# A Dynamic Self-Adaptive Music-Inspired Optimization Algorithm for the Hippocampus Localization in Histological Images: A Preliminary Study

Ali Kattan, Rosni Abdullah

**Abstract**—The hippocampus is a structure in the medial temporal lobe of the brain that is involved in episodic memory function. The texture features of the hippocampus could give better differentiation between Alzheimer's disease and normal controls. The localization of the hippocampus structure in MRI histological images is considered as a multimodal global continuous optimization problem, which is solved by means of soft computing techniques using stochastic global optimization methods. Recently, the harmony search (HS) algorithm, a music-inspired optimization method, was introduced as a new soft computing rival. However, the overall performance of this algorithm is quite sensitive to the proper settings of its parameters prior to starting the optimization process. Many have proposed HS-based variants that promote self-adaptive parameter settings. In this paper we propose a new HS-based algorithm with dynamic and self-adaptive features. Since this work represents an early step prior to considering a full implementation on actual biomedical images, the proposed algorithm is tested using a multimodal global continuous optimization benchmarking problems rather than actual hippocampus biomedical images. Results demonstrate the superiority of the proposed algorithm against many other HS-based competing methods.

**Index Terms**—biomedical imaging, computational intelligence, evolutionary algorithms, harmony search, soft computing, meta-heuristic.

## 1 Introduction

THE hippocampus is a structure in the medial temporal lobe of the mammal brain involved in episodic memory function. In patients with Alzheimer's disease (AD), smaller hippocampal volumes measured on magnetic resonance imaging (MRI) correlate with worse memory function [1]. The hippocampus has long been known for its crucial role in learning and memory processes where it has recently been demonstrated that the volume of the hippocampus is an early biomarker for AD [2]. AD is a brain disorder that destroys brain cells, causing problems with memory, thinking, and behavior severe enough to affect work, lifelong hobbies, or social life. However, the accurate diagnosis of AD can be challenging, in particular at the earlier stage. Early diagnosis of AD patients is important because it allows early treatment with cholinesterase inhibitors, which have been shown to delay institutionalization and improve or stabilize cognition and behavioral symptoms [3]. Most biomedical image acquisition techniques of the hippocampus region have many problematic features that will hamper tasks like localization and segmentation of structure in such images. These include fuzziness of the hippocampus boundaries and the relatively large image size in addition to many others. Object detection in general would impose some strict requirements related to accuracy and execution speed [4].

- *Ali Kattan, (PhD), member of IEEE, Lecturer at the Department of IT, Ishik University, Erbil, Iraq, PH-009647505335344. E-mail: ali.kattan@ishikuniversity.net*
- *Rosni Abdullah, (PhD) Professor at the School of Computer Sciences, Universiti Sains Malaysia (USM), Penang, Malaysia. E-mail: rosni@cs.usm.my*

The texture features taken only from hippocampus gives better differentiation between AD and normal controls. Therefore, the textures of hippocampus are much affected by AD [3]. The localization of structures in biomedical images is considered as a multimodal global continuous optimization problem and solved by means of soft computing techniques [2, 4]. A technique used for the proper localization of the hippocampus was initially presented in [4] and then used in [2]. The hippocampus is located by detecting, as landmarks, two regions which are usually well distinguishable within the structure: the pyramidal and granule cell layers, which belong to the Ammon's Horn (CA) and Dentate Gyrus (DG) regions, respectively as shown in Figure (1) top.

In this technique a 2D deformable model of a section of the hippocampus is made to fit the corresponding region of a histological image, to accurately localize such a structure and analyze gene expression in specific sub-regions. Once the model is defined, a similarity measure must also be defined that drives the model search towards the actual configuration of the object, i.e., that reaches its maximum when the image representation of the model is perfectly superimposed to the object as it appears in the image as shown in Figure (1). The problem then becomes a global optimization problem, that is the search of the model parameters, which maximize the similarity measure. The landscape searched by the optimization algorithm is usually strongly multimodal [2]. Therefore, the next crucial step to be taken is the selection of a good heuristic, which can deal with such a rough landscape both efficiently and effectively. Stochastic global optimization (SGO) methods, such as particle swarm optimization (PSO) and deferential evolution (DE) have been successfully used to locate the hippocampal region in biomedical images [2, 4]. However, it was shown in [2] that (DE) significantly outperforms other methods including genetic algorithm (GA) and PSO. In the aforementioned method, active shape models (ASM) are used based on deformable models in medical image analysis [5, 6]. The method parametrically deformed the model shape to match as closely as possible the shape of the hippocampus in the region to be located in the biomedical image used. The model is moved and deformed by altering its parametric representation using an optimization heuristic, which maximizes a function that measures the similarity between the model and the object itself [2, 4]. From another perspective, the problem could be also considered as a minimization problem whereby the algorithm tries to minimize the difference between the model and the object itself.

