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Proposal for a Framework for Optimizing Artificial Environments Based on Physiological Feedback

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Abstract We propose and then evaluate a new framework for finding the physical parameters of an artificial environment which give rise to given target physiological characteristics. We assume that a human is a system that takes as inputs the physical parameters of an artificial environment and outputs physiological parameters in response. We define our task as the inverse problem; we must find the best inputs from given target outputs. Our proposed framework solves the inverse problem using evolutionary computation techniques to optimize an artificial environment. We evaluate this framework using a simulation with a vibration environment and verify that it works. *J Physiol Anthropol Appl Human Sci 24(1): 77–80, 2005* http://www.jstage.jst.go.jp/browse/jpa

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1. Introduction

The 21st Century COE program, "Design of Artificial Environments on the Basis of Human Sensibility," started in 2003. Humans currently live in complex environments where physical parameters, such as temperature, light, smell, vibration, sound, visual stimulus, and others, are controlled artificially. These physical stimuli deeply influence us psychologically and physiologically. We do not, however, know what the best artificial environment is for a given activity in our daily lives. The objective of this COE project is to make the relationship between these physical parameters and their psychological and physiological effects clear and to propose artificial environments which are best suited to us in our daily lives.

The cues for optimizing an artificial environment are the physiological and/or psychological reactions of humans in the environment. The conventional approach of environmental physiology is to estimate the relationship between environmental physical parameters and human physiological parameters by measuring the physiological data of human subjects under several different environmental conditions. Using this approach, environmental physiologists have tried to design artificial environments for our daily activities and daily lives that offer the best physiological conditions.

It must be said, however, that this approach is limited from the system optimization point of view. As previously mentioned, the conventional approach is to input physical environmental data such as temperature or light to a system (a human) and measure its system output (physiological data). In other words, this is an approach of measuring outputs from inputs (see the feed-forward arrow in Fig. 1). However, optimizing an artificial environment requires us to determine the physical parameters of an artificial environment for human activities which offers the best physiological conditions, i.e. to determine the inputs from the outputs (see the feed-back arrow in Fig. 1). This type of task is called an inverse problem in general. It is hard to introduce optimization methods to the conventional feed-forward approach, and their optimization inevitably requires the use of a trial-and-error based method.

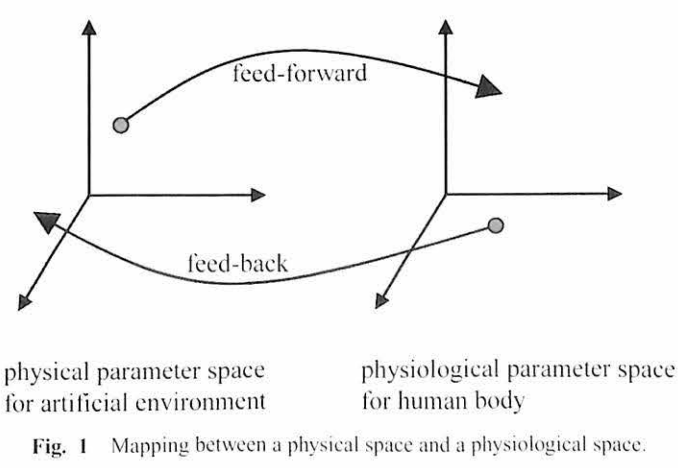

Fig. 1 Mapping between a physical space and a physiological space.

The objective of this research is:

(1) to propose a solution framework for an inverse problem that measures outputs from a human, physiological data, and determines inputs to the human, physical environmental parameters,

(2) to show a concrete solution methodology that solves this inverse problem using evolutionary computation (EC), and

(3) to evaluate the proposed method through an experimental simulation.

We describe the framework and its concrete solution in the following Section 2 and its evaluation in Section 3.

2. Proposed Framework: Physiological Feedback-based IEC Approach

Our objective in this paper is to propose a framework for finding the best physical parameters for an artificial environment that produce a given (ideal) set of physiological responses from a human in that environment. Next, we show a systematic solution method for the framework. This is not, however, an environmental/physiological research paper that determines the ideal physiological conditions for a specific purpose.

To deal with the task in Fig. 1 as an inverse problem, the following three conditions are necessary:

(1) feed-forward calculation: coordinates in a physical space must be mapped to a physiological space,

(2) fitness calculation: a fitness (or evaluation) function must be constructed for the mapped physiological space, and

(3) feedback search: it must be possible to conduct an optimization search of the physical space based on the fitness function.

Under these conditions, our proposed framework for optimizing the physical parameters of an artificial environment based on the measured physiological data can be realized using the following procedure:

(1) a mapping is created from a physical space to a physiological space corresponding to the normal measurement of physiological data under a certain artificial environment.

(2) a fitness function in a physiological space is defined as a distance in a physiological space between the ideal (or target) physiological data vector and the physiological data vector that is measured in the above (1).

