Chapter 9
Human Motion Retrieval System Based on LMA Features Using Interactive Evolutionary Computation Method

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Abstract. Recently, many motion data have been created because 3D CG animations have become in great demand for movie and video game industries. We need any tools that help us to efficiently retrieve required motions from such a motion data pool. The authors have already proposed a motion retrieval system using Interactive Evolutionary Computation (IEC) based on Genetic Algorithm (GA) and motion features based on Laban Movement Analysis (LMA). In this paper, the authors especially clarify the usefulness of the system by showing experimental results of motion retrievals practically performed by several users. The results indicate that the proposed system is effective for retrieving motion data from a motion database including many motions more than one thousand.

Keywords: Motion Retrieval, Interactive Evolutionary Computation, Genetic Algorithm, Laban Movement Analysis.

1 Introduction

Advances in recent computer hardware technology have made possible 3D rendering images in real time and 3D CG animations have become in great demand for movie and video game industries. Many 3D CG/Animation creation software products have been released so far. However, with the use of such software products, it is still difficult for end-users to create 3D CG animations. For computer animation creation, character design is very important factor but very hard work. Especially, its motion design is very laborious work.

To solve this problem, we have already proposed a motion generation and editing system using Interactive Evolutionary Computation (IEC) [1] based on Genetic Algorithm (GA) [2] that allows us to generate required motions easily and intuitively. However, since the system employs GA for IEC, it needs several existing motion data represented as genes used for the initial generation of GA. The user has to prepare several motion data which are similar to his/her required

T. Watanabe and L.C. Jain (Eds.): Innovations in Intell. Machines – 2, SCI 376, pp. 117–130.
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motions. To prepare such motion data, the easiest way is to retrieve those from a motion database.

Hence, we have been studying motion retrieval systems and already proposed a new motion retrieval system using Interactive Evolutionary Computation [3]. This system allows the user to retrieve motions similar to his/her required motions easily and intuitively only through the evaluation repeatedly performed by scoring satisfaction points to retrieved motions without entering any search queries. The IEC method of the system is based on Genetic Algorithm, so that motion data should be represented as genes practically used as similarity features for the similarity calculation in the system. To extract motion features, we newly defined mathematical expressions of the features using Laban Movement Analysis (LMA) [4]. Because not only the idea of LMA is intuitively understandable for us but also motion features specified in LMA are possible to be represented as mathematical expressions.

In this paper, we describe that the LMA-based motion features are available for the similarity calculation in the system from the results of analyzing them using SOM visualization [3]. Furthermore, we especially clarify the usefulness of the proposed motion retrieval system by showing experimental results of motion retrievals practically performed by several users. The results indicate that the proposed system is effective for retrieving motion data from a motion database including many motions more than one thousand.

The remainder of this paper is organized as follows: First, we introduce the IEC method based on GA and Laban Movement Analysis. Next, we describe related work. And then, a feature extraction method for motion data and gene representation of motions are explained. After that, we explain the detail of our proposed motion retrieval system and present evaluation results to clarify the usefulness of the system. In the last section, we conclude the paper.

2 Interactive Evolutionary Computation and Laban Movement Analysis

In this section, we explain about Interactive Evolutionary Computation (IEC) and Laban Movement Analysis (LMA).

2.1 IEC Method Based on GA

IEC is a general term for methods of evolutionary computation that use human interactive evaluation to obtain optimized solutions [1]. In the IEC method, first of all, a system presents some candidate solutions to the user, and then the user evaluate them by giving a numerical score depending on his/her requirement. After that, the system again presents some solutions more suitable for the user requirement solved by a certain algorithm like GA. After several trials of this operation, the user obtains his/her most desirable solution. In this way, since the IEC method is intuitive and useful to deal with problems depending on human feelings, we decided to employ IEC method based on GA for our motion retrieval system.

2.2 Laban Movement Analysis

LMA is a movement analysis system for the dance which is created by Rudolf Laban. LMA is based on relationships between human body movements and emotions. In LMA, human body movement is explained by features of *Effort* and *Shape* as shown in Table 1. Each feature has two opposite forms which are *Fighting Form* and *Indulging Form*. *Fighting Form* means a strong, direct(linear) and sudden movement, and *Indulging Form* means a weak, indirect(spiral) and sustained movement.

