J. Yaghob (Ed.): ITAT 2015 pp. 121–126
Charles University in Prague, Prague, 2015

Planning Fitness Training Sessions Using the Bat Algorithm

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Abstract: Over fairly recent years the concept of an artificial sport trainer has been proposed in literature. This concept is based on computational intelligence algorithms. In this paper, we try to extend the artificial sports trainer by planning fitness training sessions that are suitable for athletes, especially during idle seasons when no competition takes place (e.g., winter). The bat algorithm was used for planning fitness training sessions and results showed promise for the proposed solution. Future directions for development are also outlined in the paper.

1 Introduction

Sport becomes highly addictive for many people in the world. A few decades ago, people around the world spend their free time doing different activities, like: short walks through the park, visiting the cinema or galleries, fishing, visiting a thermal spa and also meet friends. A lot of leisure studies also proved this. However, over recent decades, lifestyles have been substantially changed especially because of globalization that has transformed the whole earth into a global village. Due to a lack of time as well as personal willingness, people do not want to live like they used to. For this reason, different kind of new activities have emerged over recent past years. One of the bigger revitalizations has been sport which has became extremely in popular because of the emergence of different mass sports events. For instance, the main mass sport events are:

- Triathlon - This discipline consists of three sports: swimming, cycling and running. Additionally, there are different distances which vary from short via medium to long distances. One of the more famous distances is the Ironman triathlon [1, 2, 3], which is also known as the hardest one day sport event. Ironman consists of 3.8 km of swimming, 180 km of cycling and 42.2 km of running.
- Road marathons - A road marathon [4] consists of 42.2 km pure running and is a challenge for myriad of people. Big city marathons especially are the most popular and attract large numbers of runners. Some marathons can accommodate more than 40,000 runners [5, 6].
- Recreational cycling marathons - This kind of mass [7, 8] sports events was very popular approximately 10 years ago but still represents a challenge for numerous participants. The current world economic problems increased the prices of cycles and consequently less participants could participate on cycling marathons.

Participants of the mentioned events participate mostly because of two goals. The first goal is to enjoy (in other words: to have a nice time) and the second is to finish the trial. Usually, finishers are awarded with medals which are big stimulants for participants. In this case, every year many more participants have also began to take these competitions more seriously, i.e., semi professional. In line with this, they invest much more time in preparations for competitions. Unfortunately, there is a long way for good preparations for such kinds of competitions. This good preparation consists of proper sports training, good eating and also good resting. To maintain all these factors as high as possible is very hard for numerous athletes, since they do not have enough experience. Newbie athletes especially suffer from the unwanted effects of irregular training called over-training syndrome [9, 10, 11] which is reflected in reduced form. One of the possible solutions for avoiding this is to hire a personal trainer or join diverse training groups. However, these cost a lot of money and therefore many of them can not afford them.

In order to break this barrier, we began the development of an artificial sport trainer. An artificial sports trainer was presented recently in [12] and is based on computational intelligence [13] algorithms that are able for plan the sports training over both short-term and long-term. This trainer is also able to discover the different habits of athletes, avoid over-training, etc. Data for the artificial sports trainer are obtained from sports trackers [14] and sports watches like Garmin.

This paper, extends the artificial sport trainer with planning fitness training sessions. These kinds of training sessions are very important for athletes especially during idle seasons. In Europe, the idle season is usually during winter months when the athletes prepare their form for the whole season. Planning fitness sessions were performed using a bat algorithm [15, 16] which is a member of the computational intelligence family. The planning of the fitness sessions was defined as a constraint satisfaction problem, where the bat algorithm searches for feasible solutions arising when the number of constraint violations achieved the value of zero.

Organization of the remainder of this workshop paper is as follows: in section 2 we discuss about characterists of fitness training, while section 3 presents swarm intelligence algorithms and bat algorithm. Experiments and results are presented in section 4, while section 5 concludes the paper.

2 Characteristics of Fitness Training

This study, focused on fitness training in regard to cycling. Incorporation of strength training in cyclists preparatory periods has received more attention over the last two decades. Most of the serious and competitive cyclists also include strength training in their training programs. It is also evident in some previous research that adding strength training to an endurance training program can increase endurance performance [17, 18].

