# Interactive Bacterial Evolutionary Algorithm for Work Pace Optimization of Cobots

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***Abstract*—As cobots become more popular in manufacturing, the close cooperation between the robot and the human operator becomes more complex. This paper proposes a method for optimizing the robot's work pace by interactive bacterial evolutionary algorithm. One of the main contributions is the interactivity of the optimization via the operator's feedback. Beside the operator's subjective evaluation, heart rate signals are also measured. The paper focuses mainly on the concept of this method tested with the help of some volunteers. Preliminary tests show that the algorithm is able to find comfortable configurations with less then $1\%$ of them evaluated.**

***Index Terms*—human-robot interaction, ergonomics, work pace, bacterial evolutionary algorithm, cobot**

## I. Introduction

The evolution of robots and also robotics has already taken a huge step since the first appearence of the word "Robot" in Karel Čapek's science-fiction play Rossum Universal Robots in the beginning of the 20th century. Robots make our lives more and more convenient in many aspects. Industrial robotics evolved a lot since the first introduction of Robert C. Devol's Unimate to nowadays [1]. Currently a new kind of robot and with it a new kind of field in science is rising. Cooperative robotics, shortly cobotics, is the field of robots developed for realizing cooperation with human operators. The safety requirements are much higher for a cobot than for an industrial robot. The details can be found in the standards dealing with this topic [2] [3] [4].

In such a situation, where a robot has a close cooperation with the operator new factors become more important. For an ergonomic cooperation the robot needs to adjust its behavior in such a way that the operator can get to an optimal stress level in order to achieve the flow experience during work. Such experience is achieved when the individual is focusing mainly on the task which they have self-confidence in and no internal (fatigue etc.) or external (fear from the robot etc.) factors are disturbing [5].

In close cooperation between human and robot, caused by the new situation, there are multiple external factors from the operator's perspective which can be regulated and better conditions can be realized at the workplace by a sophisticated program from the robot side. The behavior of the robot can be described by the following parameters: the velocity of the movement between two points; the acceleration of the movement; the time of immobility at one point; and the trajectory between two points. These factors can change the operator's work pace as well, which is important for achieving high performance for a longer period of time.

An optimal work pace is essential and different for every individual. For a person with a higher skill level in the process the same work pace can lead to boredom which can cause loss in the performance through mental stress. On the other hand, for a less skilled person experiencing the same work pace, the working process can be exhausting, also leading to performance loss. Fatigue is a human factor which plays an immediate role in manufacturing quality deficit rates [6].

Thus, the optimization of the cobot's work pace is a crucial task for realizing a smooth cooperation between the robot and the human. Evolutionary algorithms such as the Bacterial Evolutionary Algorithm (BEA) [7] can be utilized for this purpose. It is important to consider the feedback from the human as well. Hence, we propose an interactive algorithm which considers the subjective evaluation of the human about the process and a physical parameter calculated from the heart rate changes of the human. The novelties of this paper are the slightly modified bacterial evolutionary algorithm, its usage in an interactive framework, and its application for the work pace optimization of cobots.

The structure of the paper is as follows. Section II introduces the problem via the implemented scenario and explains the experimental setup. In Section III the proposed algorithm is described. Section IV presents the experimental results. Conclusions are drawn in Section V.

## II. Problem Statement

The science of dealing with cobots and human-robot interactions became more and more important recently. Cobots occupy increasingly more space as their abilities are evolving. However, most of the cobot applications are low-level tasks as [8] states, meaning that there is a huge need for the development of ergonomic human-robot interaction (HRI) and teaching according to [9]. In [10] a KUKA iiwa cobot was used as a "Third hand" which is similar in functionality to the freedrive mode of the UR robots. In [11] a Kinect sensor based system capable of answering the operator's requests was implemented. The need of ergonomic interaction methods in

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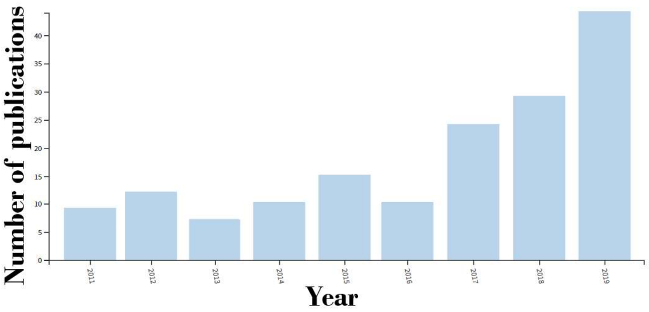


Fig. 1. Publications with keywords Artificial Intelligence and Ergonomics (source: webofknowledge.com databases)

HRI is high and artificial intelligence can be a key element in the search as the trend can be seen in Fig. 1. Robots with cognitive and optimizational skills inside can be the leaders of future manufacturing, where both the operators' and the employers' side will be more satisfied. Using the interaction between the human and the robot as one of the inputs for the optimization is a primary contribution of this paper. The main goal is to enable the system to optimize the cycletime in a way that is ergonomic and has a low level of disturbance during the process.