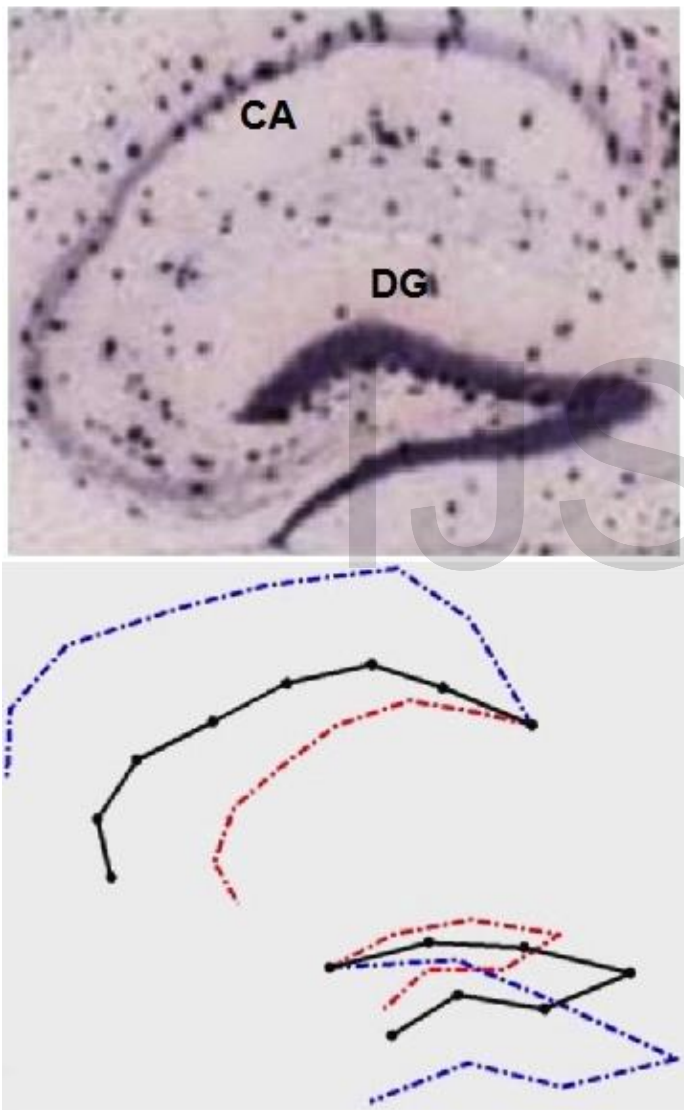



**Figure (1) Example of a hippocampus histological image (top) and a hippocampus model (bottom). The dotted lines in the model represent the lower and upper limits for the possible deformation of the model [4]**

SGO methods such as GA are commonly used in computational neuroscience [7-9]. In order to solve global optimization of continuous functions, SGO algorithms proved to be effective optimization techniques as they do not require special conditions or mathematical properties of the objective functions [10]. A recent SGO method is the harmony search (HS) algorithm [11], which is similar in concept to other SGO methods such as PSO and GA in terms of combining the rules of randomness to imitate the process that inspired it [12]. The HS algorithm is a relatively young meta-heuristic that was inspired from the improvisation process of musicians and is used successfully for many optimization problems with continuous design variables [12-14]. However, the algorithm capabilities are quite sensitive to the settings of its parameters affecting its overall performance and its ability to converge to a good solution [10, 15].

In this work, the development of a new HS-based algorithm having self-adaptive features is introduced. The proposed algorithm enables the dynamic settings of some of the important algorithm's parameters using new quality measure. Since this work represents an early step prior to considering a full implementation on actual biomedical images, the proposed algorithm is tested using multimodal global continuous optimization benchmarking problems rather than actual hippocampus biomedical images. Results demonstrate the superiority of the proposed algorithm against many other SGO methods including recent variants of HS making it a potential candidate method for a hippocampus localization and detection in MRI histological images.