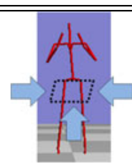
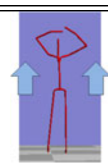
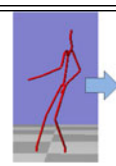
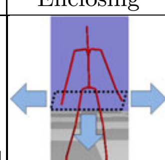
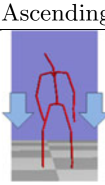
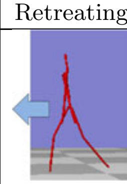
Effort. *Effort* is a mechanical feature of human movement. *Effort* has three elements which are *Weight*, *Space* and *Time* elements, each of which has two opposite forms. What these elements mean are as follows.

- Weight: Dynamism of body movement, e.g. it can be represented as energy or speed of movement.
- Space: Bias of direction of body movement, e.g. it can be represented as trajectory of movement.
- Time: Temporal Alternation of movement, e.g. it can be represented as the change of acceleration of movement.

Shape. *Shape* is a shape feature of the whole body movement. *Shape* has three elements which are *Table plane*, *Door plane* and *Wheel plane*. Each of them also has two opposite forms. *Shape* feature means spread and movement of body silhouette projected on each of the following three planes.

- Table plane: Spread of body silhouette projected on the transverse plane.
- Door plane: Spread of body silhouette projected on the frontal plane.
- Wheel plane: Movement of body silhouette projected on the sagittal plane.

Table 1. *Effort* and *Shape* elements.

	Weight	Space	Time	Table Plane	Door Plane	Wheel Plane
Fighting Form	Strong	Direct	Sudden	 Enclosing	 Ascending	 Retreating
Indulging Form	Weak	Indirect	Sustained	 Spreading	 Descending	 Advancing

3 Related Work

For the motion retrieval, there are some researches. Müller et al. proposed content-based retrieval of motion capture data by using various kinds of qualitative features describing geometric relations [5]. Liu et al. proposed content-based motion retrieval algorithm by partitioning the motion database and constructing a motion index tree based on a hierarchical motion description [6]. These researches are focused on methods of motion indexing or matching. In contrast, our research purpose is to provide a motion retrieval system having an intuitive interface that makes it possible to retrieve motion data interactively and easily.

For the feature extraction method of motions by using LMA, Fangtsou et al. proposed a feature extraction method of motions by using LMA [7]. However, this method does not use *Shape* feature of LMA. Our defined motion features include *Shape* features. Yu et al. proposed a motion retrieval system which allows the user to retrieve motions via Labanotation [8]. This system requests the user to prepare motion data for the queries. Our proposed system does not request any search queries because the system employs IEC method.

IEC is proposed as the interactive calculation method that the user evaluates target data interactively, and finally the system outputs optimized solution based on its evaluated values. The remarkable point where IEC is useful is that the necessitated operation is only the evaluation against data by the user. The data is optimized based on the user's subjective evaluation. So, the system can consider requirements of the user. There are some experimental systems of IEC researches. Ando, et al. proposed a music composition support system for the classical music using IEC [9]. Cho proposed image and music retrieval system using Interactive Genetic Algorithm [10]. Faffi, et al. proposed a design system for Microelectromechanical Systems (MEMS) using IEC [11]. Nishino, et al. proposed an integral 3D-CG contents system based on IEC [12]. By their proposed IEC framework, it is possible to create various attributed 3D-CG contents. Usually, IEC method is based on GA. There is a system [13] that generates some various walk motions using GA. However, there is not any motion data retrieval system using IEC that retrieves and presents motion data according to the user requirement from a motion database. In this paper, we propose such a motion retrieval system using IEC method based on GA.

4 Motion Features Using Laban Movement Analysis

As previously described, we have been developing a motion retrieval system using IEC method based on GA. To use GA, it is necessary to represent motions as their corresponding genes. For that, we newly define motion features as mathematical expressions based on the idea of LMA.