A combination of endurance and strength training (concurrent training) might therefore be a potential training strategy for promoting muscle oxidative capacity. It might be related to an improved cycling economy, as observed after adding strength training to the ongoing endurance training, namely because a stronger muscles at a certain intensity operates longer with a lower percentage of maximum capacity. It is well-known that adding strength training to endurance training can increase the maximal strengths and rate of force developments in cyclists. In theory, this may improve pedaling characteristics by increasing peak torque in the pedal stroke, reducing time to peak torque and reducing the pedaling torque relative to maximal strength, which in turn may allow for higher power output and/or increased blood flow.

The most important thing for developing a cycling strength program is to know, which muscle groups are the most active during the pedal stroke. Some previous studies have detected a strong correlation between cycling performance and some strength exercises, like leg presses, squats, and deadlifts [17, 18, 19, 20]. Some of the more useful exercises for fitness training are presented in Figs. 1 to 3.

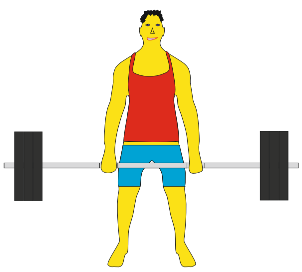

Figure 1: Deadlift exercise

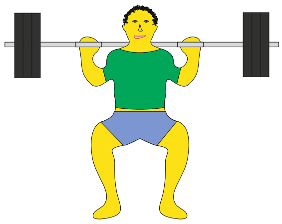

Figure 2: Squats exercise

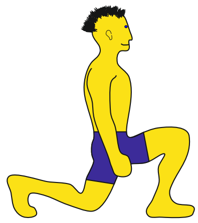

Figure 3: Lunge exercise

For the smart planning of sports training, quantifications, regulating the intensity of a workout is the key for success as indicated as basic knowledge in sports training literature. This fact also holds for fitness training. As an estimate of the intensity of a fitness workout, two main measures are employed like a:

- the number of repetitions per set of exercises (NR),
- the maximum amount of weight that can be generated in one maximum contraction (1RM).

The logic behind the first measure is as follows. The heavier the weight, the higher the intensity and the fewer repetitions (also reps) an athlete will be able to lift it for. On the other hand, the 1RM determines the desired load for an exercise (typically as a percentage of the 1RM). Let us notice that a coach determines the measure of 1RM for a definite athlete using tests at the beginning of the fitness training and then calculates the number of repeats (NR) in regard to this characteristic value.

3 Swarm Intelligence Based Algorithms

Swarm intelligence (SI) is a paradigm that belongs to computational intelligence (CI). According to the [21], SI concerns the collective, emerging behavior of multiple, interacting agents that are capable of performing simple actions. While each agent may be considered as unintelligent, the whole system of multiple agents shows some self-organizational behavior and thus can behave like some sort of collective intelligence. The basic pseudo-code of SI-based algorithms is presented in Algorithm 1. Nowadays, the bat algorithm is one of the promising members of the SI family. It is very easy to implement and shows efficient results especially when solving small dimensional problems.

Algorithm 1 Swarm Intelligence

```
initialize_population_with_random_candidate_particles;
eval = evaluate_each_particle;
while termination_condition_not_meet do
    move_particles_towards_the_best_individual;
    eval += evaluate_each_particle;
    select_the_best_individuals_for_the_next_generation;
end while
```

Next subsection describes the mentioned algorithm in detail.

3.1 Bat Algorithm

The bat algorithm was developed by Yang in 2010. The main purposes of this algorithm were to be: simple, efficient and applicable to varios problem domains. The inspiration for the bat algorithm came from the phenomenon of the echolocation characteristics of some types of microbats. Developer used a three simplified rules describing the bat behavior, as follows [22]:

- All bats use echolocation to sense distance to target objects.
- Bats fly randomly with the velocity v_i at position x_i, the frequency $Q_i \in [Q_{min}, Q_{max}]$ (also the wavelength λ_i), the rate of pulse emission $r_i \in [0,1]$, and the loudness $A_i \in [A_0, A_{min}]$. The frequency (and wavelength) can be adjusted depending on the proximities of their targets.
- The loudness varies from a large (positive) A_0 to a minimum constant value A_{min}.