The rest of this paper is organized as follows: section 2 gives a background of the HS algorithm. Section 3 presents related works covering some recent HS-based algorithms with self-adaptive features. Section 4 introduces the proposed method along with the empirical results in section 5. Section 6 is the discussion and the conclusions are given in section 7.

## 2 Background

The original HS algorithm, referred to as classical hereafter, was introduced as an alternative optimization technique for linear programming, non-linear programming and dynamic programming [16]. The method can handle discrete and continuous variables with similar ease [11]. HS concept is based on the improvisation process of musicians in a band where each note played by a musician represents one component of the harmony vector. The harmony vector represents a solution vector **x**, having the size N representing all musician notes associated with a harmony quality value, an aesthetic measure, as shown in Figure (2). The harmony vector is analogous to N dimension variables and the harmony quality represents the fitness function $f(x)$. The computational procedure for the classical HS algorithm is given in Figure (3). For a complete description of the algorithm refer to [11].

The classical HS algorithm required statically setting a certain number of parameters prior to starting the optimization process. However, the algorithm capabilities are quite sensitive to these parameters' settings affecting its overall performance and its ability to converge to a good solution where these parameters need to be skillfully assigned in order to obtain good results [17].

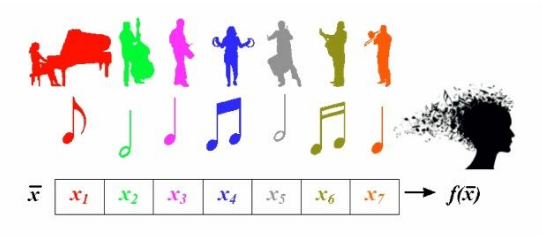



**Figure (2) The harmony vector and its mathematical representation**

1 Initialize the algorithm parameters (HMS, HMCR, PAR, **BW**, MAXIMP)
2 Initialize the harmony memory HM with random values drawn from vectors $[x^L, x^U]$
3 Iteration itr=0
4 **While** itr < MAXIMP **Do**
5 Improvise new harmony vector $x'$
6 Harmony Memory Consideration:

$$\acute{x}_i \leftarrow \begin{cases} \acute{x}_i \in \{x_{i1}, x_{i2}, \ldots, x_{iHMS}\} & with\ probability\ HMCR \\ \acute{x}_i \in X_i & with\ probability\ (1 - HMCR) \end{cases}$$

7 **If** probability HMCR **Then**
Pitch Adjustment:

$$\acute{x}_i \leftarrow \begin{cases} \acute{x}_i \pm rnd(0,1) \cdot BW & with\ probability\ PAR \\ \acute{x}_i & with\ probability\ (1 - PAR) \end{cases}$$

Bounds check:

$$\acute{x}_i \leftarrow \min(\max(\acute{x}_i, x_i^L), x_i^U)$$

**EndIf**
8 **If** x' is better than the worst harmony in HM **Then**
Replace worst harmony in HM with x'
9 itr= itr+1
10 **EndWhile**
11 Best harmony vector in HM is the solution

**Figure (3) The computational procedure for classical HS algorithm**

## 3 Related Works

Two of the HS algorithm optimization parameters, namely the pitch-adjustment rate (PAR) and the bandwidth (BW) are considered to have a great influence on the quality of the final solution [10]. Many recent works have proposed "self-adaptive" HS variants that would automatically tune and find the best settings for these two optimization parameters achieving better results than that of the classical. However, many of these variants have also introduced new additional parameters, which in some cases would also require an additional effort to set their initialization values manually prior to starting the optimization process and depending on the problem considered. In addition, many of these rivals have forced a relationship between the value of these parameters and the current iteration count imposing a linear monotonic change that is bounded by a maximum integer value (MAXIMP), as in the algorithm of Figure (3), where this value is selected subjectively by the user to signal termination. Consequently, the selection of such integer value would affect the whole optimization process.

The Improved HS (IHS) [18] and Global-best HS (GHS) [19] were the first two early attempts to auto-tune these parameters. The value of these parameters would be computed in every iteration based on the current improvisation rate value, which is bound by MAXIMP. Both of these algorithms have reported superiority over the classical HS in a number of domains. However, each algorithm has its own limitations and many have criticized the methods' approach used in adjusting these optimization parameters [10, 17, 20].

