ESANN 2014 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 23-25 April 2014, i6doc.com publ., ISBN 978-287419095-7. Available from http://www.i6doc.com/fr/livre/?GCOI=28001100432440.

Swim Velocity Profile Identification through a Dynamic Self-adaptive Multiobjective Harmonic Search and RBF Neural Networks

Helon V. H. Ayala[1], Luciano F. da Cruz[1], Leandro S. Coelho[1,2] and Roberto Z. Freire[1]

1- Pontifical Catholic University of Parana - PUCPR, Industrial and Systems Engineering Graduate Program – PPGEPS. Imaculada Conceição 1155, Curitiba, Parana – Brazil.
2- Federal University of Parana - UFPR, Department of Electrical Engineering - DEE/PPGEE. Polytechnic School of UFPR, Curitiba, Parana – Brazil.

Abstract. Technology has been successfully applied in sports, where biomechanical analysis is one of the most important areas used to raise the performance of athletes. In this context, this paper focuses on swim velocity profile identification using Radial Basis Functions Neural Networks (RBF-NN) trained by the Gustafson-Kessel clustering combined with a novel Dynamic Self-adaptive Multiobjective Harmony Search (DS-MOHS). One study case is analyzed, from real data acquired of an elite female athlete, swimming breaststroke style. Better results are obtained by DS-MOHS when compared with standard multiobjective harmony search in terms of accuracy and generalization of the model.

1 Introduction

From 1980s, Artificial Neural Networks (ANN) have received considerable attention from researchers, as they presented themselves as great tools for nonlinear identification and time series forecasting. Radial Basis Functions Neural Networks (RBF-NN) are a special type of ANN which are formed by three layers, namely (i) input layer, (ii) hidden layer and (iii) output layer. RBF-NN has its most general form when all parameters are obtained through supervised learning to define the output weights [1].

A stochastic optimization algorithm called Harmony Search (HS) was proposed in 2001 [2] and has found many successful applications for several problems, including NN training [3]. Several adaptations of the original HS algorithm have been made so as to obtain better quality solutions. Among them, dynamic self-adaptive approaches were set, so as to adaptively set the search parameters during the search procedure [4] and multiobjective versions of the original HS have also been proposed in the literature [5]-[7].

One of the more complex areas of interest in biomechanics is the study of human swimming propulsion. In a recent study [8], the authors investigate the use of differential evolution algorithm applied to RBF-NN training for swim velocity profile identification.

The present paper proposes the use of the RBF-NN training through the Dynamic Self-adaptive Multiobjective Harmony Search (DS-MOHS) approach for time series forecasting applied to the identification of swim velocity profiles. The overall identification procedure based on RBF-NN training uses the Gustafson-Kessel (GK) clustering algorithm [9], multiobjective optimization and the Penrose-Moore

ESANN 2014 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 23-25 April 2014, i6doc.com publ., ISBN 978-287419095-7.
Available from http://www.i6doc.com/fr/livre/?GCOI=28001100432440.

pseudo-inverse. The efficiency of DS-MOHS is compared to the classical MOHS approach.

The remainder of this paper is organized as follows. Section II covers background information multiobjective optimization, MOHS and DS-MOHS. Section III gives a brief mathematical description of RBF-NN models and its proposed training procedure. Section IV describes a study case to the swimming velocity identification. Section V, provides the results and discussions. The conclusions and future research directions are stated finally at Section VI.

2 Harmonic Search for Multiobjective Optimization

The HS algorithm emulates the musician performance when seeking the best of harmony (in an aesthetic sense). Thus the HS algorithm seeks the best state, that is, the global optimum, determined on the basis of the objective function given by the current problem. The following steps define the HS optimization procedure [10] as proposed by Geem et al. in [2], where the full description about the procedure can be found:

Step 1. Initialization of the algorithm. The optimization problem is given by minimize $f(x)$, subject to $x_i \in X_i$, $i = 1, ..., N$. The control parameters, namely (i) The size of the harmony memory matrix (HMS); (ii) the harmony memory considering rate (HMCR); (iii) the pitch adjusting rate (PAR); and (iv) stopping criterion (maximum number of improvisations t_{max}) are specified in this step.

Step 2. Random initialization of the harmony memory. The harmony memory (HM) keeps all vectors of decision variables found. It is initialized with randomly generated solution vectors using a uniform distribution in the present step.