The algorithm's pseudo-code is presented in Algorithm 2.

The main bat algorithm components [23] are summarized as follows:

- *initialization* (lines 1-3): initializing the algorithm parameters, generating the initial population, evaluating this, and finally, determining the best solution $\mathbf{x}_{best}$ in the population,
- *generate_the_new_solution* (line 6): moving the virtual bats in the search space according to the physical rules of bat echolocation,
- *local_search_step* (lines 7-9): improving the best solution using random walk direct exploitation (RWDE) heuristic,

Algorithm 2 Bat algorithm

Input: Bat population $\mathbf{x_i} = (x_{i1}, \dots, x_{iD})^T$ for $i = 1 \dots Np$, MAX_FE.

Output: The best solution $\mathbf{x}_{best}$ and its corresponding value $f_{min} = \min(f(\mathbf{x}))$.

```
1:  init_bat();
2:  eval = evaluate_the_new_population;
3:  f_min = find_the_best_solution(x_best); {initialization}
4:  while termination_condition_not_meet do
5:      for i = 1 to Np do
6:          y = generate_new_solution(x_i);
7:          if rand(0,1) > r_i then
8:              y = improve_the_best_solution(x_best)
9:          end if{ local search step }
10:         f_new = evaluate_the_new_solution(y);
11:         eval = eval + 1;
12:         if f_new ≤ f_i and N(0,1) < A_i then
13:             x_i = y; f_i = f_new;
14:         end if{ save the best solution conditionally }
15:         f_min=find_the_best_solution(x_best);
16:     end for
17: end while
```

- *evaluate_the_new_solution* (line 10): evaluating the new solution,
- *save_the_best_solution_conditionaly* (lines 12-14): saving the new best solution under some probability A_i,
- *find_the_best_solution* (line 15): finding the current best solution.

Generating the new solution is governed by the following equation:

$$
\begin{aligned}
Q_i^{(t)} &= Q_{min} + (Q_{max} - Q_{min}) N(0,1), \\
\mathbf{v}_i^{(t+1)} &= \mathbf{v}_i^t + (\mathbf{x}_i^t - \mathbf{best}) Q_i^{(t)}, \\
\mathbf{x}_i^{(t+1)} &= \mathbf{x}_i^{(t)} + \mathbf{v}_i^{(t+1)},
\end{aligned} \tag{1}
$$

where $N(0,1)$ is a random number drawn from a Gaussian distribution with zero mean and a standard deviation of one. A RWDE heuristic implemented in the function *improve_the_best_solution* modifies the current best solution according to the equation:

$$
\mathbf{x^{(t)}} = \mathbf{best} + \varepsilon A_i^{(t)} N(0,1), \tag{2}
$$

where $N(0,1)$ denotes the random number drawn from a Gaussian distribution with zero mean and a standard deviation of one, ε being the scaling factor, and $A_i^{(t)}$ the loudness.

Contemporary work on bat algorithms captures many variants and application domains. Some recent works are presented in papers [24, 25, 26, 27, 28]

3.2 Bat Algorithm for Planning Fitness Sessions

Based on the original bat algorithm, we have developed a modified bat algorithm for planning fitness sessions. Development of this algorithm demanded the following four steps:

- determining the fitness exercises,
- defining constraints,
- modifying the original bat algorithm,
- representing the results and their visualizations.

In the remainder of this paper, all these steps are described in detail.

Selecting Fitness Exercises. We need to determine specific exercises for different muscle groups before the fitness training can start. Although sports medicine recognizes more than 15 muscle groups that must be included within fitness training, we focus on four groups (i.e., legs, core, arms and back) in this preliminary study. Furthermore, some of these groups can be repeated during the training. Each muscle group is associated with three prescribed exercises as presented in Table 1.