When a human being retrieves a motion, it is thought that the motion is retrieved by focusing on a local part movement such as hands and feet as well as overall movement. Existing LMA-based feature proposed by Fangtsou [7] does not include the information of overall movement. For our LMA feature, *Effort* is focusing on a local part movement of the motion, and *Shape* is focusing on overall movement of the motion.

4.1 LMA-Based Motion Features

To extract body movement features from motion data, we define them as mathematical expressions according to the idea of motion features specified in LMA. In our system, we focus on end-effectors of a human body to extract its features, i.e., its root, left hand, right hand, left foot and right foot.

Feature extraction method for *Effort* is as follows.

1. Weight
   Weight element in LMA represents active emotion derived from the energy and speed of movement. To extract this feature, we focus on speeds of end-effectors in a motion.
   Let F be the number of motion frames and $v_n(f)$ be the speed of an end-effector n in a motion frame f. We calculate Weight feature $Weight_n$ of an end-effector n by the next equation.
$$Weight_n = \sum_{f=1}^{F} |v_n(f)|/F \; . \tag{1}$$
2. Space
   Space element in LMA represents concentrated or unconcentrated emotion derived from the trajectory of movement. To extract this feature, we focus on distributions of speed vectors of end-effectors in a motion and define Space feature value as a norm of a covariance matrix of all speed vectors about each end-effector in a motion.
   Let $V(= [V_1^n V_2^n V_3^n])$ be a speed vector in $\mathbb{R}^3$ and $\mu_i(= E(V_i^n))$ be the mean of V_i^n about an end-effector n. We calculate Space feature $Space_n$ as a norm of a covariance matrix A_n of a speed vector of an end-effector n by the following equations. In the practical calculation, each of V_1^n, V_2^n and V_3^n means a vector about the complete frames in a motion.
$$A_n = \begin{bmatrix} E[(V_1^n - \mu_1^n)(V_1^n - \mu_1^n)] & \cdots & E[(V_1^n - \mu_1^n)(V_3^n - \mu_3^n)] \\ \vdots & \ddots & \vdots \\ E[(V_3^n - \mu_3^n)(V_1^n - \mu_1^n)] & \cdots & E[(V_3^n - \mu_3^n)(V_3^n - \mu_3^n)] \end{bmatrix} . \tag{2}$$
$$Space_n = ||A_n|| = \max_{1 \le j \le 3} \sum_{i=1}^{3} |a_{ij}^n| \; . \tag{3}$$
3. Time
   Time element represents tension emotion derived from sudden or sustained movement. To extract this feature, we calculate the acceleration of a motion. Let F be the number of motion frames and $a_n(f)$ be the acceleration of an end-effector n in a motion frame f. We calculate Time feature $Time_n$ of an end-effector n by the next equation.

$$Time_n = \sum_{f=1}^{F} |\frac{d}{df} a_n(f)|/F \; . \tag{4}$$

As for the feature of *Shape*, we use the mean about all frames of RMS (Root Mean Square) of distances between each end-effector and the root (Center of Mass) of a skeleton in each motion frame.

Let F be the number of motion frames, N be the number of end-effectors and $P(n, f)$ be the coordinate value of an end-effector n in a motion frame F. Then we calculate each Plane feature by the following equations.

$$TablePlane = \frac{1}{F} \sum_{f=1}^{F} \sqrt{\frac{1}{N} \sum_{n=1}^{N} (P_x(n, f) - P_x(root, f))^2} \; , \tag{5}$$

$$DoorPlane = \frac{1}{F} \sum_{f=1}^{F} \sqrt{\frac{1}{N} \sum_{n=1}^{N} (P_y(n, f) - P_y(root, f))^2} \; \; and \tag{6}$$

$$WheelPlane = \frac{1}{F} \sum_{f=1}^{F} \sqrt{\frac{1}{N} \sum_{n=1}^{N} (P_z(n, f) - P_z(root, f))^2} \; . \tag{7}$$

