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# SELECTION OF RELEVANT PARAMETERS FOR HUMAN LOCOMOTION UNSUPERVISED CLASSIFICATION

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A method for the automatic selection of the most relevant parameters for human locomotion classification is proposed. A set of 36 statistical parameters extracted from video sequences showing three basic movement types is used. Because the unsupervised classification is based on the k-means clustering algorithm, the sets of relevant parameters are determined by applying binary optimization metaheuristics using a clustering evaluation measure as objective function. Considering that the objective function is multimodal, all combinations which maximize it are retained. The binary versions of Particle Swarm and Black Hole algorithms were modified to manage the multiple solutions of the optimization process. The experiments revealed that the Black Hole algorithm leads to better results, even if it is considered a simplified version of the Particle Swarm Algorithm.

*Keywords*: human locomotion, k-means clustering, binary optimization, nature-inspired metaheuristics

## 1. INTRODUCTION

Human action recognition is an important task in computer vision. It has a wide spectrum of applications in many areas such as medicine, video surveillance, social activity recognition, and robotics. There are two parts in action recognition: action description, which aims at extracting motion information from video sequences, and action classification, which involves machine learning techniques to make models that assign the correct action labels.

In literature there are many approaches related to the field. In [27], locomotion is classified using a neural network and data is obtained using portable devices placed on the subjects. In [1] it is proposed a medical application using pattern recognition techniques for ankle joint movement classification. Using a robust representation of spatial temporal words and an unsupervised approach during learning, [16] proposes a model to learn and recognize human actions in video. A novel method based on skeleton information provided by RGB-D cameras is proposed in [22]. Other approaches of human action recognition are proposed in [5, 19, 23, 25].

This approach is part of a human locomotion analysis and classification project. Video datasets contain basics human locomotion performed by a single subject in a sagittal plane. Therefore, a set of postural and kinematic descriptors are extracted from video sequences and stored in a relational database. Based on statistical analysis of the extracted descriptors, an unsupervised classification method is applied. The main goal of this work is to identify the most relevant statistical parameters sets for classification, considering that the motion type is known for all video sequences. In order to do that, the binary versions of two nature-inspired (NI) optimization metaheuristics are applied: Particle Swarm Optimization (PSO) and Black Hole Algorithms (BHA).

In latest decades, the interest for NI algorithms has increased, due to their ability to solve optimization problems more quickly. In [21], a local search approach for NP-Hard problems expressed as binary programs is proposed. A modified hybrid multiagent swarm optimization approach for Mixed-Binary Nonlinear problems is proposed in [26], while [6] proposes a binary PSO algorithm for solving the multi-objective resource allocation problem. A binary version of BHA is used in [17] for solving a feature selection problem in biological data. Other NI optimization approaches are mentioned in the third section.

The rest of the paper is organized as follows. In the second section, some aspects related to human motion recognition are briefly described. The binary versions of PSO and BHA are described in the third section. The experiments and results are presented in the fourth section, followed by conclusions in the last section.

## 2. HUMAN LOCOMOTION

A framework to integrate knowledge representation in human locomotion is proposed in [14]. The main purpose is to achieve an ontology with clear and accurate rules that describe human locomotion through extracted descriptors from video sequences [24, 11]. The experiments were performed using the KTH video dataset describing human actions [20]. There are three classes of human locomotion in the KTH video dataset: walking, jogging and running, performed by 25 human subjects. The motion plain of the human body in KTH video datasets is sagittal, which allows extraction of the following parameters: a) the joint angles of the legs; b) the angle of the human torso to the vertical; c) the length step. The identified descriptors (Table 1) that can be extracted from video sequences are postural descriptors (angles, step length) and a kinematic descriptor (velocity). A tool to facilitate the measurement of these descriptors was developed, in which the description points of the segments that form angles and length are manually selected and automatically computed. All measurement values are stored in a relational database called HLO database.

*Table 1*
Descriptors for human locomotion

| Code | Name | Description |
|---|---|---|
| a_b | Angle bent | The angle of the human torso to the vertical. |
| a_la | Angle left ankle | The angle of left foot's ankle. |
| a_lk | Angle left knee | The angle of left foot's knee. |
| a_ra | Angle right ankle | The angle of right foot's ankle. |
| a_rk | Angle right knee | The angle of right foot's knee. |
| a_l | Angle legs | The angle formed by the right and left leg in sagittal plane. |
| l_st | Length step | The distance between two successive heal touches of the ground. |
| v_st | Velocity by step length | Velocity computed using the length step, the time when the step begins and ends and the frame rate of the video file. |
| v_of | Velocity by optical flow | Velocity is automatically determined by using optical flow techniques, regardless of the length of the step. |

