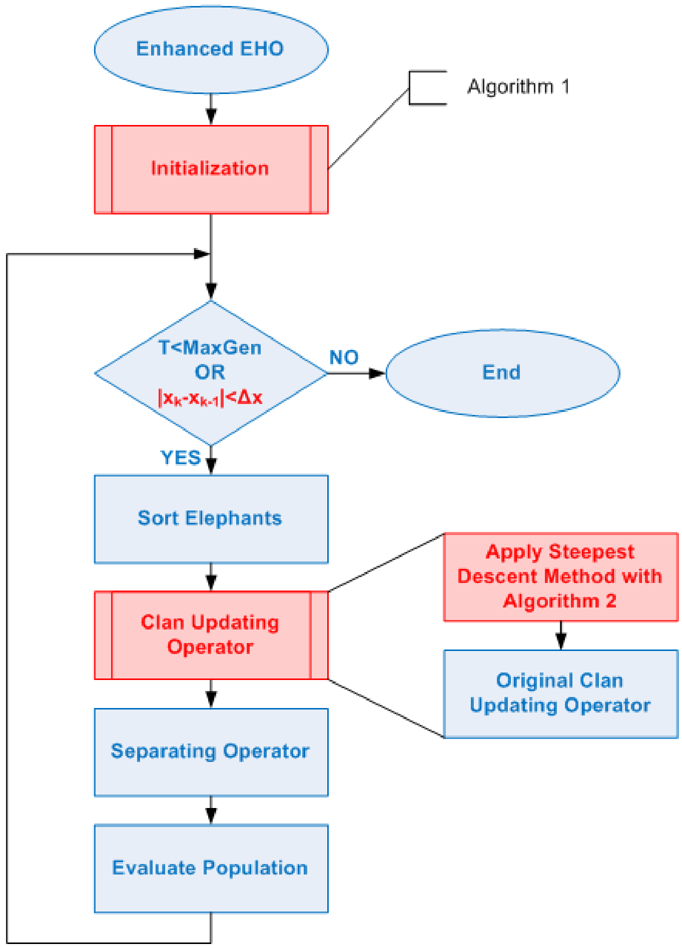


FIGURE 4: Enhanced Elephant Herding Algorithm

$$(n_{Eval} < Max_{Eval}) \wedge (|\ f_{Cost}(x_{k-1}) - f_{Cost}(x_k)\ | > \triangle f) \tag{18}$$

where the first inequality in (18) is monitoring the number of function evaluations (n_{Eval}), until a maximum number is reached (Max_{Eval}). The second inequality monitors the evolution of the cost function (f_{Cost}), and the method is stopped when it presents a decrease lower than $\triangle f$, an arbitrary small constant.

V. SIMULATIONS AND RESULTS

To validate the claims in the presented work, simulations were performed, comparing: (1) original EHO method tuned with parameters obtained from [18] (i.e.: $P = 500$, $g_i = 1$ for $i = 1, ..., N$, $\beta = 2$, $\xi = 0.7$, $\alpha = 0.1$, population size of 100 elephant divided in 5 clans, and the maximum number of function evaluations of 3000), (2) the initialization of the clans population methodology presented in Section III, and the new EEHO (3) with and (4) without considering the stopping criteria from eq. (18), where $\triangle f = 10^{-5}$. In all simulations performed, $M_C = 10.000$ $Monte\ Carlo$ runs are considered, with added noise from $\sigma^2 = -30\ dB$ to $\sigma^2 = -5\ dB$ with increments of $5\ dB$ of variance. The SOCP algorithm [14] was simulated applying the same layout and model conditions (5), considered here as the state of the art of non-metaheuristic methods. The root mean square error (RMSE) in (19) is used as the performance metric, in order to dissipate any effect of the source distribution in the search space, namely, sources located outside the sensors convex hull.

$$RMSE = \sqrt{\sum_{i=1}^{M_c} \frac{||\mathbf{x_i} - \widehat{\mathbf{x}}_\mathbf{i}||^2}{M_c}}, \tag{19}$$

In eq. (19), $\widehat{\mathbf{x}}_\mathbf{i}$ denotes the estimate of the true source location, $\mathbf{x_i}$, in the i_{th} Monte Carlo run. Fig. 5 and 6 show simulation results considering $N = 9$ and $N = 12$ sensors, respectively.

