Expert Systems with Applications 41 (2014) 5788–5803

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

An improved global-best harmony search algorithm for faster optimization

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ARTICLE INFO

Keywords:
Harmony search
Global-best harmony search
Periodic and sign function
Exploration and exploitation
Opposition-based learning
Numerical optimization

ABSTRACT

In this paper, an improved global-best harmony search algorithm, named IGHS, is proposed. In the IGHS algorithm, initialization based on opposition-based learning for improving the solution quality of the initial harmony memory, a new improvisation scheme based on differential evolution for enhancing the local search ability, a modified random consideration based on artificial bee colony algorithm for reducing randomness of the global-best harmony search (GHS) algorithm, as well as two perturbation schemes for avoiding premature convergence, are integrated. In addition, two parameters of IGHS, harmony memory consideration rate and pitch adjusting rate, are dynamically updated based on a composite function composed of a linear time-varying function, a periodic function and a sign function in view of approximate periodicity of evolution in nature. Experimental results tested on twenty-eight benchmark functions indicate that IGHS is far better than basic harmony search (HS) algorithm and GHS. In further study, IGHS has also been compared with other eight well known metaheuristics. The results show that IGHS is better than or at least similar to those approaches on most of test functions.

1. Introduction

In recent years, a relatively new meta-heuristic algorithm, called harmony search (HS), was proposed by Geem, Kim, and Loganathan (2001). Like other heuristic algorithms imitating natural phenomena or artificial ones, HS is also a heuristic algorithm inspired by artificial phenomenon, i.e., musical harmony. It was developed by Geem in 2001 through simulating the improvisation process of musicians. Owing to its impressive advantages such as easy implementation, lesser adjustable parameters and quick convergence (Mahdavi, Fesanghary, & Damangir, 2007; Wang et al., 2013), HS has been paid more and more attention and has been very successfully applied to a wide range of optimization problems, such as function optimization (Alatas, 2010; Al-Betar, Doush, Khader, & Awadallah, 2012; Ashrafi & Dariane, 2013; Chen, Pan, & Li, 2012; Cobos, Estupiñań, & Pérez, 2011; Geem & Sim, 2010; Omran & Mahdavi, 2008; Pan, Suganthan, Tasgetiren, & Liang, 2010; Wang & Huang, 2010; Wang & Guo, 2013; Wu, Qian, Ni, & Fan, 2012; Yadav, Kumar, Panda, & Chang, 2012; Zou, Gao, Wu, & Li, 2010), job shop scheduling (Liu & Zhou, 2013; Wang, Pan, & Tasgetiren, 2010, 2011; Yuan, Xu, & Yang, 2013), knapsack problem (Zou, Gao, Li, & Wu, 2011), the training of neural networks (Kulluk, Ozbakir, & Baykasoglu, 2011, 2012), network design (Geem, 2006, 2009), and many others (Askarzadeh & Rezazadeh, 2012; Leandro dos Santos Coelho & Diego Luis de Andrade Bernert, 2009; Geem, 2008; Wang & Li, 2013; Wang et al., 2013). Among them, numerical function optimization problems have been investigated by more and more researchers during the last few years. That is to say, many variants of HS have been developed to improve its convergence performance for global optimization. For example, on the basis of HS, Omran and Mahdavi (2008) proposed a Global-best harmony search (GHS for short) algorithm which took advantage of direction information of the best individual (best harmony) to guide the search, and GHS has achieved better performance than standard HS. Later, in order to overcome the weakness of parameters of HS chosen by hand, Wang and Huang (2010) introduced a self-adaptive harmony search (SAHS) algorithm which eliminates the selection of the values of parameters *PAR* and *bw*. Namely, SAHS dynamically updates the parameter *PAR* at first and then generates a new harmony vector according to the maximum and minimum values of the decision variables in the harmony memory (HM) with some associated probability. Meantime, Pan et al. (2010) proposed a self-adaptive global best harmony search (SGHS) algorithm, in which a new improvisation scheme is proposed and those control parameters are dynamically changed by a learning mechanism or dynamically decreased with generation counter. Experimental results show that SGHS is more effective in finding better solutions than some HS variants such as HS, IHS (Mahdavi et al., 2007) and GHS.

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http://dx.doi.org/10.1016/j.eswa.2014.03.016
0957-4174/

Moreover, SGHS has been successfully applied to train neural networks (Kulluk et al., 2011). Then, Geem and Sim (2010) introduced a novel technique, named parameter-setting-free (PSF) technique, which alleviates the burden of manually searching the best parameters setting. Alatas (2010) proposed a chaotic harmony search (CHS) algorithm, where some random numbers needed are generated by using a chaotic sequence instead of a random sequence. Zou et al. (2010) developed a novel global harmony search (NGHS) algorithm, in which a novel position updating scheme and genetic mutation mechanism are employed. Cobos et al. (2011) presented a novel variant of HS, called GHS + LEM, which is based on GHS and a novel technique from learnable evolution models (LEM). Yadav et al. (2012) proposed an intelligent tuned harmony search (ITHS) algorithm through borrowing some concepts from the decision making theory. The ITHS can intelligently maintain a proper balance between intensification and diversification based on its consciousness or previous experience. Chen et al. (2012) proposed a new harmony search variant, called NDHS, which employed a novel memory consideration rule and a new pitch adjustment scheme. Besides, HS may be hybridized with other heuristic algorithms such as the artificial bee colony (ABC) algorithm and the bat algorithm. For example, two hybrid algorithms, HHSABC (Wu et al., 2012) and HS/BA (Wang & Guo, 2013) were proposed by Wu et al. (2012) and Wang and Guo (2013), respectively. More recently, Ashrafi and Dariane (2013) proposed a novel approach, called AIP_MS, which is based on melody search (MS) with a novel alternative improvisation procedure (AIP). When compared with HS, IHS, GHS, SGHS, NGHS and basic MS, AIP_MS has achieved better solutions than other state-of-the-art HS variants in most of the cases.