In the space of the extracted descriptors, a statistics is performed by computing the minimum, maximum, average, and standard deviation for each descriptor, for each type of human locomotion performed by each subject [12]. The results are 36 statistical parameters stored in the HLO relational database, from which ten parameters were intuitively selected to be more relevant in human locomotion description. The most relevant statistical parameters were: *average a_b, maximum a_b, average a_l, maximum a_l, minimum a_lk, minimum a_rk, average l_st, maximum l_st, average v_st* and *average v_of.*

A k-means clustering algorithm was applied on all combinations of the ten selected statistical parameters and the results were evaluated using the purity measure, defined by:

$$purity = \frac{1}{N}\sum_{i=1}^{n} \max_j \left|cluster_i \cap class_j\right| \tag{1}$$

where $N$ is the number of data vectors, $cluster_i$, $i = 1, N$ are the clusters determined and $class_j$, $j = 1, N$ are the known classes containing the data vectors [13, 14].

To improve the precision of results, the most relevant parameters for human locomotion classification should be automatically selected. Further on, NI meta-heuristics using a clustering evaluation measure as an objective function is applied to select the sets of relevant parameters.

## 3. BINARY OPTIMIZATION BY NATURE-INSPIRED METAHEURISTICS

NI metaheuristics are evolutionary algorithms which model the strategies of beings for feeding, survival or perpetuation of the species, but also other natural or artificial phenomena encountered in nature. NI algorithms are based on a population of individuals (*possible solutions*) which are initially placed in randomly chosen positions in a multidimensional search space (*problem domain*), after which they evolve in the search space for a number of iterations (*evolution loop*), trying to enhance their status (*objective function*). The *parameters* of the optimization problem are encoded in individuals' positions, thus the number of dimensions of the search space is equal to the number of parameters. The evolution loop is stopped when a *stop condition* is met and the position in which, during evolution, an individual reaches the best status is considered to be the optimization problem *solution* [4]. In some NI metaheuristics, a *selection strategy* is used to keep constant the population size if descendants are created during the evolution. Usually, the solution is searched in the continuous space trying to optimize a single objective function but, for almost all NI metaheuristics, versions for multi-objective [3], combinatorial [2] or binary optimizations were developed.

### 3.1. BINARY PROGRAMMING

The general form of a binary optimization (binary programming) problem is:

$$\min_x f(x),\ x \in \{0,1\}^n \subset \Omega \tag{2}$$

where $\Omega$ is the problem domain which might also contain a set of restrictions, and n is the dimension of the problem. It is similar to the general single-objective optimization, but it includes a new restriction – parameter's components have only two values: '0' and '1'. Once the number of possible solutions is finite and known, it is obvious that such problems require dedicated solving methods only in case of high values of dimension $n$ and complex expressions of the objective function. In the following paragraphs, $x = \{x_i,\ i = 1,\dots N\}$ is the set of $N$ possible solutions (number of individuals), and $x_i(t) = \left(x_i^1(t),\ \dots, x_i^n(t)\right)$ are their positions in the problem domain in the $t^{th}$ iteration, where $n$ is the dimension of the problem. The following subsections briefly describe the binary versions of PSO and BHA.

### 3.2. BINARY PARTICLES SWARM OPTIMIZATION

PSO is one of the most known and performant NI algorithms which model bird and fish swarming behavior [8]. In the continuous space, particles' movement is described by:

$$x_i(t+1) = x_i(t) + v_i(t+1) \times \Delta t,\ i = 1,\dots N \tag{3}$$

where $v_i(t)$ is the velocity of the $i^{th}$ particle in the $t^{th}$ iteration, and $\Delta t = 1$ is the time interval [4]. Velocity is computed as:

$$v_i(t+1) = w \times v_i(t) + \left(c_1 \times r_1 \times \left(x_i^b - x_i(t)\right)\right) + \left(c_2 \times r_2 \times \left(x^b - x_i(t)\right)\right),\ i = 1,\ldots N \quad (4)$$

where $w$ is the movement inertia weight, $c_1$and $c_2$ are the local and global learning coefficients, $x_i^b$ is the best reached position of the $i^{th}$ particle, $x^b$ is the best position reached by any particle in the population and $r_1$, $r_2$ are random values [4]. The moving strategy is collaborative, meaning that the best reached position of each individual and the global best position reached by any individual in the population are used when the new positions are computed.