The self-adaptive harmony search (SHS) algorithm is "an almost-parameter-free harmony search algorithm" [10]. In this method some of the parameters are automatically adjusted according to its self-consciousness. The PAR is decreased linearly with from 1.0 to 0.0 as a function of the iteration count that is bounded by MAXIMP. The BW on the other hand was replaced altogether and the new harmony is updated according to the maximal and minimal values in the harmony memory (HM). It was indicated that such technique would result in the new harmony making better utilization of its own experiences. The BW is computed for each dimension variable based on the highest and lowest value of the HM for that dimension variable. The formulas used in SHS are given in Eq. (1) through (3).

$$trial(i) = HM(int(rnd() \times HMS + 1)) \quad \ldots (1)$$
$$trial(i) = trial(i) + [\max(HM^i) - trial(i)] \times rnd[0,1) \quad \ldots (2)$$
$$trial(i) = trial(i) - [trial(i) - \min(HM^i)] \times rnd[0,1) \quad \ldots (3)$$

The technique used in SHS would avert the need for any initial setting involving the PAR and BW values. Based on a number of full-factorial experiments involving the harmony memory consideration rate (HMCR) and the HM size (HMS), it was found that a HMS size of around 50 and a HMCR value of 0.99 are the most suitable to use for a number of continuous optimization problems. The maximum iteration count for all the problems considered was set to a value of 100,000.

The self-adaptive GHS (SGHS) algorithm [15] is based on the GHS algorithm [19] and employs a new improvisation scheme with an adaptive parameter tuning method. Three parameters are adjusted dynamically during the optimization process in SGHS, namely the HMCR, the PAR and the BW. It is assumed that the HMCR and PAR values are normally distributed in the range of [0.9,1.0] and [0.0,1.0] respectively with mean values HMCRm and PARm. It uses a standard deviations of 0.01 for the HMCR and 0.05 for the PAR. The HMCRm and the PARm are initially set prior to starting the algorithm at 0.98 and 0.9 respectively. Then SGHS starts with a HMCR & PAR values generated according to the normal distributions of these two. After a specified number of iterations, referred to as learning period (LP), which was selected at a value of 100, both the HMCRm and the PARm are recalculated by averaging all the recorded HMCR and PAR values during this period and then the procedure is repeated. It was mentioned that such approach would result in appropriate values that can be gradually learned to suit the particular problem and the particular phases of the search process. The dynamic value of the BW is set in a fashion that is similar to that used in the IHS algorithm, i.e. as function of the current iteration count and MAXIMP value and as given in Eq. (4). To sum up, the SGHS algorithm still requires the initial value setting of $BW_{min}$, $BW_{max}$, HMCRm, PARm and the new parameter LP. These parameters must be determined manually before starting the optimization process.

$$BW(itr) = \begin{cases} BW_{max} - \frac{BW_{max} - BW_{min}}{MAXIMP} \times 2itr & if\ itr < MAXIMP/2 \\ BW_{min} & if\ itr \geq MAXIMP/2 \end{cases} \quad \dots (4)$$

Another recent self-adaptive HS variant is the harmony search with adaptive pitch adjustment (HSASP) algorithm [20]. In this algorithm, the bandwidth value is adapted dynamically using a technique inspired from the velocity clamping in particle swarm optimization. Arguing that the simultaneous dynamic change of both the HMCR and the PAR can cause a twist of global and local search (a contradiction to the concept used in the SGHS algorithm), the HSASP algorithm uses a high fixed value of 0.995 for the HMCR parameter while the PAR, as in SHS, is decreased linearly from 1.0 to 0.0 during the optimization process. It was indicated that a large HMCR value would increase convergence rate of the algorithm in most cases and provides better performance [10, 18, 19]. It was argued that the technique used in SHS [10] using the lowest and the highest values of the *ith* dimension variable in the HM, given previously in Eq. (1) through Eq. (3), would eliminate the benefits of the exploration of search space outside the current boundary confined within a minimum and a maximum current values and would result in non-uniform distribution of position of the new harmony. In the HSASP method the improvisation process also considers using the current high and low values of each dimension variable within the HM. However, the improvisation would introduce two new terms, the *range* and the value λ and as given in Eq. (5) through Eq. (8). The bandwidth parameter BW is replaced with *λ×range* where it is argued that stochastic oscillation in each dimension is restricted to the current range of harmony position and is regulated by the parameter λ with values ranging from 0.2 to 0.8.

$$range(i) = max\big(HM(i)\big) - min(HM(i)) \quad \dots (5)$$

$$trial(i) \pm \lambda \times range(i) \times rnd() \quad \dots (6)$$

$$If\ trial(i) < x^{L}(i)\ then\ trial(i) = x^{L}(i) \quad \dots (7)$$

$$If\ trial(i) > x^{U}(i)\ then\ trial(i) = x^{U}(i) \quad \dots (8)$$

The proposed technique has shown to attain good results in comparison to other methods including SHS [10] and the classical HS [11]. However, it still requires several manual setting for the newly introduced parameter λ. The best values were found to be 0.3, 0.4 and 0.5 considering the problems selected. As for other parameters, the HMS was set at 50 with the memory initialized using the common uniform random initialization and the maximum iteration count was set manually based on the problem dimensionality.