Muscle groups	Exercise
LEGS	LEG PRESS, SQUATS, LUNGE
CORE	LEG SCISSORS, PLANK, LEG LIFTS
ARMS	PULLDOWN, PUSH UPS, UNDERARM ISOMETRIC EXERCISE
LEGS	LEG PRESS, SQUATS, LUNGE
BACK	BACK EXTENSION, DEADLIFT, BAR ROWS
CORE	LEG SCISSORS, PLANK, LEG LIFTS
LEGS	LEG PRESS, SQUATS, LUNGE
ARMS	PULLDOWN, PUSH UPS, UNDERARM ISOMETRIC EXERCISE

Table 1: Muscle groups and associated exercises

On the other hand, the intensities of the exercises must be determined in a fitness training plan. This intensity is associated with a measure 1RM measured for a specific athlete. Here, three levels of intensity are supported in our study, where each level is mapped according to the 1RM, as can be seen in Table 2.

Intensity	1RM measure
HIGH	1RM $>$ 80%
MEDIUM	60% $<$ 1RM $\leq$ 80%
LOW	1RM $\leq$ 60%

Table 2: Intensity mapping

Note that the data in Tables 1 and 2 were specified according to the suggestions of fitness trainers.

Defining constraints The purpose of the fitness training plan is to prescribe sufficient numbers of exercises for each of the prescribed muscle groups, their number of repeats (NR) and the proper intensities (%1RM) such that an athlete simultaneously develops all the muscle groups needed for building the cyclist's basic form. Therefore, trainers determine the proper amount of a specific exercise in the plan in regarding to the others. In order to regulate the relations between exercises in the fitness training plan, the following constraints are defined:

- at least four exercises must have the number of repeats over 25 times (i.e., NR>25),
- each training plan should have at least two exercises of high intensity,
- each muscle group repeating in Table 1 more than once does not have the same exercise,
- if the last exercise in the fitness training plan was of higher intensity, the next exercise should be of medium or high intensity.

In the remainder of this paper, these constraints were captured within the algorithmic structure of the original bat algorithm for planning the fitness training plan.

Modifying the original bat algorithm Each solution in the modified bat (MBA) algorithm consists of 24 floating-point elements representing the fitness training plans for some athlete. The elements of the solution are divided into three groups of elements. In other words, the solution is expressed as

$$\mathbf{x_i} = (x_{i1},\ldots,x_{i8},x_{i9},\ldots,x_{i16},x_{i17},\ldots,x_{i24})^T, \qquad (3)$$

where elements $x_{i1},\ldots,x_{i8}$ denote exercises from Table 1, $x_{i9},\ldots,x_{i16}$ are the number of repeats NR and $x_{i17},\ldots,x_{i24}$ the corresponding intensity, respectively. This means, each fitness training plan consists of eight exercises with an assigned number of repeats and corresponding intensities. While the number of repeats is selected from interval NR $\in [1,40]$, parameters exercises and intensities are drawn from the interval $[0,1]$, and their proper values are encoded as indices into a discrete set of features according to the following equations

$$ex(x_{i,j}) = \lceil 3.0 \cdot x_{i,j} \rceil, \quad \text{for } j = 1,\ldots,8, \qquad (4)$$
$$int(x_{i,j}) = \lceil 3.0 \cdot x_{i,j} \rceil, \quad \text{for } j = 17,\ldots,24, \qquad (5)$$

where $ex(x_{i,j})$ and $int(x_{i,j})$ determine the element in the feature sets as represented in Tables 1 and 2. For instance, the function intensity can obtain the following values from the feature set

$$int(x_{i,j}) = \begin{cases} \text{HIGH}, & \text{if } 0 \leq x_{i,j} < \frac{1}{3}, \\ \text{MEDIUM}, & \text{if } \frac{1}{3} \leq x_{i,j} < \frac{2}{3}, \\ \text{LOW}, & \text{if } \frac{2}{3} \leq x_{i,j} < 1, \end{cases}$$

respectively. The planning of the fitness training sessions is defined as a constraint satisfaction problem that is formally defined as