The Binary Particle Swarm Optimization (BPO) algorithm is similar to PSO, but it was modified [9] to operate in the multidimensional binary domain, by considering the velocity as a probability that the new position's coordinate is zero or one [10]. Thus, the new positions are computed by:

$$x_i(t+1) = \begin{cases} 0 \ \ if \ \ r \geq S\left(v_i(t+1)\right) \\ 1 \ \ if \ \ r < S\left(v_i(t+1)\right) \end{cases}, \quad i = 1,\ldots N \quad (5)$$

where $r \in [0; 1]$ is a random value and $S$ is the sigmoid function used to compute the binary value selection probability:

$$S(x) = 1/(1 + e^{-x}) \quad (6)$$

Velocity is computed as in the PSO, but it must be noticed that, if its value is too large or too small, the sigmoid function saturation inhibits particle's position change [10]. To avoid this limitation of the problem domain exploration, the velocity values are restricted to an interval $[-v_{max}, v_{max}]$ . However, the $v_{max}$ value has to be carefully chosen to avoid the algorithm to be trapped in local solutions.

### 3.3. BINARY BLACK HOLE ALGORITHM

The BHA was proposed in [7] as a heuristic approach for data clustering. However, BHA is quite controversial, because the moving strategy is similar to that used by PSO [18]. After the initialization step and after each evolution loop, all individuals (stars) are evaluated and the one with the best value of the objective function becomes the black hole ($BH$) and begins to attract the other stars:

$$x_i(t + 1) = x_i(t) + r \times (x_{BH} - x_i(t)),\ i = 1,\ldots N \quad (7)$$

where $x_{BH}$ is the position of $BH$ and $r \in [0; 1]$ is a random value. In fact, $x_{BH}$ corresponds to the global best position $x^b$ used in PSO, a reason for which BHA is considered a simplified version of PSO. All stars whose distance to BH is lower than the radius of the event horizon are absorbed by BH and replaced by newly created stars in random positions [7], increasing the chances of discovering the optimal solution [4]. The radius of the event horizon is computed as:

$$R = f_{BH} \Big/ \sum_{i=1}^{n} f_i \tag{8}$$

where $f_{BH}$ and $f_i$ are the fitness values of the $BH$ and $i^{th}$ star, respectively $i = 1,\dots N$. Even if BHA does not use other tuned parameters, the experiments presented in [4] revealed that a scaling factor applied to the movement step can improve the convergence of the algorithm.

The Binary Black Hole Algorithm (BBHA) is also similar to BHA with the observation that a transfer function has to be used in order to force the stars to move in a binary space. In contrast to BPSO, in [17] the hyperbolic tangent function is used as transfer function: $S(x) = abs(\tanh(x))$. First, $x_i(t+1)$, $i = 1,\dots N$ are computed using (7) and then the transfer function is applied.

$$x_i(t+1) = \begin{cases} 0 \ \ if \ \ r \geq abs\big(\tanh\big(x_i(t+1)\big)\big) \\ 1 \ \ if \ \ r < abs\big(\tanh\big(x_i(t+1)\big)\big) \end{cases}, \quad i = 1,\dots N \tag{9}$$

Utilization of the hyperbolic tangent as transfer function is justified by its better performances, compared to the sigmoid function [15].

### 3.4. BPSO AND BBHA FOR PARAMETERS SELECTION

The main goal of the proposed parameters' selection method is to determine the minimal set of parameters which maximize the purity measure (1) computed for the k-means clustering results. The objective function evaluation requires the k-means clustering algorithm to be applied for the set of locomotion parameters which correspond to the value of the argument. The problem can be approached as a multi-objective optimization, in which case the objectives should be: (a) the purity measure – to be maximized, and (b) the number of parameters – to be minimized. However, the first objective has a higher importance, so that only clustering purity is used in this approach to evaluate the solutions. The number of parameters is used as a secondary criterion to discriminate between different solutions. On the other hand, it must be noticed that, due to the reduced size of the training dataset, the same number of correctly assigned data items is obtained for more combinations of the same number of parameters. Thus, BPSO and BBHA were modified to handle multimodal objective functions. Instead of a single best global solution (in BPSO) and a single BH (in BBHA), a *set of best individuals* is stored during the evolution loop of each algorithm. To ensure solutions' diversity, all individuals with the best value of the objective are stored in this set without taking into account the number of parameters. When computing the new positions of individuals, the *global best position* and *BH position*, respectively, are randomly chosen from the set of *best individuals*. It must be noticed that, in BPSO, the *personal best position* is also involved in particle's new position calculation. To avoid increasing of memory requirements, a single *personal best position* is stored for each particle. In this case, the number of parameters is used in the evaluations. The new position is compared to the previous personal best: (a) if the purity values are different, the one with the best value is chosen, (b) if the purity values are equal and the number of parameters are different, the one with the lower number of parameters is stored, and (c) if both purity and the number of parameters have the same value, the new personal best is randomly chosen between the two positions. Also, in BPSO, the adaptive strategy related to the inertia weight proposed in [15] is used. It decreases during the evolution loop from $w_{\max}$ to $w_{\min}$:

$$w_k = w_{\max} - (k/nIterations) \times (w_{\max} - w_{\min}) \tag{10}$$

where $w_k$ is the inertia weight in the $k^{th}$ iteration and *nIterations* is the total number of iterations.