Step 3. New harmony improvisation. A new harmony vector $x^{new} = (x_1^{new}, x_2^{new}, ..., x_N^{new})$ is generated by improvisation based on the following rules: (i) memory consideration, (ii) pitch adjustment, and (iii) random selection.

Step 4. Update HM. If the new harmony is better than any of the ones contained in HM (in terms of the objective function *f(x)*), x^{new} is included in the harmony memory and the worst harmony in HM is excluded.

Step 5. Repeat *Steps 3* and *4* until the maximum number of improvisations (stopping criterion) has been made.

2.1 Multiobjective Harmony Search

In order to cope with multiobjective problems, the original HS algorithm previously stated has been adapted to MOHS. The MOHS changes Steps 1 and 4 from standard HS, as stated below.

Step 1: *Initialization of the algorithm.* For a multiobjective optimization task, the following problem definition is to minimize $f_q(x)$, subject to $x_i \in X_i$, $q = 1, …, M$; $i = 1, ..., N$, where $f_q(x)$ is the q-th objective function and M is the total number of objective functions. The control parameters HMS, HMCR, PAR and t_{max} are also set.

ESANN 2014 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 23-25 April 2014, i6doc.com publ., ISBN 978-287419095-7. Available from http://www.i6doc.com/fr/livre/?GCOI=28001100432440.

Step 4: *Update HM*. Whenever the new harmony x^{new} is found to be better than any contained in HM, it is included in the harmony memory and the worst harmony in HM is excluded. In order to rank the solutions in HM, MOHS uses the concept of non-dominance and crowding distance (as in NSGA-II [11]) at each improvisation.

2.2 Dynamic Self-adaptive Multiobjective Harmony Search

The use of dynamic self-adaptation for adjusting the control parameters of HS has been developed recently in [4]. The definition of the parameters PAR and *bw* (it is an arbitrary distance bandwidth in the *i*-th dimension and *r* is a random number generated using uniform distribution in the range [0,1]) are automatic and independent of the iteration count (in opposition with other self-adaptive techniques).

The concept of Best-to-Worst ratio (*BtW*) in multiobjective optimization measures quality of the solutions stored in HM in approximating its current best in each objective and is calculated as

$$\mathrm{BtW} = \max_i \frac{f_i(x^b)}{f_i(x^w)} \tag{1}$$

where $f_i(x^b)$ and $f_i(x^w)$ are the best and worst value of the *i*-th objective function (restricting to the case of minimization of all *M* objective functions). *BtW* is calculated before each iteration. The PAR control parameter is then set dynamically based on the actual BtW value, as follows [4]

$$\mathrm{PAR} = (\mathrm{PAR}_{min} - \mathrm{PAR}_{max})\mathrm{BtW} + \mathrm{PAR}_{max} \tag{2}$$

where PAR_{min} and PAR_{max} may be set to small value greater than zero (e.g. 0.1) and 1, respectively. The PAR value is thus set according to the quality of the solutions in the HM. Whenever the *BtW* value decreases, conversely the PAR value increases in order to make use of the local exploitation ability of HS – making new modifications to x^{new}. If *BtW* increases, what means that there are higher quality solutions in the HM, PAR decreases to emphasize exploration and causing perturbation in the current HM [4].

The pitch bandwidth is adjusted on the basis of the standard deviation of the solution vectors in the memory along for each dimension [4]

$$bw_i = C.\mathrm{StdDev}(HM^i) \tag{3}$$

where StdDev(HM^i) represents the standard deviation of the *i*-th dimension among all solutions contained in the HM, and the factor *C* is adopted as [4] having *AccRate* as the number of accepted improvisations in HM in the last 100 iterations, $AccC_{th}$ as the threshold (set as 20%) at which *C* starts to decrease [4].

$$C = \begin{cases} 2 & ,\text{if AccRate} \geq \text{AccC}_{th} \\ 2\dfrac{\text{AccRate}}{\text{AccC}_{th}} & ,\text{if AccC}_{th} > \text{AccRate} > 1 \\ 0.1 & ,\text{if AccRate} \leq 1 \end{cases} \tag{4}$$

Equations (1)-(4) are applied at each harmony improvisation in *Step 3*, in order to calculate the current PAR and *bw* values to be applied in the process.

ESANN 2014 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 23-25 April 2014, i6doc.com publ., ISBN 978-287419095-7. Available from http://www.i6doc.com/fr/livre/?GCOI=28001100432440.