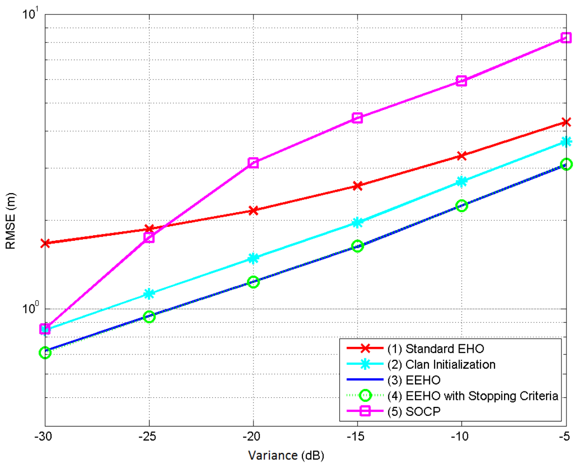


FIGURE 5: Simulation Results with $N = 9$ sensors

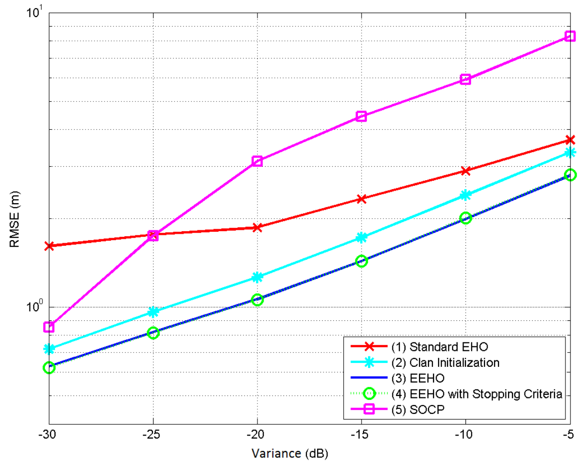


FIGURE 6: Simulation Results with $N = 12$ sensors

As it can be seen from the results of Figs. 5 and 6, the initialization procedure imply a reduction of the RMSE. Although the decrease of the error is more evident for low values of noise, where a reduction of about 1 m is observed, the proposed EEHO offers improvements for high values of the noise power as well. It is worth mentioning that the standard EHO implemented in [18] only outperformed state of the art methods for high noise values and had some degradation for lower values of noise, situation that is no longer present when performing the clan initialization. It can also be seen that EEHO has only a marginal reduction of the error, compared with its counterpart using only the clan initialization, since its major achievement is the enhancement of the convergence rate as stated previously. Interestingly, although the performance of EHO is fairly good in noisy environments, it exhibits limited performance in low-noise environments [18], where it fails to outperform deterministic methods, such as the considered SOCP. This result inspired us to study alternative approaches which would complement its performance, both in terms of accuracy and convergence rate, such as the *intelligent* initialization and local search schemes proposed here. From Figs. 5 and 6, one can see that these schemes allowed us a significant error reduction for low noise power, which is maintained (with somewhat narrowed margin) throughout the whole considered span of noise powers. Another important feature to highlight here is the fact that EEHO performs virtually the same with and without the implementation of the stopping criteria in eq. (18). This result indicates that EEHO algorithm converges before the maximum number of function evaluations is achieved. To get a better comprehension of this behavior, more simulations were performed, applying the same stopping criteria to standard EHO. The results are shown in Fig. 7 to 10 in the form of histograms, with the number of function evaluations for different noise variances.

The above histograms show the comparison of the standard methods with our enhanced one in terms of the number of function evaluations. As it can be seen by the results, regardless of the fact that a stopping criteria was added to the standard EHO algorithm, it required the maximum number of generations available for most of the times and stopped only when this limit was achieved, independently of the stopping criteria. In huge contrast, it can be seen that the enhanced algorithm requires much lower number of iterations, and the maximum number of evaluations was never attained. Therefor, the simulations results corroborate the effectiveness of the two proposed schemes (initialization and refinement), indicating that the new EEHO algorithm gained more accuracy and a faster convergence rate compared with its counterpart, the standard EHO.

VI. CONCLUSION AND FUTURE WORK

In this work two major contributions were presented to enhance the performance of EHO algorithm applied to the