## 4. EXPERIMENTS AND RESULTS

BPSO and BBHA were applied to select the relevant parameters of human locomotion described in the second section. Recall that, in this experiment, there are nine descriptors and for each one, four statistical values were computed, so that the full set contains 36 statistical parameters. The total number of combinations is $2^{36}$, which is approximately $6.87 \times 10^{10}$. By applying the NI metaheuristics, the number of evaluated combinations decreases considerably.

### 4.1. ALGORITHMS SETTINGS

Evaluation of each combination of parameters requires the k-means algorithm to be applied. Because it is based on randomly chosen centroids positions, the final solution can be different from an execution to another. To increase results' accuracy, an objective evaluation is performed by running k-means several times (*nAttempts*) and choosing the best from the obtained clustering results. The following parameters were used in the optimization algorithms:

BPSO: #particles = 50, #iterations = 2500, inertia weight $w_{\min} = 0.4$, $w_{\max} = 0.9$, local and global learning coefficients $c_1 = c_2 = 2$, maximum velocity $v_{\max} = 6$, and the number of k-means runs *nAttempts* = 100.

BBHA: #stars = 50, #iterations = 2500, and *nAttempts* = 100.

It is noted that the number of individuals and iterations were chosen so that the total number of objective function evaluations is the same in both BPSO and BBHA. In fact, there are 1.25e5 evaluations, which means, that considering the *nAttempts* parameter, the total number of k-means runs is 1.25e7.

### 4.2. RESULTS

The results presented in this section were obtained by a single run of the optimization processes. The full set of statistical parameters contain the minimum (m), maximum (M), average (A) and standard deviation (D) computed for each descriptor presented in Table 1, for each human subject and each movement type included in the KTH dataset [20]. Thus, the input dataset contains 75 records (25 persons × 3 locomotion types) and each of them contains 36 statistical parameters. Because it can be intuitively considered that the kinematic parameters (velocities) have a higher relevance in human motion analysis, two different experiments were performed, with and without considering these parameters. Table 2 lists the results obtained by BBHA and BPSO in these two cases. Column *#Sols* contains the number of distinct combinations which maximize the Purity measure in each case. The number of statistical parameters in each solution varies within the interval specified by the column *#Parameters in solutions*. It is obvious that a too great number of parameters is not convenient, so that column *#Sols** presents the number of solutions which contain at most eight statistical parameters (referred below as "*reduced set of solutions*"). Concerning the number of combinations which also contain the minimum number of parameters, in the first case (BBHA, Postural + kinematic) there are five combinations, in all the other cases it is only one combination that minimizes the number of parameters, as presented in Table 3. The last column of Tables 3, 4, and 5 is organized as follows: the first line of the column head shows the human locomotion descriptors (Table 1); the second line shows the considered statistics (m = minimum, M = maximum, A = average, D = standard deviation); and the digit "1" in the column indicates that the corresponding parameter is included in the best solutions.

*Table 2*

Number of solutions obtained by BBHA and BPSO

| Algorithm | Parameters | #Parameters | Best purity | #Sols | #Parameters in solutions | | #Sols* |
|---|---|---|---|---|---|---|---|
| | | | | | min | max | |
| BBHA | Postural+ kinematic | 36 | 0.987 | 3063 | 3 | 19 | 587 |
| | Postural | 28 | 0.987 | 5 | 2 | 4 | 5 |
| BPSO | Postural+ kinematic | 36 | 0.987 | 327 | 4 | 15 | 193 |
| | Postural | 28 | 0.973 | 3 | 8 | 9 | 1 |

*Table 3*

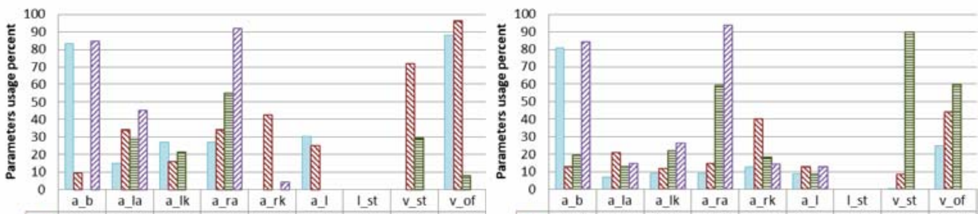
Parameters included in the best solutions obtained by BBHA and BPSO