3 Radial Basis Functions Neural Networks

Radial Basis Functions Neural Networks (RBF-NN) is a type of artificial neural networks, where the Gaussian function is the most widely used radial basis function.

The proposed RBF-NN training adjusts the Gaussian basis function centers using the GK clustering algorithm [9]. The multiobjective optimization methods optimize the widths and locally the centers of the Gaussian basis functions. In the present work, the lower and upper bounds for the RBF centers are set respectively as 80% and 120% of the minimum and maximum values of the centers obtained by the GK clustering algorithm.

The training procedure splits the observed data into training (50%), validation (25%) and test (25%) sets. Being so, the multiple correlation metric defined as

$$R^2 = 1 - \frac{\sum_{t=1}^{Ns} [y(t) - \hat{y}(t)]^2}{\sum_{t=1}^{Ns} [y(t) - \bar{y}]^2} \tag{5}$$

where N_s is the total number of samples, y(t) is the actual data, $\bar{y}$ its average and $\hat{y}(t)$ is the output predicted by the model. For training and validation phases we have R^2_{tr} and R^2_v respectively.

The following objective functions are defined according to Step 1 for both MOHS and DS-MOHS.

$$f_1(x) = \frac{1}{1 + R^2_{tr}}, \; f_2(x) = \frac{1}{1 + R^2_v} \tag{6}$$

Being so, the training procedure aims at accuracy of the model and its generalization. It is important to mention that a value for R^2 between 0.9 and 1.0 is considered sufficient [12].

4 Data Acquisition System for Swim Velocity Profile

Technology can be used as a complementary tool to give important information which will be the difference in the competition environment, where the performance of high level athletes must be sought at all times. With the purpose to reach a technologic tool to support swim velocity profile identification, a data acquisition system was used to acquire data from breaststroke style swam for 25 meters by an elite female swimmer. For details, please refer to [8].

5 Simulation Results

The parameters set for MOHS are 100, 0.95, 0.5 and 10% of each decision variable range for HMS, HMCR, PAR and *bw*, respectively. For sake of comparison, the parameters for DS-MOHS are set as 100 and 0.95 for HMS and HMCR respectively.

ESANN 2014 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 23-25 April 2014, i6doc.com publ., ISBN 978-287419095-7. Available from http://www.i6doc.com/fr/livre/?GCOI=28001100432440.

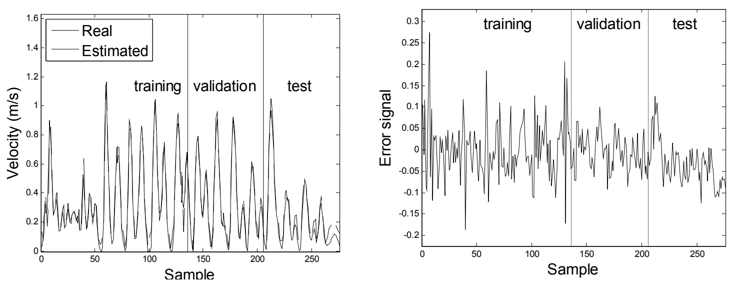
Each algorithm is tested in 30 runs with different initial conditions and termination criterion of 300,000 improvisations. It has been tested the algorithm progressively increasing the number of neurons in the hidden layer of the RBF-NN from 4 to 9. The best trade-off solution is termed hereafter as the one with the least harmonic mean of the fitness values obtained after normalization.

Table 1 shows the mean and standard deviation values of the Hypervolume (HV) [13] and Euclidian Distance (ED) indicators obtained by MOHS and DS-MOHS after 30 runs, as well as the multiple correlation coefficients for training, validation and test phases obtained by the most trade-off solution from DS-MOHS. We can see that, for all number of neurons tested, DS-MOHS outperforms MOHS in both HV and EV metrics. It is possible to see that while there is a trend for the values for the training and validation phases to grow according to the number of neurons, the value for the test phase decreases. This fact suggests the compromise of complexity and generalization. In Fig. 1(a) and (b) can be seen the one-step-ahead prediction for the most trade-off solution obtained by DS-MOHS and the error signal to the same case.

By comparing the results in this paper to the previous work [8], it can be verified that the new approach using DS-MOHS has provided better approximation results for the breaststroke style than the MDE (Modified Differential Evolution).