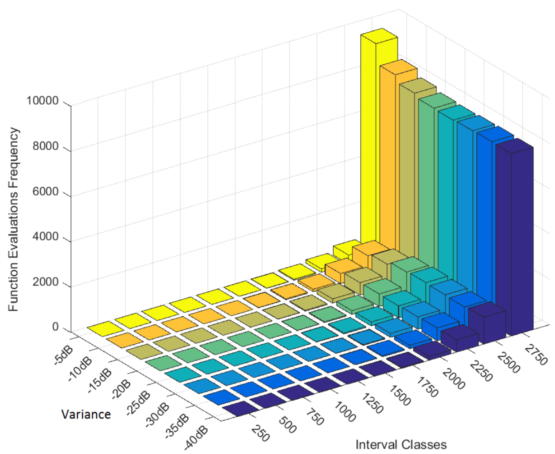


FIGURE 7: Simulation Results for Standard EHO, with $N = 9$ sensors

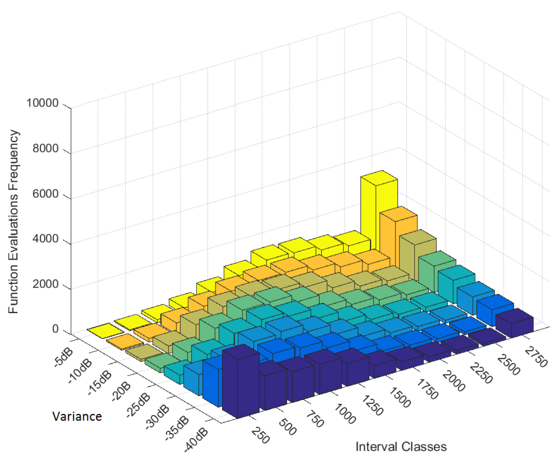


FIGURE 8: Simulation Results for EEHO, with $N = 9$ sensors

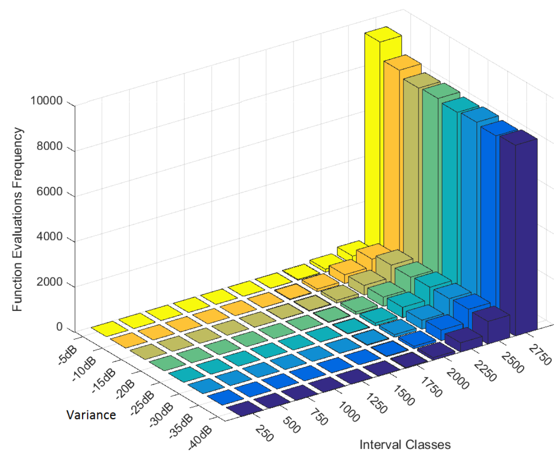


FIGURE 9: Simulation Results for Standard EHO, with $N = 12$ sensors

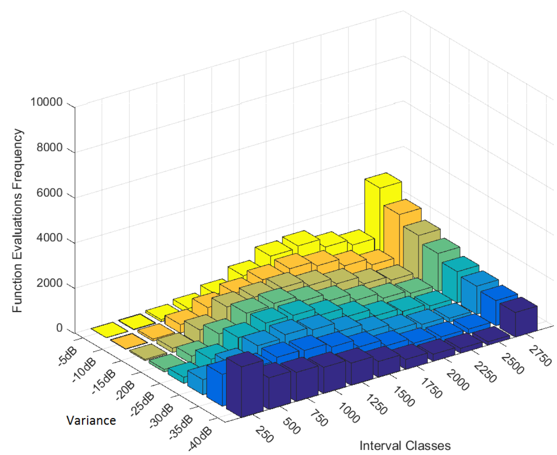


FIGURE 10: Simulation Results for EEHO, with $N = 12$ sensors

energy based localization problem. The proposed schemes take the particularity of the problem at hand and use it in their advantage, unlike the general EHO. Firstly a method for clan initialization was introduced on the estimation of the distance between the acoustic source and the sensors. It was shown that the proposed methodology implies in better accuracy for high values of noise, where other methods tend to fail. Secondly, a discretized version of the SDG method based on finite differences was incorporated in the clan update operator, which allowed us to obtain a substantially faster converge rate. The simulation results validated the productiveness of the proposed schemes, allowing EEHO to reduce the localization error for roughly $1\ m$ for low noise powers, while it matched the performance of EHO in noisy environments. However, the latter result was achieved with significantly less number of clan generations, which makes EEHO more suitable for real-time applications and networks with limited energy resources. On the one hand, the superiority of the proposed algorithm over the deterministic ones is owed to the fact that we tackle the localization problem directly, rather than apply approximations/relaxations to it in order to bypass its non-convexity. On the other hand, its supremacy over the existing metaheuristic approach is due to the neglection of the observation information for the initialization stage of the latter one, which we showed here can be a big overlook, since it can lead to faster convergence and enhanced localization accuracy.

Regarding future work, testing other nature-inspired algorithms, will receive our attention. Moreover, integrating metaheuristic together with deterministic methods to form hybrid algorithms which can take advantage of the strengths of the two approaches and minimize their their weaknesses might be of interest as well. Finally, testing the algorithm with measured data from real implementation with broadband signal for acoustic event detection and localization will be of interest.

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