| Algorithm | Parameters | Best purity | a_b mMAD | a_la mMAD | a_lk mMAD | a_ra mMAD | a_rk mMAD | a_l mMAD | l_st mMAD | v_st mMAD | v_of mMAD |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BBHA | Postural+ kinematic | 0.987 | 1000 | 0100 | 0000 | 0000 | 0000 | 0000 | 0000 | 0010 | 0000 |
| | | | 0000 | 0100 | 0000 | 1000 | 0000 | 0000 | 0000 | 0010 | 0000 |
| | | | 1000 | 0000 | 0000 | 0001 | 0000 | 0000 | 0000 | 0010 | 0000 |
| | | | 0000 | 0000 | 1000 | 0001 | 0000 | 0000 | 0000 | 0100 | 0000 |
| | | | 1000 | 0000 | 0000 | 0001 | 0000 | 0000 | 0000 | 0100 | 0000 |
| | Postural | 0.987 | 0000 | 0000 | 0010 | 0000 | 0000 | 0010 | 0000 | | |
| BPSO | Postural+ kinematic | 0.987 | 1000 | 0100 | 0000 | 0001 | 0000 | 0000 | 0000 | 0010 | 0000 |
| | Postural | 0.973 | 0011 | 0001 | 0100 | 0011 | 0000 | 0011 | 0000 | | |

In Figures 1 and 2, the number of occurrences for each statistical parameter in the full set and in the reduced set of solutions is evaluated as percents of the total number of solutions. Analysis of data in Table 3, Figures 1 and 2 shows that the kinematic parameters (average and maximum of the two velocities) are almost all the time included in the relevant parameters. Regarding the postural parameters, the bent angle and ankle angles are also relevant for human locomotion characterization. Less expected is the fact that the number of occurrences of step length is 0, which, in our previous works, was (intuitively) considered one of the most relevant. This can be explained as follows: (a) for the *running* locomotion type and for all subjects, the standard deviation of the step length average is enough large, and (b) for some subjects, the value of the walking step length is close to the value of the jogging length step.

Figure 3 evaluates the occurrences for the case in which only the postural parameters were considered in k-means clustering. Due to the reduced number of solutions, only few parameters appear in the combinations. More relevant are the results obtained by BPSO, in which the bent angle, legs angle and ankles angles have the most numerous occurrences.

The performances of BBHA and BPSO can be evaluated by analyzing the graphs depicted in Figure 4, which show the number of new optimal solutions generated in each interval of 50 iterations.



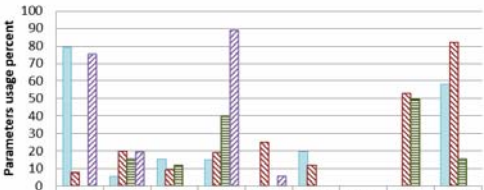

| | a_b | a_la | a_lk | a_ra | a_rk | a_l | l_st | v_st | v_of |
|---|---|---|---|---|---|---|---|---|---|
| m | 83.51 | 14.95 | 27.29 | 27.36 | 0.00 | 30.40 | 0.00 | 0.00 | 88.05 |
| M | 9.17 | 33.86 | 15.83 | 34.12 | 42.67 | 25.04 | 0.00 | 71.76 | 96.05 |
| A | 0.00 | 28.57 | 21.29 | 54.65 | 0.00 | 0.00 | 0.00 | 29.25 | 7.54 |
| D | 84.62 | 44.92 | 0.00 | 91.67 | 4.15 | 0.00 | 0.00 | 0.00 | 0.00 |

a. Results of BBHA

| | a_b | a_la | a_lk | a_ra | a_rk | a_l | l_st | v_st | v_of |
|---|---|---|---|---|---|---|---|---|---|
| m | 80.73 | 7.34 | 9.17 | 9.17 | 12.54 | 8.87 | 0.00 | 0.31 | 24.77 |
| M | 12.23 | 20.49 | 11.62 | 14.37 | 39.76 | 12.23 | 0.00 | 7.95 | 43.73 |
| A | 18.96 | 12.54 | 22.02 | 59.33 | 17.74 | 7.95 | 0.00 | 89.60 | 59.63 |
| D | 84.10 | 14.37 | 25.99 | 93.58 | 14.07 | 12.54 | 0.00 | 0.00 | 0.00 |