### *A. The Implemented Scenario*

As an initial test, a simple situation with a hand-in task was designed where the objective was to improve the working conditions. The layout of the simple scenario is shown in Fig. 2. A cooperative robot is handing over plastic workpieces for validation. The operator is instructed to pick up the plastic workpiece and try to fit it on a counterpiece. After the check the operator puts the workpiece aside and waits for the upcoming one.

Three variables are needed in this simplified scenario as illustrated in Fig. 2, where A, B and their 10 cm lifted copies are the dedicated points in space, and $T$ values are the correspoding times the robot's movements take. Vertical movements have a fixed timing of 0.5 seconds, while three other parameters are selected to describe the adaptive part of the work schedule. The first variable $T_{forward}$ describes the time when the robot is handing over the workpiece into the working area. The second variable $T_{backward}$ is the returning time of the robot. The third variable $T_{idle}$ describes how much time the robot waits until it reaches out for a new workpiece. Each variable is in the range of $[0.2; 2)$ seconds with a $0.1$ second resolution. Thus, each variable has 18 valid values. In this oversimplified scenario we end up having $18^3$ combinations for the setup of such movements, which adds up to a total of 5832. It can be easily concluded that solving this in a brute-force manner is not effective. In addition, when this concept is switched to a real world interpretation, the complexity of this problem increases further. The brute-force method of fine-tuning the parameters becomes almost impossible. Fortunatelly, artificial intelligence methods can be used here to create a setup quickly. Therefore, we propose

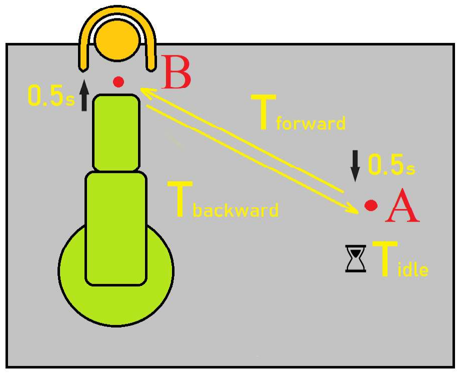


Fig. 2. Layout of the simple scenario

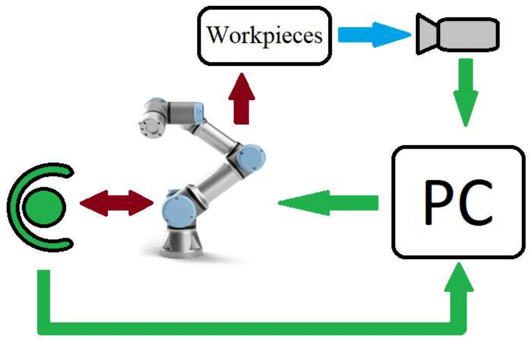


Fig. 3. Block diagram of the experiment

a bacterial evolutionary algorithm using interactive fitness function to optimize these variables.

### *B. Experimental Setup*

In the experiments a UR3e collaborative robot was used as a manipulator with a 3D printed hand with one finger open. The used camera was a Basler ACA800-510UC with an objective with focal length of 6 mm and a PC installed. The workpieces used in the experiments were plastic bottlecups and the counterpiece was a plastic bottle. The camera was adjusted in the way that the cups can be easily seen. Hough circle search [12] was used to determinate the position of the circles. To get an easy callibration routine, homogenous coordinate transformation, with 4 predefined point-pairs was used to transfer the cups' positions to the robot's coordinate system. A working cycle is complete when the camera does not see any cups waiting to be delivered. Five cups were used in one cycle. The block diagram is depicted in Fig. 3.