There are two contradicting techniques to change the PAR in the methods introduced above. The PAR either starts from a minimum value and ends with a maximum one as in IHS, GHS and SGHS [15, 18, 19] or it starts from a maximum value and ends with a minimum one as in SHS and HSASP [10, 20]. Regardless of the technique, the PAR behavior is predetermined in these methods to be monotonic and does not take into account the quality of solutions in the current HM. A larger value of the PAR would result in further modification to the newly created dimensional variable thereby enhancing the local exploitation ability of the algorithm, whereas a smaller value of the PAR would result in the new harmony vector to select its dimensional values by perturbing the corresponding values in the HM, thus enlarging the search area and diversity of the HM [10]. The main difference among these methods is choosing which one to take place first, local exploitation or enlarging the search area and diversity? i.e. start with large PAR value or small PAR value? There is no link between the "quality" of the current solutions and the PAR value setting.

## 4 Proposed Method

The proposed method utilizes the Best-to-Worst (BtW) ratio of the current HM. The concept of BtW was introduced earlier by the authors for the training of artificial neural networks using the HS algorithm [12, 21]. The words "best" and "worst" are part of the HS algorithm nomenclature whereby the algorithm basically tries to find the "best" solution among a set of solutions stored in the HM by improvising new harmonies to replace those "worst" ones as in the algorithm given in Figure (3). At any time the HM would contain a number of solutions including a best solution and a worst solution in terms of their stored quality measures, i.e. fitness function values. With minimization problems in mind, the BtW value is a value in the range [0,1] and as given by the ratio of the current best harmony fitness value to the current worst harmony fitness value in HM. This is expressed in Eq. (9) where a higher BtW value in this case indicates that the quality of current HM solutions is approaching that of the current best. If maximization problems are considered however, then the problem could be treated as minimization one by using the inverse of the fitness function. In both cases a higher BtW value indicates that the quality of current HM solutions is approaching that of the current best.

$$BtW = \frac{f(\bar{x}_{best})}{f(\bar{x}_{worst})} \quad \dots (9)$$

The PAR value in the proposed method is adjusted dynamically based on the value of the current BtW ratio rather than the value of the current iteration count. This is shown in Figure (4) where as search progresses, the BtW value would eventually decrease owing to having better quality solutions in HM. This behavior is expressed in Eq. (10) and Eq. (11) where the PAR becomes a function of the BtW value and not the iteration count. Unlike the methods introduced in the previous section, the PAR change is not monotonic and is not bound by a MAXIMP value. The PAR is to increase or decrease in response to the quality of current solutions in the HM represented by the computed BtW ratio.

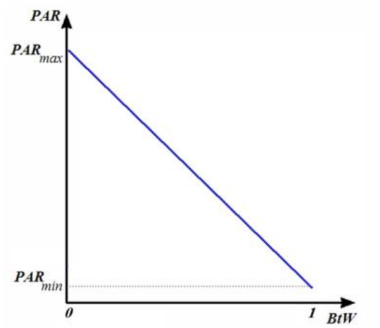



**Figure (4) The dynamic setting of PAR in the proposed method**

$$mslope = \frac{PAR_{max} - PAR_{min}}{0-1} = PAR_{min} - PAR_{max} \qquad \ldots (10)$$

$$PAR = mslope \cdot BtW + PAR_{max} \qquad \ldots (11)$$

$PAR_{max}$ is set at the value of 1.0, as in many of the methods presented earlier, and $PAR_{min}$ is set at a small value that is greater than zero. Setting $PAR_{min}$ to zero might inhibit the pitch adjustment process completely in case of HM stagnation; a condition in which BtW becomes close to unity awing to having similar solutions in HM. If the BtW value decreases, indicating a range of different quality solutions, then the PAR value increases to reflect the local exploitation ability of the algorithm and cause further modifications to the newly created harmony. On the other hand if the BtW value increases, indicating a higher quality solutions within the HM, then the PAR value decreases to enlarge search area and diversity by causing the values of the newly created harmony to be selected by perturbing the corresponding values in the HM.