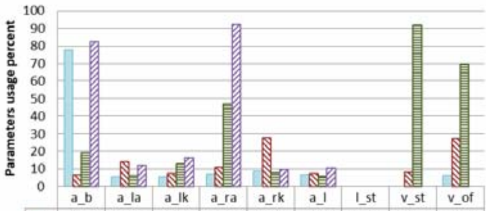
b. Results of BPSO

Fig. 1. Parameters usage percent in all solutions generated by the two algorithms (postural and kinematic parameters)




| | a_b | a_la | a_lk | a_ra | a_rk | a_l | l_st | v_st | v_of |
|---|---|---|---|---|---|---|---|---|---|
| m | 79.42 | 5.61 | 15.48 | 15.14 | 0.00 | 19.56 | 0.00 | 0.00 | 58.33 |
| M | 7.14 | 19.56 | 9.01 | 18.88 | 24.66 | 11.73 | 0.00 | 52.72 | 81.97 |
| A | 0.00 | 15.31 | 11.56 | 39.46 | 0.00 | 0.00 | 0.00 | 49.49 | 15.14 |
| D | 75.17 | 19.05 | 0.00 | 88.95 | 5.44 | 0.00 | 0.00 | 0.00 | 0.00 |

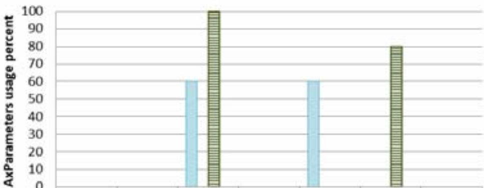
a. Results of BBHA




| | a_b | a_la | a_lk | a_ra | a_rk | a_l | l_st | v_st | v_of |
|---|---|---|---|---|---|---|---|---|---|
| m | 77.84 | 5.67 | 5.67 | 7.22 | 8.76 | 6.70 | 0.00 | 0.00 | 6.19 |
| M | 6.70 | 13.92 | 7.22 | 10.82 | 27.84 | 7.22 | 0.00 | 8.25 | 27.32 |
| A | 19.07 | 6.19 | 12.89 | 46.91 | 7.73 | 5.67 | 0.00 | 91.75 | 69.59 |
| D | 82.47 | 11.86 | 16.49 | 92.27 | 9.79 | 10.31 | 0.00 | 0.00 | 0.00 |

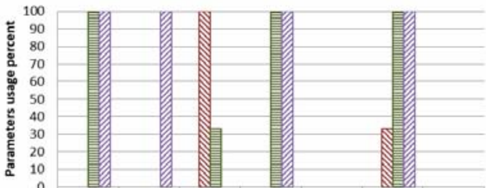
b. Results of BPSO

Fig. 2. Parameters usage percent in the reduced set of solutions generated by the two algorithms (postural and kinematic parameters, combinations containing at most eight parameters)




| | a_b | a_la | a_lk | a_ra | a_rk | a_l | l_st |
|---|---|---|---|---|---|---|---|
| m | 0.00 | 0.00 | 60.00 | 0.00 | 60.00 | 0.00 | 0.00 |
| M | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| A | 0.00 | 0.00 | 100.00 | 0.00 | 0.00 | 80.00 | 0.00 |
| D | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

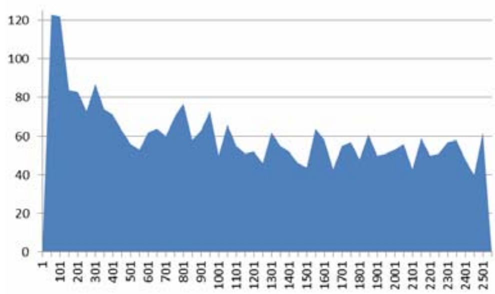
a. Results of BBHA



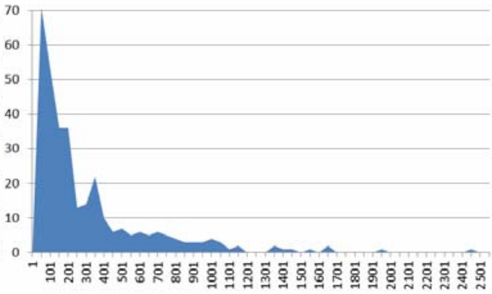

| | a_b | a_la | a_lk | a_ra | a_rk | a_l | l_st |
|---|---|---|---|---|---|---|---|
| m | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| M | 0.00 | 0.00 | 100.00 | 0.00 | 0.00 | 33.33 | 0.00 |
| A | 100.00 | 0.00 | 33.33 | 100.00 | 0.00 | 100.00 | 0.00 |
| D | 100.00 | 100.00 | 0.00 | 100.00 | 0.00 | 100.00 | 0.00 |

b. Results of BPSO

Fig. 3. Parameters usage percent in the full set of solutions generated by the two algorithms (postural parameters only)




a. Results of BBHA




b. Results of BPSO

Fig. 4. Frequency of new solutions generation

BBHA generates about 50 new optimal solutions in each group of iterations, up to the end of the evolution loop, which leads to the idea that new optimal solutions can be generated and also that the value of the objective function can be improved by increasing the number of iterations. In contrast to BBHA, the frequency for which BPSO generates new optimal solutions is much lower. It decreases continuously and, after the first 1100 iterations, new optimal solutions are only occasionally generated, which means that BPSO is trapped in some local solutions. The parameters of BPSO should be fine-tuned in order to improve solutions' diversity.

