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Optimal design of fuzzy classification systems using PSO with dynamic parameter adaptation through fuzzy logic

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ABSTRACT

In this paper a new method for dynamic parameter adaptation in particle swarm optimization (PSO) is proposed. PSO is a metaheuristic inspired in social behaviors, which is very useful in optimization problems. In this paper we propose an improvement to the convergence and diversity of the swarm in PSO using fuzzy logic. Simulation results show that the proposed approach improves the performance of PSO. First, benchmark mathematical functions are used to illustrate the feasibility of the proposed approach. Then a set of classification problems are used to show the potential applicability of the fuzzy parameter adaptation of PSO.

1. Introduction

Fuzzy logic or multi-valued logic is based on fuzzy set theory proposed by (Zadeh, 1965a), which helps us in modeling knowledge, through the use of if-then fuzzy rules (Yen & Langari, 1998).

The fuzzy set theory provides a systematic calculus to deal with linguistic information (Kulkarni, 2001), and that improves the numerical computation by using linguistic labels stipulated by membership functions (Jang, Sun, & Mizutani, 1997; Zadeh, 1965b, 1997).

Particle swarm optimization (PSO) that was introduced by Kennedy and Eberhart in 1995 (Kennedy & Eberhart, 1995, 2001), maintains a swarm of particles and each particle represents a possible solution. These particles "fly" through a multidimensional search space, where the position of each particle is adjusted according to your own experience and that of its neighbors (Engelbrecht, xxxx).

PSO has recently received many improvements and applications (Bingül & Karahan, 2011). Most of the modifications to PSO are to improve convergence and to increase the diversity of the swarm (Engelbrecht, xxxx). For example, S. Muthukaruppan, M.J. Er proposed a hybrid particle swarm optimization based fuzzy expert system for the diagnosis of coronary artery disease (Muthukaruppan & Er, 2012). Chunshien Li, Tsunghan Wu proposed an adaptive fuzzy approach to function approximation with PSO and the recursive least squares estimator (Li & Wu, 2011). So in this paper we propose an improvement to the convergence and diversity of PSO through the use of fuzzy logic. Basically, fuzzy rules are used to control the key parameters in PSO to achieve the best possible dynamic adaptation of these parameter values (Abdelbar, Abdelshahid & Wunsch, 2005; Valdez, Melin & Castillo, 2011). First, benchmark mathematical functions are used to illustrate the feasibility of the proposed approach. Then a set of classification problems are used to show the potential applicability of the fuzzy parameter adaptation of PSO.

The rest of the paper is organized as follows. Section 2 describes the proposed methodology. Section 3 shows how the experiments were performed with the proposed method and the simple method using the benchmark functions defined in Section 2. Section 4 shows how to perform the statistical comparison with all its parameters and analysis of results. Section 5 shows the design of fuzzy classifier. Section 6 shows the methodology to follow for the design of fuzzy classifier. Section 7 shows how the experiments were performed with the proposed method and the simple method in the design of fuzzy classifier. Section 8 shows how to perform the statistical comparison with all its parameters and analysis of results. Section 9 shows the conclusions of the design of fuzzy classifier design. Finally, the conclusions of this paper are presented.

2. Methodology for parameter adaptation

The dynamics of PSO is defined by Eqs. (1) and (2), which are the equations to update the position and velocity of the particle, respectively.

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (1)$$

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1(t)\lfloor y_{ij}(t) - x_{ij}(t)\rfloor + c_2 r_{2j}(t)\lfloor \hat{y}_j(t) - x_{ij}(t)\rfloor \quad (2)$$

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Parameters c_1 and c_2 were selected to be adjusted using fuzzy logic, since those parameters account for the movement of the particles.

The parameter c_1 or cognitive factor represents the level of importance given the particle to its previous positions.

The parameter c_2 or social factor represents the level of importance that the particle gives the best overall position.

Based on the literature (Engelbrecht, xxxx) the recommended values for c_1 and c_2 must be in the range of 0.5 and 2.5, plus it is also suggested that changing the parameters c_1 and c_2 dynamically during the execution of this algorithm can produce better results.

In addition it is also found that the algorithm performance measures, such as: diversity of the swarm, the average error at one point in the execution of the algorithm, the iterations themselves, needs to be considered to run the algorithm, among others. In our work all the above are taken in consideration for the fuzzy systems to modify the parameters c_1 and c_2 dynamically changing these parameters in each iteration of the algorithm.