As inputs for the BEA the following data were used. A simple feedback typed in by the experimenter is the first of these. This number is based on the feedback of the operator on a scale of 1 to 10, where the number represents the subjective feeling of the operator regarding the overall satisfaction of the cycle both in terms of work pace and the robot's behavior. Here 1 means the least satisfied and 10 means the most satisfied answer. Heart rate signals were also measured as an input

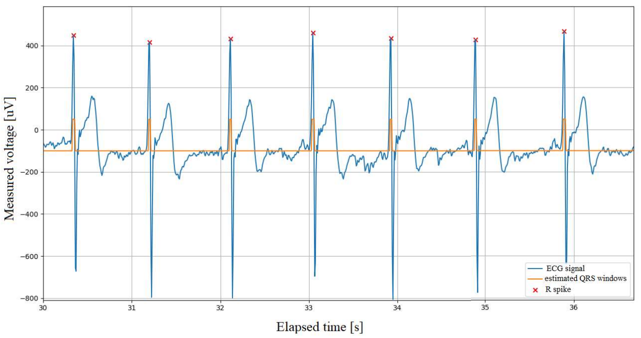


Fig. 4. Measured and processed ECG signal during an experiment (blue: measured ECG signal; orange: approximation of QRS place; red crosses: R maxima)

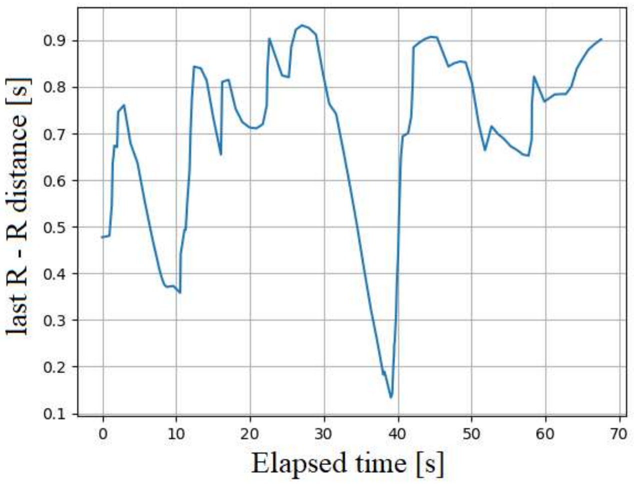


Fig. 5. R-R distances during the experiment

since differences in the heart rate can indicate mental stress or fright. For this purpose a Polar H10 sportbelt was used. A measurement during the experiment is illustrated in Fig. 4. The cycletime is also used as an input.

After processing the ECG signals the R-R distances are calculated as an input for the algorithm. One of the results of this calculation during the experiment is shown in Fig. 5.

To make sure that the worker accomodates to the new setup we used five repetitions of the task. This takes around $1.5$ minutes which is usually long enough for the heart rate to adapt to the newly experienced work pace. This length of each trial is also needed for the human collaborator to be able to determine their satisfication with the behavior of their robotic assistant.

## III. Proposed Algorithm

As a proposed algorithm for this experiment a bacterial evolutionary algorithm is applied. An advantage of this kind of algorithm compared to others is its fast convergence within a few function calls, as observed in [13].

In BEA a population of candidate solutions evolves from generation to generation [7]. Each individual (bacterium) is a possible solution for the optimization problem. First, an initial population is created randomly. Then, until the maximum generation number is reached two operators are executed after each other. The bacterial mutation operates on each bacterium one by one. First, a number of clones of the original individual are generated. Then, the same random segment is changed randomly in each clone except one which is left unmutated. After this, the best clone transfers the mutated segment to the other clones. Then, this process is repeated for the other yet unmutated segments of the clones. After the final step the best clone is kept and the rest of the clones are discarded. The other operator is the gene transfer which operates on the entire population. First, the individuals are ordered according to their fitness value. Then, a random individual is selected from the superior half of the population, which will be the source bacterium; and another random individual is selected from the inferior half of the population, which will be the destination bacterium. After this, the source bacterium transfers a random segment of its chromosome to the destination bacterium. Then, the population is reordered and this process is repeated until the predefined number of infections is reached. After that, the algorithm continues with the bacterial mutation step.

In this research the bacterial mutation operator is modified a little. Instead of applying it to each individual in the population, the operator is applied by a given probability to each individual. The other novelty is the interactive characteristic of the algorithm which is realized in the fitness calculation. In interactive evolutionary algorithms the fitness value of the individuals is determined by a human [14]. In this research we combine the human's subjective evaluation with other objective, measurable values in the fitness calculation.

The evaluation of the above mentioned $5832$ combinations is a huge task, which is why a guided search is used. The algorithm is running through $3$ generations with $5$ individuals. The probability of bacterial mutation is $0.2$ for each bacterium. In the bacterial mutation $3$ mutated clones are used. In each generation $3$ infections are executed in the gene transfer operation. This results in $41$ fitness calls calculating with the expected value of the mutation. This means that the algorithm is able to find a satisfactory suboptimal solution (see Section IV-B) evaluating only approximately $0.7\%$ of the configuration space.