Concerning the reduced sets of solutions generated by BBHA and BPSO, it must be noticed that among the 780 solutions (587 of BBHA + 193 of BPSO) there are 27 common solutions – shown in Table 4. It is a fairly small number, which means there are still many unexplored solutions – the number of iterations and / or individuals must be increased.

*Table 4*
The best solution obtained by both BBHA and BPSO

| **Algorithm** | **Purity** | **# parameters in solution** | **a_b mMAD** | **a_la mMAD** | **a_lk mMAD** | **a_ra mMAD** | **a_rk mMAD** | **a_l mMAD** | **l_st mMAD** | **v_st mMAD** | **v_of mMAD** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **BBHA and BPSO** | 0.987 | 5 | 1001 | 0000 | 0000 | 0001 | 0000 | 0000 | 0000 | 0100 | 0010 |
| | | 5 | 1001 | 0000 | 0000 | 0001 | 0000 | 0000 | 0000 | 0010 | 0100 |
| | | 6 | 1001 | 0000 | 0000 | 1001 | 0000 | 0000 | 0000 | 0100 | 0010 |
| | | 6 | 1001 | 0000 | 0000 | 0001 | 0000 | 0100 | 0000 | 0010 | 0010 |
| | | 6 | 1001 | 0100 | 0000 | 0001 | 0000 | 0000 | 0000 | 0010 | 0100 |
| | | 6 | 1001 | 0000 | 0000 | 0011 | 0000 | 0000 | 0000 | 0010 | 0100 |
| | | 6 | 1001 | 0100 | 0000 | 0001 | 0000 | 0000 | 0000 | 0010 | 0010 |
| | | 6 | 1001 | 0001 | 0000 | 0001 | 0000 | 0000 | 0000 | 0010 | 0010 |
| | | 6 | 1101 | 0000 | 0000 | 0001 | 0000 | 0000 | 0000 | 0010 | 0100 |
| | | 7 | 1001 | 0000 | 1000 | 0001 | 0100 | 0000 | 0000 | 0010 | 0010 |
| | | 7 | 1000 | 0100 | 0000 | 0011 | 0000 | 0000 | 0000 | 0010 | 1100 |
| | | 7 | 1001 | 0100 | 0010 | 0001 | 0000 | 0000 | 0000 | 0010 | 0100 |
| | | 7 | 1001 | 0000 | 0000 | 0011 | 0000 | 0000 | 0000 | 0010 | 1100 |
| | | 7 | 1001 | 0001 | 0000 | 0001 | 0100 | 0000 | 0000 | 0010 | 0100 |
| | | 7 | 1001 | 0000 | 0000 | 0101 | 0001 | 0000 | 0000 | 0010 | 0010 |
| | | 7 | 1001 | 0000 | 0000 | 0011 | 0100 | 0000 | 0000 | 0010 | 0100 |
| | | 7 | 1001 | 0000 | 0000 | 0101 | 0100 | 0000 | 0000 | 0010 | 0100 |
| | | 7 | 1001 | 0100 | 0000 | 0001 | 0100 | 0000 | 0000 | 0010 | 0100 |
| | | 7 | 1001 | 0000 | 0010 | 0001 | 0100 | 0000 | 0000 | 0010 | 0100 |
| | | 7 | 1001 | 0000 | 0000 | 0001 | 0100 | 0100 | 0000 | 0010 | 0100 |
| | | 8 | 1000 | 0100 | 0000 | 0011 | 0000 | 0100 | 0000 | 0010 | 1100 |
| | | 8 | 1001 | 0010 | 0000 | 0011 | 0000 | 0000 | 0000 | 0010 | 1100 |
| | | 8 | 1001 | 0000 | 0000 | 0011 | 0100 | 0000 | 0000 | 0100 | 1100 |
| | | 8 | 1001 | 0000 | 0000 | 0011 | 0000 | 1000 | 0000 | 0010 | 1100 |
| | | 8 | 1001 | 0001 | 0000 | 0010 | 0100 | 0000 | 0000 | 0100 | 1100 |
| | | 8 | 1001 | 0000 | 0010 | 0011 | 0000 | 0000 | 0000 | 0010 | 1100 |
| | | 8 | 1001 | 0000 | 0010 | 0011 | 0100 | 0000 | 0000 | 0010 | 0100 |