For measuring the iterations of the algorithm, it was decided to use a percentage of iterations, i.e. when starting the algorithm the iterations will be considered "low", and when the iterations are completed it will be considered "high" or close to 100%. To represent this idea we use:

$$Iteration = \frac{Current\ Iteration}{Maximum\ of\ Iterations} \quad (3)$$

The diversity measure is defined by Eq. (4), which measures the degree of dispersion of the particles, i.e. when the particles are closer together there is less diversity as well as when particles are separated then diversity is high. As the reader will realize the equation of diversity can be considered as the average of the Euclidean distances between each particle and the best particle.

$$Diversity\ (S(t)) = \frac{1}{n_s}\sum_{i=1}^{n_s}\sqrt{\sum_{j=1}^{n_x}(x_{ij}(t) - \bar{x}_j(t))^2} \quad (4)$$

The error measure is defined by Eq. (5), which measures the difference between the swarm and the best particle, by averaging the difference between the fitness of each particle and the fitness of the best particle.

$$Error = \frac{1}{n_s}\sum_{i=1}^{n_s}(Fitness(x_i) - MinF) \quad (5)$$

Therefore for designing the fuzzy systems, which dynamically adjust the parameters of c_1 and c_2, the three measures described above were considered as inputs. It is obvious that for each fuzzy system the outputs are c_1 and c_2.

In regards to the inputs of the fuzzy systems, the iteration variable has by itself a defined range of possible values which range from 0 to 1 (0 is 0% and 1 is the 100%), but with the diversity and the error, we perform a normalization of the values of these to have values between 0 and 1. Eq. (6) shows how the normalization of diversity is performed and Eq. (7) shows how the normalization of the error is obtained.

$$DiverNorm = \begin{cases} if\ MinDiver = MaxDiver\{DiverNorm = 0 \\ if\ MinDiver \neq MaxDiver\{DiverNorm = FbNorm \end{cases} \quad (6)$$

$$FnNorm = \frac{Diversity - MinDiver}{MaxDiver - MinDiver}$$

Eq. (6) shows two conditions for the normalization of diversity, the first provides that where the maximum Euclidean distance is equal to the minimum Euclidean distance, this means that the particles are exactly in the same position so there is no diversity. The second condition deals with the cases with different Euclidean distances.

$$ErrorNorm = \begin{cases} if\ MinF = MaxF\{ErrorNorm = 1 \\ if\ MinF \neq MaxF\ \{ErrorNorm = \frac{Error - MinF}{MaxF - MinF} \end{cases} \quad (7)$$

Eq. (7) shows two conditions to normalize the error, the first one tells us that when the minimum fitness is equal to the maximum fitness, then the error will be 1; this is because the particles are close together. The second condition deals with the cases with different fitness.

The design of the input variables can be appreciated in Figs. 1, 2 and 3, which show the inputs iteration, diversity, and error respectively, each input is granulated into three triangular membership functions.

For the output variables, as mentioned above, the recommended values for c_1 and c_2 are between 0.5 and 2.5, so that the output variables were designed using this range of values. Each output is granulated in five triangular membership functions, the design of the output variables can be seen in Figs. 4 and 5, c_1 and c_2 respectively.

Having defined the possible input variables, it was decided to combine them to generate different fuzzy systems for dynamic adjustment of c_1 and c_2. Based on the combinations of possible inputs, there were seven possible fuzzy systems, but it was decided to consider only the systems that have more inputs (since we previously considered fuzzy systems with only a single input), so that eventually there were three fuzzy systems which are defined below.

The first fuzzy system has iteration and diversity as inputs, which is shown in Fig. 6. The second fuzzy system has iteration and error as inputs and is shown in Fig. 7. The third fuzzy system has iteration, diversity, and error as inputs, as shown in Fig. 8.

To design the rules of each fuzzy system, it was decided that in early iterations the PSO algorithm must explore and eventually exploit. Taking into account other variables such as diversity, for example, when diversity is low, that is, that the particles are close together, we must use exploration, and when diversity is high we must use exploitation.

The rules for each fuzzy system are shown in Figs. 9–11, for the fuzzy systems 1, 2 and 3, respectively.

Also for the comparison of the proposed method with respect to the PSO without parameter adaptation, we considered benchmark mathematical functions, defined in Haupt & Haupt, xxxx; Marcin, 2005, which are 27 in total, and in each we must find the parameters that give us the global minimum of each function. In Fig. 12 there is a sample of the functions that are used.

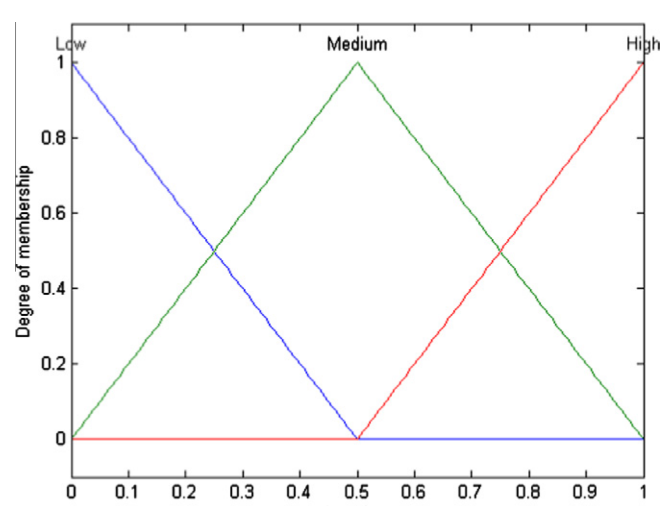

Fig. 1. Input 1: iteration.