The pitch-adjusting process is accomplished by using a dynamic bandwidth value (DBW) that considers each harmony vector component (dimension variable) separately and as given in Eq. (12) and Eq. (13).

$$ActiveBW(i) = C \cdot StdDev(x_{HM}^{i}) \qquad \ldots (12)$$
$$DBW(i) = rnd(-Active\ BW(i), Active\ BW(i)) \qquad \ldots (13)$$

The ActiveBW for the considered dimension variable is computed by calculating the standard deviation of the respective HM column. The DBW of the dimension variable is a random value confined within the positive and negative range of the ActiveBW for that dimension variable. This is similar in concept to settings used in the SHS and the HSASP methods presented earlier in that it considers the current high and low values existing within the HM for each dimension variable. The standard deviation in this case represents how much variation exists from the average of each component vector value in the HM. A value of C>1.0 would extend the dynamic bandwidth value so that it would not eliminate the benefits of the exploration of search space outside current boundary confined within a minimum and a maximum [20]. Based on a number of experiments, using a value of C=2.0 makes the performance of our proposed algorithm comparable to those presented earlier.

Termination in all other methods presented earlier is the same as that of the classical HS; specifying a maximum number of iterations as stipulated by MAXIMP value selection [10, 15, 17, 20]. The proposed algorithm also uses this standard termination condition whereby the total number of optimization cycles is bounded by using a MAXIMP value. The proposed method however adds an additional termination conditions that is "OR"ed with the standard one. With minimization considered, if the current fitness function value of the best solution within HM is less than a very small value *delta*, then this would also signal termination.

## 5 Empirical Results

The localization of the hippocampus in histological images is considered as a multimodal global continuous optimization problem whereby the algorithm tries to minimize the difference between the model and the object itself and as shown in Figure (1). It was stated earlier that this work is an early step prior to considering a full implementation on actual biomedical images. Tests were conducted using two multimodal benchmarking functions rather than actual biomedical images. The benchmarking optimization functions are shown in Figure (5) and Figure (6). In addition to the function's 3D graph, which gives a visual idea about the function's surface nature, the function's equation, range and optimal value are also included. The Generalized Schwefel 2.26 function is considered deceptive in that the global minimum is geometrically distant, over the parameter space, from the next best local minima. Therefore, the search algorithms are potentially prone to convergence in the wrong direction. The Rastrigin function is a non-convex function used as a performance test problem for optimization algorithms. It is a typical example of non-linear multimodal function. This function is a fairly difficult problem due to its large search space and its large number of local minima. These two multimodal functions have been commonly used as optimization problems in the evolutionary computation field [22, 23] and are characterized by having many local optima in addition to single global optima. The number of local optima increases exponentially with the dimension of the problem. This appears to be the most difficult test for optimization algorithms [22].