(3) an EC searches for the optimum parameters in a physical space based on the fitness function defined above in (2), which results in the optimization of the artificial environment.

The reason why EC is used for optimizing an artificial environment in our proposed framework is the following:

(a) it is necessary to adopt an optimization method that converges quickly in a high dimensional physical space; our task requires measuring the subjects' physiological data as mentioned above in (1), and slow convergence increases the subject's fatigue.

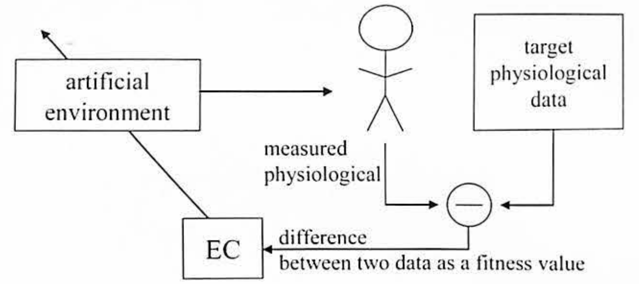

Fig. 2 Proposed framework to optimize an artificial environment based on physiological feedback.

(b) fitness values are not calculated using an explicit fitness function, but are based on the measured data as mentioned above in (2). This is why it is difficult to adopt optimization methods that use explicit information from the fitness function, such as its gradient.

(c) our proposed framework can be interpreted as an extension of interactive EC (IEC) (Takagi, 2001).

Figure 2 shows our proposed framework for optimizing an artificial environment based on physiological feedback. Our task, as discussed in this paper, is to determine the physical parameters of the artificial environment that makes the physiological conditions of a human subject in the environment match given target physiological conditions. In the initial stage of this experiment, we determine the target physiological data. The EC generates multiple physical parameter vectors for artificial environments; each vector corresponds to one environment. We measure the physiological data for a subject in each environment. The distance between the target data and each measured data in a physiological space is calculated and used as a fitness value for each of the physical parameter vectors. These fitness values are fed back in to the EC, and the EC generates new physical-parameter vectors using the fitness values and evolutionary operations. This searching procedure is iterated until the measured data reaches the target data.

The proposed framework in Fig. 2 can be said to be an extension of normal IEC. IEC is a system that optimizes a target system based on human subjective evaluation. Over the past 10 years, IEC has been applied to wide variety of fields such as artistic creation, engineering, education and therapy. In one application, for example, a user subjectively evaluates the sound of multiple hearing aids generated by EC and rates the results for entry back into the EC. The EC then generates new characteristics for multiple hearing aids and presents them to the user for evaluation. This procedure is repeated until the user is satisfied. Our proposed framework in this paper is an extension where the subjective feedback is replaced with physiological feedback.

In our proposed framework, we search for a target point in a physical space which corresponds to a target point in physiological space based on the mutual mapping between the physical space and the physiological space. A related work was an impression-based media database retrieval system test

conducted in our laboratory. That system searched for an optimum point in a physical space defined for images or music that corresponded to the given target point in a physiological space (Takagi, 2004). In this sense, both optimization frameworks are similar.

3. Evaluation of the System by Experimental Simulation

We evaluated the validity of our proposed framework through physiological simulation under a vibrational environment. The task was to search an eight dimensional (8-D) vibration-parameter space and find one vibration-parameter vector that lead to a given target 4-D physiological vector.

The physiological characteristics of the virtual human used in our experiment were made using a neural network (NN) that was trained from previously measured real data. This NN corresponds to the "feed-forward" part in Fig. 1.

The real data were measured using the vibration chair shown in Fig. 3. The eight vibration parameters of the chair shown in Fig. 3 were controlled, and the four kinds of physiological data shown in Table 1 were measured. This data was gathered from 15 subjects under 12 different vibrational conditions. That is, we trained 15 NNs using each measured data and simulated 15 virtual humans.

We used a genetic algorithm (GA), which is one of the four major EC techniques, to search a vibration physical space using the target physiological data. We defined the Euclidean distance between the given target physiological vector and a measured one as the fitness value for the GA search. This meant that the GA searched for vibration parameters whose corresponding measured physiological data were closer to the target data. These measured physiological data were calculated by a pseudo human, i.e. the trained NN, in our simulation experiment.

The experimental configurations of the NN and GA are shown in Table 1. The reason why the GA population size was fewer than that of a normal GA search is that we considered the practical conditions for a real (non-simulation) measurement; while it is not rare for a normal GA to search for a global optimum in several hundred generations using a population size of several hundred, the number of real physiological measurements that are feasible for each real human subject is quite limited in practice because of human fatigue and reliability of measurement. Our framework is required to work well even under disadvantageous practical conditions.