The fitness evaluation of the individuals is calculated by Equation (1), which contains the subjective feeling of the configuration, realizing the interactivity between the cobot and the human operator. The subjective feeling is an integer value between $1$ (worst) and $10$ (best). Equation (1) also includes two pieces of measurable information; the difference of the reference measurement from the mean R-R distances proportionalized to the reference measurement and multiplied by $-10$, and the cycletime divided by $-2$ to encourage shorter work cycles, boosting productivity. The higher the fitness the better the individual. Presuming that the heart rate of the volunteers does not change dramatically (more than $50\%$), the

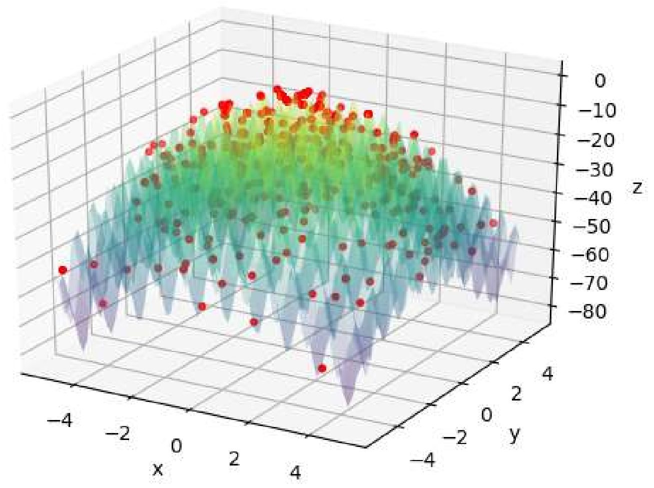


Fig. 6. Inverted 2D Rastrigin function

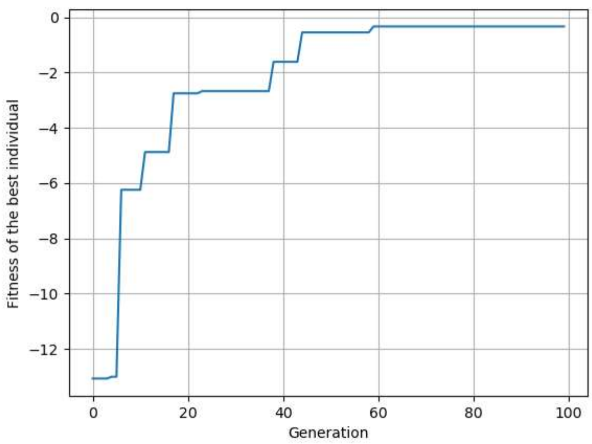


Fig. 7. Fitness curve of optimization over the 2D Rastrigin problem

fitness values should be in the range of $[-7, 9.7]$. During the optimization it is guaranteed that the best fitting individual will be kept, due to the behavior of the two executed bacterial operators.

$$fitness = SF - 10\frac{RR_{ref} - \overline{RR}}{RR_{ref}} - \frac{CT}{2} \qquad (1)$$

Here $SF$ is the subjective feeling points given by the volunteer, $RR_{ref}$ is the reference R to R distance measured before the experiment, $\overline{RR}$ is the mean of the R to R distances, $CT$ is the cycletime which is equal to the sum of the three variables to be optimized, $CT = T_{forward} + T_{backward} + T_{idle}$.

## IV. Experimental Results

### A. Benchmark using Rastrigin Test Function

The validation of the algorithm is performed on a benchmark function, the two-dimensional Rastrigin function illustrated in Fig. 6. The continuous domain of the search space is $[-5.12, 5.12] \times [-5.12, 5.12]$. The property of this function is the huge amount of local minima it has, thus, it is difficult to find the global optimum, therefore it is commonly used for testing similar algorithms.

For testing the algorithm by the Rastrigin function, the algorithm parameters are as follows. The number of generations is 100; the number of individuals is 20; the probability of mutation is 0.2; 3 mutated clones and 10 infections are used in the bacterial mutation and in the gene transfer operations, respectively. The fitness evolution is depicted in Fig. 7.

### B. Work Pace Optimization

When solving the work pace optimization problem a human operator is involved in the evolutionary process. A picture of the experiment can be seen in Fig. 8 where the operator is acomplishing the task in cooperation with the robot.