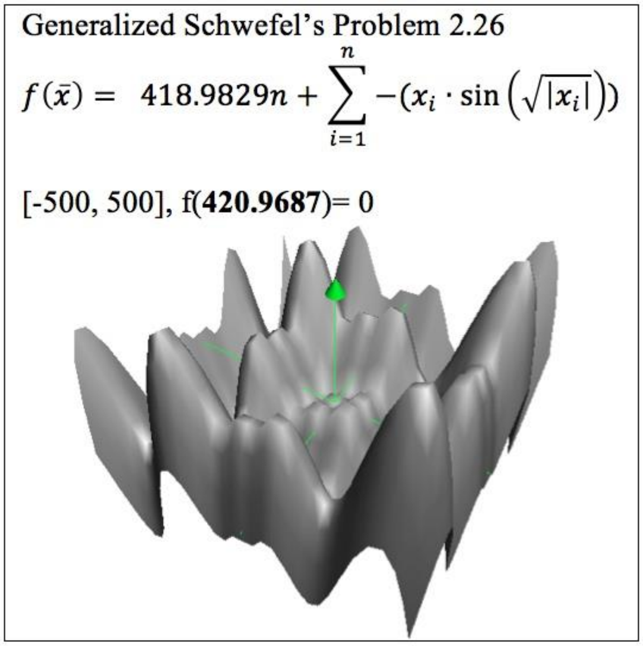



**Figure (5) Rastrigin's multimodal benchmarking problem**

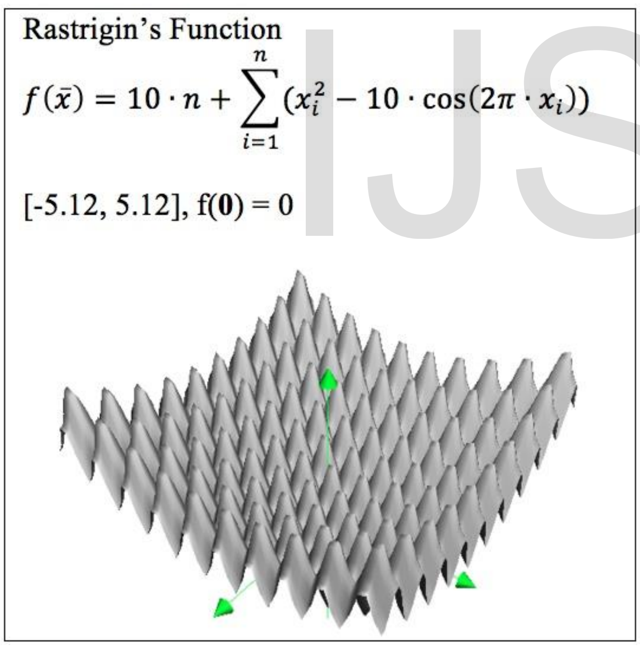



**Figure (6) Generalized Schwefel 2.26 multimodal benchmarking problem**

The value settings for the HMS and the HMCR where investigated thoroughly in SHS and HSASP [3, 10] and common values are used for these two in the proposed method. With minimization problems in mind, fitness function values that are less than delta = 1.0E-50 are considered to be practically zero and would cause immediate termination otherwise termination is bound by the MAXIMP value. Table (1) summarizes the parameter settings used in the proposed DSHS.

**Table (1) Parameter settings for DSHS**

| N | HMS | HMCR | $PAR_{min}$ | $PAR_{max}$ | MAXIMP |
|---|---|---|---|---|---|
| 100 | 50 | 0.99 | 0.1 | 1.0 | 6.0E+05 |

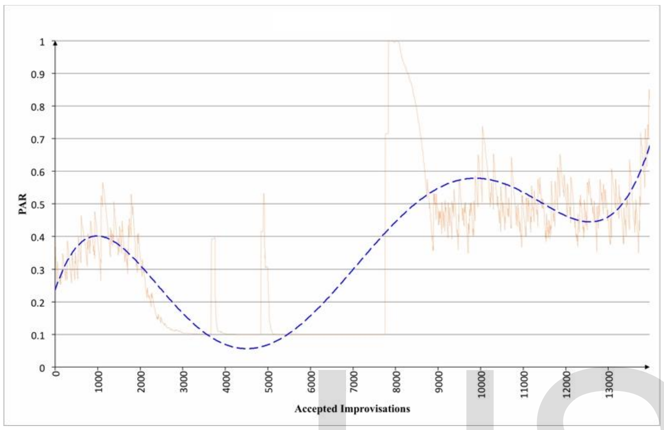
In each test the proposed DSHS algorithm was run for 30 times and the bootstrap-t statistical analyses were carried out with 95% confidence interval for all test functions to verify the method. Table (2), given at the end of the paper, shows the results of the proposed method in comparison to others. The ODE results column in this table represents the results of the opposition-based differential evolution (ODE) SGO method [24] and was obtained from [20]. ODE is a recent variant of DE and represents a state-of-the-art evolutionary algorithm. In case of HSASP, the reported results are associated with different λ value and these are shown in square brackets in its respective column in the table. The best-attained value with its associated iteration count and the last iteration for which the proposed DSHS algorithm terminated are given in the last column.