The training data used for the NN learning were not used as the target physiological data, but rather independent test data were used instead. We determine the test data distributing in a 4-D physiological space equally; two trisection points of the range between maximum and minimum values of each of four physiological variables were combined, and we obtained 16

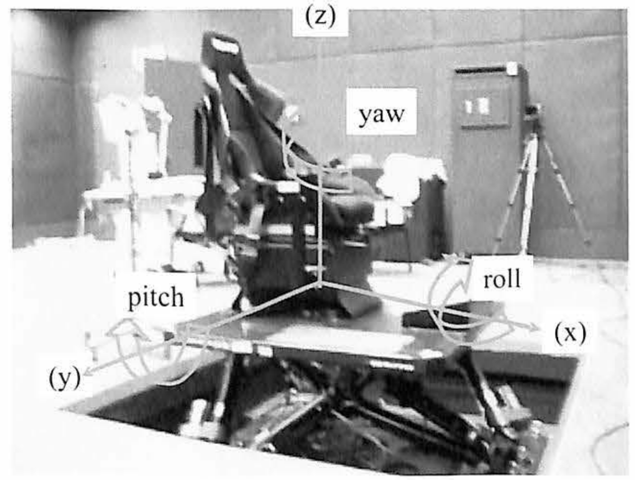

Fig. 3 Vibration environment.

Table 1 Experimental conditions for (a) NN and (b) GA
(a) NN conditions

NN type	3 layered feed-forward NN trained by a back propagation learning algorithm
# of neurons	(8, 6, 4) in (input, hidden, output) layers
8 input variables	frequency and amplitude of 12 variables in Fig. 1 except frequencies of y axis and roll and amplitudes of x axis and y axis. The values of these four exceptions were fixed during the entire experiment
4 output variables	systolic blood pressure, diastolic blood pressure, heart rate, and gravity of breathing frequency. Each of four data is calculated from the difference between before and after the three minute vibration experiment.
(b) GA condition	
population size	10
selection operator	roulette wheel selection and elitism strategy
crossover operator	2-point crossover with 90% crossover rate, i.e. 1 of 10 is an elite parent
mutation operator	1% mutation rate

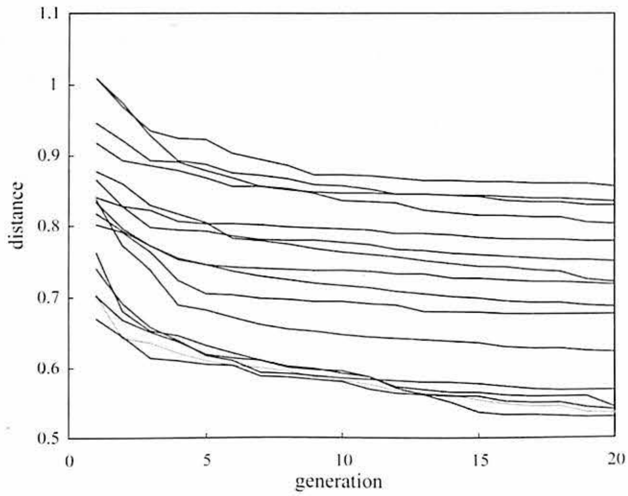

Fig. 4 Average GA convergence curves of 16 target points for 15 virtual humans.

($=2^4$) test target points.

Figure 4 shows the experimental results. As the ranges for the four physiological variables were different, the four variables were normalized to [0,1]. This means that the maximum distance in a normalized 4-D space is $(1^2+1^2+1^2+1^2)^{0.5}=2$.

4. Discussion and Conclusions

The experimental results show that the proposed framework tries to reach the global optimum physical data that corresponds to the target physiological data, but its performance appears to be poor.

Complexity is the key for analyzing these results. Standard deviations (SDs) for the 15 subjects' four normalized physiological data were 0.081925, 0.133518, 0.126558, and 0.116373. If we assumed that the measured data for one person fluctuate as much as these SDs, then the target for convergence is the Euclidean distance calculated from them, i.e., 0.232 or less. The volume of the target area that is calculated by the product of these four SDs occupies only 0.016% of a normalized 4-D space. This means that this search is roughly as complex as trying to find 1 or 2 in 10,000. This may be one reason why a population size of 10×20 generations was not sufficient for the target area to be reached.

However, an even more essential reason would be the lack of simulation data, especially physical data. Each of the eight physical variables used for simulation varied by only one or two, and one of the eight variables was constant. As a result, the GA tried to find the peak (global optimum) for a wide, flat plane. It is not easy to find a peak in a desert area, while it is easy to find a peak in mountainous area.

In conclusion, we can say that (1) the proposed framework showed the potential to design an artificial environment, but (2) it is necessary to prepare more pairs of physical–physiological data sets to show the effectiveness clearly.

The next steps are therefore to improve the evaluation simulation based on this discussion and to show the effectiveness of our proposed framework by using real physiological measurements to optimize an artificial environment.

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