$$\text{Minimize} \quad f(\mathbf{x}_i) = \sum_{k=1}^{k<4} \chi_k(\mathbf{x}_i),$$

$$\text{subject to} \sum_{j=8}^{15} y_j \geq 4,$$

$$\sum_{j=16}^{24} z_j \geq 2,$$

$$x_{i,1} \neq x_{i,4} \neq x_{i,7} \wedge x_{i,2} \neq x_{i,6} \wedge x_{i,3} \neq x_{i,8},$$

$$int(x_{i,j}) \equiv \text{HIGH} \Rightarrow int(x_{i,j+1}) \neq \text{HIGH},$$

where

$$y_j = \begin{cases} +1 & \text{if } x_{i,j} \geq 25, \\ +0 & \text{otherwise,} \end{cases}$$

and

$$z_j = \begin{cases} +1 & \text{if } int(x_{i,j}) \equiv \text{HIGH}, \\ +0 & \text{otherwise,} \end{cases}$$

The proper solution to the problem is found, when the $f(\mathbf{x}) = 0$.

Representation of Results. Although the results could be visualized, the numerical results in the tables are presented only in this preliminary version of the modified bat algorithm.

4 Experiments and Results

The results of our experiments are illustrated in Tables 3 to Table 5, where the tables represent the three sets of exercises. An athlete has some free time for resting after finishing each set. We run algorithm 25 times and after the run we selected three generated training sessions which were successfully found by bat algorithm.

Exercise	Reps[NR]	Intensity[1RM]
LUNGE	26	HIGH
LEG SCISSORS	23	LOW
PULLDOWN	18	MEDIUM
SQUATS	27	HIGH
BAR ROWS	40	MEDIUM
LEG LIFTS	22	HIGH
LEG PRESS	35	MEDIUM
PUSH UPS	39	LOW

Table 3: First set of fitness workouts

Exercise	Repeats	Intensity
SQUATS	34	LOW
LEG SCISSORS	22	MEDIUM
UNDERARM ISOMETRIC	40	HIGH
LEG PRESS	15	LOW
BAR ROWS	36	HIGH
LEG LIFTS	27	LOW
LUNGE	15	MEDIUM
PULLDOWN	22	LOW

Table 4: Second set of fitness workouts

Exercise	Repeats	Intensity
LEG PRESS	21	HIGH
LEG LIFTS	29	MEDIUM
UNDERARM ISOMETRIC	28	MEDIUM
LUNGE	39	MEDIUM
BACK EXTENSION	15	LOW
PLANK	35	MEDIUM
SQUATS	25	HIGH
PUSH UPS	38	MEDIUM

Table 5: Third set of fitness workouts

The obtained results were evaluated by human trainer who evaluated and approved it. The obtained results confirm that the idea of automatic fitness training sessions was worth investigation and the promising results also show the potentials of the solution when used in practice. On the other hand, we would also like to present some problems and bottlenecks which we encountered during development. Firstly, it seems that it will be good to test our idea with evolutionary algorithms in the future. Experiments showed that the success of the bat algorithm in satisfying all constraints was about 25% of runs only. The problem is that the bat algorithm is highly dependent on the best solution. From this reason, our algorithm went into local optimum a lot of times. We believe that advanced mechanisms e.g. arithmetic crossover would behave much better. Moreover, using adaptive and self-adaptive bat variants could also be suggested since we spent a lot of time tuning parameters. On the other hand, many more constraints should be defined in order to have very precise solutions which should be very similar to those solutions created by the human sport trainer.

5 Conclusions

In this workshop paper, we presented a simple, yet efficient solution for planning fitness training sessions automatically. The bat algorithm was employed in order to tackle this problem. This algorithm successfully generated training sessions which were evaluated and confirmed by a human trainer who had more than 20 years of experience. In the future, there are many tasks to do in this direction like for example testing with other nature-inspired algorithms, employing arithmetic crossover and taking more constraints and exercices into account.

Acknowledgement

The research reported in this paper has been partially supported by the Czech Science Foundation grant 13-17187S.

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