## 6 Discussion

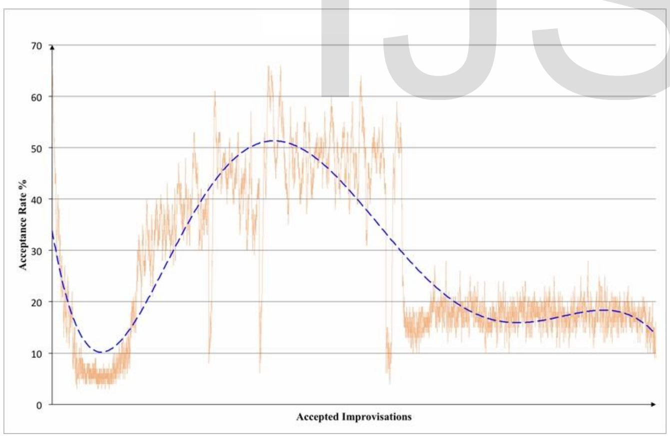
As given in Table (2), the optimization results obtained using the proposed method were superior in comparison to other SGO methods. In the Rastrigin problem the proposed DSHS method was able to terminate earlier based on the opted precision for the minimum fitness value (delta <= 1.0E-50), which could be practically considered as zero value. In all of the self-adaptive rival methods considered in this work, the MAXIMP value selection must guarantee that the method would be able to converge to a good solution in a number of optimization cycles that is less than MAXIMP. Such value could be manually selected based on "experience" however it could be also obtained empirically based on actual testing for the problems considered.

In order to explain the behavior exhibited by PAR in relation with BtW, Figure (7) shows the convergence graph obtained for one of the experiments for the Rastrigin benchmarking problem. Graphs (a) shows the PAR value while graph (b) shows the acceptance rate percentage. Both graphs are drawn against accepted improvisations. Because these graphs contain condensed data due to the large number of iterations, a trendline is included to show the general behavior where it is plotted as a sixth order polynomial. As expressed earlier in Eq. (11), PAR changes dynamically in response to the current value of BtW and is inversely proportional to BtW and as shown earlier in Figure (4). The increase in PAR values at the beginning of the optimization process indicates that the HM contains a wider range of solutions having dispersed fitness values. PAR is increased to trigger the local exploitation ability of the algorithm and cause further modifications to the newly created harmony using the DBW values based on the current active bandwidth. The next decline in PAR values was in response to having higher BtW values. This indicates that the quality of the current solutions in the HM is becoming close to that of the current best solution. In response the PAR value is decreased almost to the value of $PAR_{min}$ in order to enlarge search area and diversity by causing the values of the newly created harmony to be selected by perturbing the corresponding values in the HM. This has resulted in a higher improvisation acceptance rate as evident in the matching response shown in graph (b) of Figure (7).

Considering the problem of localization of the hippocampus in histological images, the more recent method discussed in [2] have indicated that using the DE SGO method gave better results than those obtained using PSO in [4]. In Table (2), the proposed DSHS algorithm performed much better than the state of the art ODE (which is based on DE). This work is an early preliminary step towards the implementation of the proposed DSHS algorithm in the localization of the hippocampus in biomedical images. The results obtained clearly indicate that the proposed method is a potential candidate for implementation of localization of the hippocampus in biomedical images.




**(a)**




**(b)**

**Figure (7) The convergence graph for the Rastrigin's multimodal benchmarking problem**

## 7 Conclusions

The texture features of the hippocampus could give better differentiation between Alzheimer's disease and normal controls. The localization of the hippocampus structure in MRI histological images is considered as a multimodal global continuous optimization problem that using stochastic global optimization methods. This work represents a preliminary research towards the development of an alternative dynamic and self-adaptive stochastic global optimization method that is based on the harmony search algorithm. Testing considered two commonly used multimodal global continuous optimization benchmarking problem rather than actual hippocampus biomedical images. Results indicated the superiority of the proposed method in comparison to some recent rival methods. In addition, the proposed algorithm dynamic and self-adaptive features have resulted in a competitive performance in comparison to other harmony search based methods having self-adaptive features. Future work should consider the proposed method as a potential candidate for full implementation of localization of the hippocampus in biomedical images.

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**Table (2). Optimization results of the proposed DSHS method against other SGO methods**

| Multimodal Benchmarking Function | HSASP [20] | SHS [10] | SGHS [15] | ODE [24] | Proposed Method | |
|---|---|---|---|---|---|---|
| | | | | | DSHS | Best value @iteration, Termination |
| GSchwefel 2.26 | 1.866E+00<br>(1.348E+00)<br>[λ=0.2] | 1.459E+01<br>(7.253E+00) | 3.57E+01<br>(8.60E+01) | 3.243E+04<br>(5.508E+02) | **8.18E-01**<br>**(7.19E-02)** | 6.79E-01<br>586,731<br>MAXIMP |
| Rastrigin | 1.485E+00<br>(8.498E-01)<br>[λ=0.3] | 2.040E+01<br>(3.107E+00) | 1.24E+01<br>(2.64E+00) | 6.009E+02<br>(6.880E+01) | **0**<br>**(0)** | 0<br>214,548<br>214,548 |