	MOHS		DS-MOHS		DS-MOHS (best trade-off solution)		
No. of Neurons	HV	ED	HV	ED	$R^2_{training}$	$R^2_{validation}$	R^2_{test}
4	0.51±0.05	0.61±0.05	**0.62±0.12**	**0.47±0.12**	0.9338	0.9736	0.9280
5	0.59±0.04	0.52±0.02	**0.69±0.09**	**0.43±0.08**	0.9351	0.9742	0.9139
6	0.67±0.04	0.50±0.06	**0.77±0.07**	**0.40±0.07**	0.9359	0.9744	0.9092
7	0.61±0.04	0.53±0.05	**0.76±0.06**	**0.38±0.06**	0.9406	0.9741	0.9135
8	0.65±0.03	0.47±0.04	**0.77±0.07**	**0.34±0.07**	0.9431	0.9781	0.8895
9	0.75±.03	0.35±0.06	**0.90±0.07**	**0.18±0.06**	0.9468	0.9793	0.8232

Table 1: Hypervolume (HV), Euclidean Distance (ED) metrics and multiple correlation values for the best trade-off solution for the breaststroke time-series.



(a) (b)

Fig. 1: (a) One-step-ahead prediction results and (b) error for the best trade-off solution found by DS-MOHS for training, validation and test phases using 4 neurons.

6 Conclusion

The present work showed the application of RBF-NN trained with multiobjective HS to time series modeling of real data acquired from a female elite athlete. Moreover, HS algorithm has been extended to cope with multiple objectives and further improved to a novel dynamic self-adaptive version with less project parameters.

Based on previous [8] and the present work, future research will focus on the further development of new technologies for the identification of swimming velocity profile, which may be applicable to e.g. the estimation of the parameters of the swimmer, reduction of resistance with water and the improvement of the movements of the swimmer.

References

[1] S. S. Haykin, *Neural networks and learning machines*, Prentice Hall, New York, 2009.

[2] Z. W. Geem, J. H. Kim and G.V. Loganathan, A new heuristic optimization algorithm: harmony search, *Simulation*, vol. 76, no. 2, pp. 60-68, 2001.

[3] S. Kulluk, L. Ozbakir and A. Baykasoglu, Training neural networks with harmony search algorithms for classification problems, *Engineering Applications of Artificial Intelligence*, vol. 25, no.1, pp. 11-12, 2012.

[4] A. Kattan and R. Abdullah, A dynamic self-adaptive harmony search algorithm for continuous optimization problems, *Applied Mathematics and Computation*, vol. 219, no. 16, pp. 8542-8567, 2013.

[5] J. Ricart, G. Hüttemann, J. Lima and B. Barán, Multiobjective Harmony Search Algorithm Proposals, *Electronic Notes in Theoretical Computer Science*, vol. 281, pp. 51-67, 2011.

[6] S. Sivasubramani and K.S. Swarup, Environmental/economic dispatch using multi-objective harmony search algorithm, *Electric Power Systems Research*, vol. 81, no. 9, pp. 1778-1785, 2011.

[7] S. Sivasubramani and K.S. Swarup, Multi-objective harmony search algorithm for optimal power flow problem, *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 3, pp. 745-752, 2011.

[8] L. F. Cruz, L. S. Coelho and R. Z. Freire, Swim velocity profile identification by using a modified differential evolution method associated with RBF neural network, in proceedings of the *3rd International Conference on Innovative Computing Technology* (INTECH 2013), pp. 389-395, London, 2013.

[9] E. Gustafson and W. Kessel, Fuzzy clustering with a fuzzy covariance matrix, in Proceedings of the *IEEE Conference on Decision and Control*, pp. 761-766, San Diego, 1979.

[10] L. S. Coelho and D. L. A. Bernert, An improved harmony search algorithm for synchronization of discrete-time chaotic systems, *Chaos*, Solitons and Fractals, vol. 41, no. 5, pp. 2526-2532, 2009.

[11] K. Deb, A. Pratap, S. Agarwal and T. A. M. T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, in *IEEE Transactions on Evolutionary Computation*, vol. 6, pp. 182-197, 2002.

[12] B. Schaible, H. Xie and Y. C. Lee, Fuzzy logic models for ranking process effects, in *IEEE Transactions on Fuzzy Systems*, vol. 5, no. 4, pp. 545-556, 1997.

[13] C. M. Fonseca, L. Paquete and M. López-Ibáñez, An improved dimension - sweep algorithm for the hypervolume indicator, in proceedings of the *2006 Congress on Evolutionary Computation* (CEC'06), pp. 1157-1163, Piscataway, New Jersey, 2006.