Generally speaking, adjusting schemes of parameters of HS and hybridization of HS with other heuristic techniques are the hotspots of HS from the above mentioned statements.

Although the aforementioned HS variants have shown a better performance than the classical HS, their convergence performance is still necessary to be further improved. Therefore, an improved global-best harmony search algorithm, referred to as IGHS, is proposed in this paper. To evaluate the performance of IGHS, it is compared with HS, GHS, and other eight well known algorithms over a testbed made up of twenty-eight benchmark functions. The experimental results show that IGHS outperformed HS, GHS in almost all the cases in terms of the best, worst, median, mean, standard deviation (Std.) and successful rate (SR) values of the solutions obtained by each algorithm in 30 independent runs. When compared with other eight meta-heuristic algorithms including two recent algorithms AIP_MS and Teaching–Learning-Based Optimization algorithm (TLBO) (Rao & Patel, 2013; Rao, Savsani, & Balic, 2012; Rao, Savsani, & Vakharia, 2011; Rao, Savsani, & Vakharia, 2012), the numerical results also demonstrate the effectiveness and the superiority of IGHS.

The remaining of the paper is arranged as follows. HS is summarized in Section 2. And then GHS is described briefly in Section 3. Subsequently, the proposed algorithm, called IGHS, is elaborated in Section 4. Some experimental studies regarding the numerical benchmark functions, along with their analysis and discussions are summarized in Section 5. Finally, Section 6 is devoted to conclusions and the future work.

2. Harmony search algorithm

In 2001, Geem et al. (2001) first proposed a new meta-heuristic algorithm, i.e., harmony search (HS) algorithm by mimicking the improvisation process of music players, where musicians improvise the pitches of their instruments to search for a perfect state of a harmony. That is, the process of searching for a better harmony is analogous to that of seeking better solutions to optimization problems. Like other meta-heuristic algorithms, there is a population, called harmony memory (HM), in HS. Besides, there are some control parameters such as harmony memory size *HMS*, harmony memory considering rate $HMCR \in [0,1]$ used for determining whether the value of a decision variable is to be chosen from HM, pitch adjusting rate $PAR \in [0,1]$ used for deciding whether the decision variables are to be further adjusted. In short, the HS algorithm mainly consists of five phases. These are initialization of the algorithm, improvisation of a new harmony, updating of harmony memory, etc. And it works as follows.

2.1. Problem description and initialization of HS parameters

Usually, the optimization problem can be described as follows without loss of generality.

$$min_x \quad f(x) \tag{1}$$

where $x = (x_1, x_2, \ldots, x_D) \in \Re^D$, and the feasible solution space or the solution search space is $\Omega = \prod_{j=1}^{D}[L_j, U_j]$, meanwhile, L_j and U_j are the lower bound and upper bound of the jth decision variable, respectively.

Then, the HS parameters are initialized at this step. That is, parameters *HMS*, *HMCR*, *PAR*, bandwidth *bw* for controlling the radius of search, and the number of improvisation *NI* corresponding to the number of iterations are all initialized.

2.2. Initialization of harmony memory

In HS, harmony memory is similar to a population of other meta-heuristic algorithms. Likewise, harmony memory size means population size. Thus, a set of *HMS* harmonies may be generated randomly at the step by the following equation.

$$x_{ij} = L_j + (U_j - L_j) \cdot rand(0,1) \tag{2}$$

where $i = 1, 2, \ldots, HMS, j = 1, 2, \ldots, D$; L_j and U_j are the lower bound and upper bound of the component j, respectively. And each harmony x_i representing a solution is a D-dimensional vector. Next, the objective value of each solution is evaluated according to the Eq. (1).

2.3. Improvise a new harmony

After the above initialization, the HS will generate (improvise) a new harmony vector $x' = (x'_1, x'_2, \ldots, x'_D)$ from scratch based on three rules composed of memory consideration, pitch adjustment and random selection. And the process can be shown as in Algorithm 1.

Algorithm 1. The procedure of improvising a new harmony

for $j = 1$ to D **do**
  //memory consideration
  if $rand(0,1) \leqslant HMCR$ **then**
    Choose a harmony x_i from HM randomly, $i \in [1..HMS]$
    $x'_j = x_{i,j}$
    // pitch adjustment
    if $rand(0,1) \leqslant PAR$ **then**
      $x'_j = x'_j \pm rand(0,1) \cdot bw$
    end if
  else
    $x'_j = L_j + rand(0,1) \cdot (U_j - L_j)$ // random selection
  end if
end for