One should also mention, again, that both the k-means algorithm and NI optimization algorithms are random processes whose results depend on the initial randomly chosen solutions, so that two runs of parameters' automatic selection will never lead to the same result. Thus, better results can be occasionally obtained by applying this procedure. In fact, during the experiments, the maximum value of the objective function was obtained by both algorithms. These results are presented in Table 5. The following remarks should be made: (1) both solutions of BPSO have a too large number of parameters, therefore they are not acceptable; (2) BBHA generated nine different solutions; one of these contains only two parameters (*maximum left_knee_angle* and *average velocity_step*), which makes it a very good solution, but all the other solutions include the same two parameters among others. The two parameters can be considered as being the most relevant.

*Table 5*
Other optimal occasionally obtained solutions

| Algorithm | Purity | # parameters in solution | a_b mMAD | a_la mMAD | a_lk mMAD | a_ra mMAD | a_rk mMAD | a_l mMAD | l_st mMAD | v_st mMAD | v_of mMAD |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **BBHA** | 1.00 | 2 | 0000 | 0000 | 0100 | 0000 | 0000 | 0000 | 0000 | 0010 | 0000 |
| | | 3 | 0000 | 0000 | 0100 | 0000 | 0100 | 0000 | 0000 | 0010 | 0000 |
| | | 4 | 0000 | 0000 | 0100 | 0000 | 0100 | 0010 | 0000 | 0010 | 0000 |
| | | 4 | 0000 | 0000 | 1100 | 0000 | 0000 | 0010 | 0000 | 0010 | 0000 |
| | | 4 | 0000 | 0000 | 1100 | 0000 | 0100 | 0000 | 0000 | 0010 | 0000 |
| | | 4 | 0000 | 1000 | 0100 | 0000 | 0000 | 0010 | 0000 | 0010 | 0000 |
| | | 5 | 0000 | 1000 | 0100 | 0000 | 0100 | 0010 | 0000 | 0010 | 0000 |
| | | 5 | 0000 | 0000 | 1100 | 0000 | 0100 | 0010 | 0000 | 0010 | 0000 |
| | | 6 | 0000 | 1000 | 1100 | 0000 | 0100 | 0010 | 0000 | 0010 | 0000 |
| **BPSO** | 1.00 | 15 | 1100 | 0110 | 0111 | 0011 | 1001 | 0110 | 0000 | 0010 | 0010 |
| | | 18 | 1111 | 0010 | 1011 | 1011 | 1001 | 1100 | 0000 | 0110 | 0010 |

All algorithms used in these experiments were implemented in C++ using the Microsoft Visual Studio 2017 development framework. The experiments were made on an Intel Core I3, 2.4GHz based computer with 6GB RAM and Windows 10 as operating system. The processing times presented in Table 6 were obtained for 1.25e5 evaluations of the objective function (1.25e7 runs of k-means algorithm), using the parallel versions of BBHA and BPSO, developed with the parallel computing support of Visual Studio 2017.

*Table 6*
Processing time for BBHA and BPSO

| Algorithm | # parameters | Processing time |
|---|---|---|
| **BBHA** | 36 | 7 min 03 s |
| | 28 | 6 min 30 s |
| **BPSO** | 36 | 8 min 22 s |
| | 28 | 7 min 50 s |

## 5. CONCLUSIONS AND FUTURE WORK

This work is part of a larger project related to human locomotion analysis and classification. Selection of the most relevant statistical parameters is difficult enough, even if, in the current stage of the work, their number is relatively reduced.

This is an optimization problem, so that the usage of two NI metaheuristics is proposed to solve it. The following conclusions can be drawn after analyzing the obtained results:

– by comparing the relevant statistical parameters obtained in this experiment to those intuitively chosen in previous works, only the bent angle and the velocities appear in both sets;

– the most used statistical parameters in the resulted combinations are: bent angle – minimum and standard deviation; right ankle angle – standard deviation; velocity by step length – maximum; velocity by optical flow – minimum and maximum;

– step length is not a relevant descriptor;

– at least for the current settings of the optimization algorithms, BBHA offers better results than BPSO, both in terms of accuracy and number of solutions;

– the number of individuals and iterations have to be increased in order to obtain more accurate results;

– BBHA and BPSO demonstrate their capabilities for binary optimization problems solving.

The work will be continued by applying new techniques for human locomotion analysis and classification.

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*Authors' contributions*: RL partially implemented human locomotion analysis framework; SIB implemented the binary optimization procedures, RL and SIB conducted experiments; RL and FR analyzed the results; all authors wrote the paper. All authors equally contributed.

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