The results of three experiments (three human operators) are presented in Figs. 9, 10, 11. All of them can verify

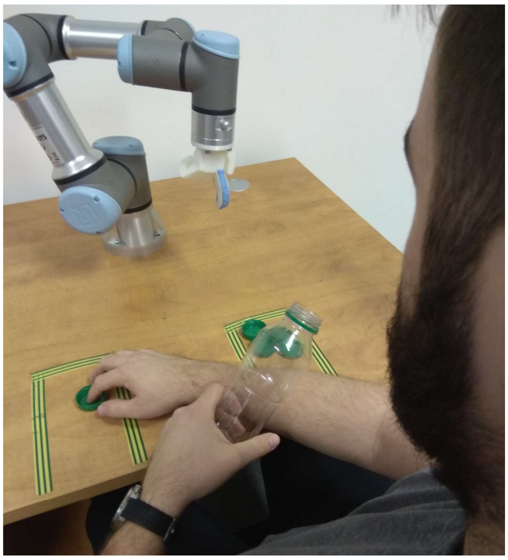

Fig. 8. Human operator during a test

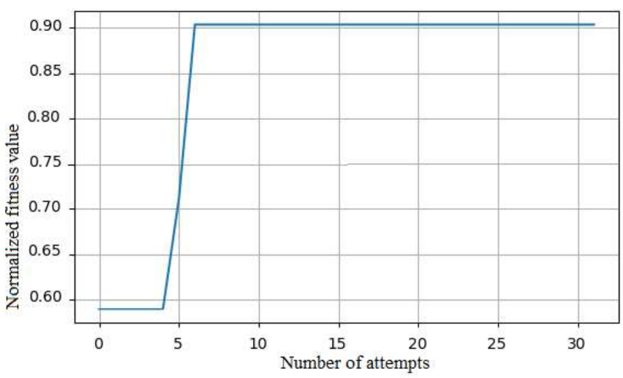


Fig. 9. Fitness function during the experiment process with the first volunteer

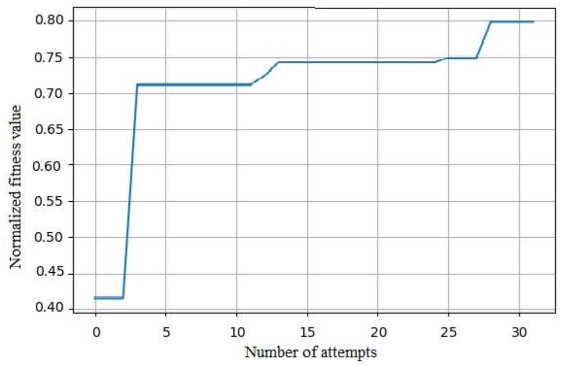


Fig. 10. Fitness function during the experiment process with the second volunteer

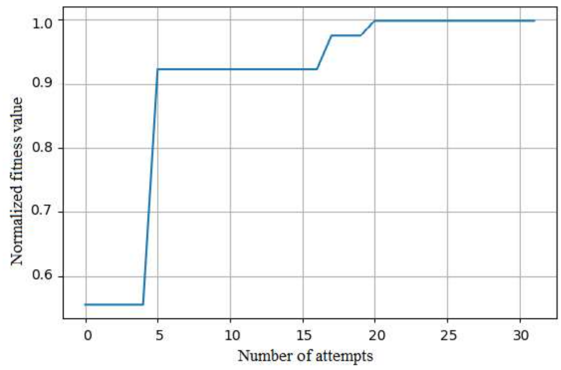


Fig. 11. Fitness function during the experiment process with the third volunteer

that the result is in the range of $80 - 99\%$, (referring to the theoretical maxima of fitness with at most $50\%$ R-R distance change as $100\%$) with evaluating less than $1\%$ of all possible values in the search space. Notice that the proposed probabilistic bacterial mutation does not necessarily occur in every generation, therefore in our measurements only $32$ fitness calls were needed instead of the expected value of fitness calls, which is $41$ for the given parameters. It can be seen that the algorithm "stucks" from time to time at certain points which could be the result of unsuccessful infections or mutations without improvement. Based on the results it can be stated that a smooth cooperation between the robot and the human could be realized with near-optimal working pace in all the three motion segments of the manipulator according to the subjective feeling of the human and the measured heart rate.

## V. Conclusions

In this paper an interactive bacterial evolutionary algorithm with probabilistic mutation rate was proposed for solving the work pace optimization problem. In the fitness evaulation subjective feeling is used based on the human operator's feedback and physically measured heart rate information as well. The proposed method could realize a smooth cooperation between the human and the robot.

In the future work we will attempt to use additional information in the human's feedback such as verbal information which could possibly be described by fuzzy sets, and other types of sensory information for the better measurement of the stress level of human operators.

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