4.2 Gene Representation

We represent motions as their corresponding genes using the LMA-based motion features. As for each of the three types of *Effort* features, we employ the mean of feature values of all end-effectors. Therefore, each chromosome consists of six genes as shown in Fig.1. A chromosome, a gene and an allele are represented as a real vector, a real number and a real value, respectively. For similarity measure of chromosomes, we choose the cosine similarity as a measure of gene similarity. Let x and y be feature vectors and θ is the angle between x and y. Then the cosine similarity sim is defined as

$$sim = \cos\theta = x \cdot y/(|x||y|) \; . \tag{8}$$

In our previous study, as for *Effort* features, we employed the maximum value among corresponding feature values of all end-effectors rather than the mean value of them because in this case we obtain better results of the motion similarity analysis using SOM visualization [3]. However, as described in the next section, we found that users regard the overall movement of a motion rather than its detail as important, so the mean value is better than the maximum value as for *Effort* features.

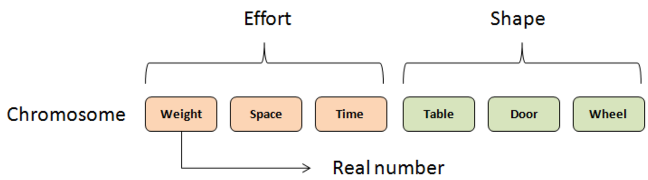


Fig. 1. Gene representation using LMA-based features.

4.3 Visualization and Analysis

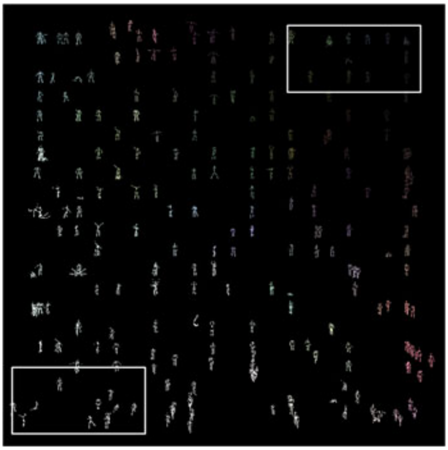
To analyze effectiveness of our defined LMA-based motion features for the motion data retrieval, we apply Self-Organizing Maps (SOM) visualization [14] to motion data using their LMA-based features as the feature vectors of SOM. Using SOM layout, similar feature data are located in the same area and it arranges each data in grid, and thus SOM is useful for analyzing similarities among data records of a database. Fig.2 shows SOM layout of our motion database including 296 motions that is a commercial product called "RIKIYA" [15]. Each motion is colored according to its *Effort* and *Shape* features.

The color gradation in Fig.2(a) illustrates that there are positive correlations between *Effort* feature values. Besides, this color gradation indicates emotions expressed in human movements become more active with the color gradient from black at top-right to white at bottom-left. Actually, as shown in Fig.2(c), bottom-left motions become more active compared to top-right motions. By contrast, the color gradation in Fig.2(b) illustrates there are poor correlations between *Shape* feature values. Consequently, motions are divided into similar shape motion groups clearly. For example, motions such as cartwheel, open-arms or something are drawn yellow in Fig.2(d) (upper) which are zoom-in figures of the regions within rectangular lines in Fig.2(b). This means these motions have high TablePlane feature value and DoorPlane feature value. This is intuitively correct. Similarly, motions including mainly walk motions are drawn blue or purple in Fig.2(d) (lower). This means these motions have low TablePlane feature value and WheelPlane feature value. This is also intuitively correct. These observations may clarify that our proposed LMA-based motion features introduced in the previous section are available as similarity features for motion data.

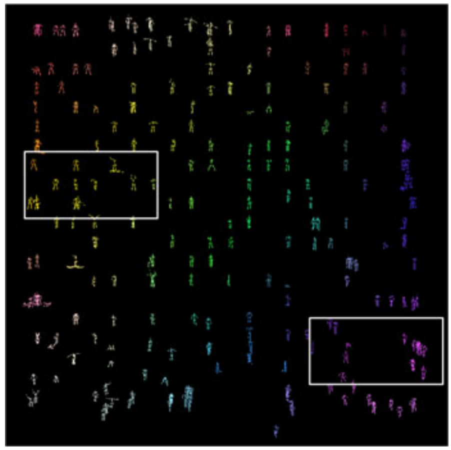
4.4 Genetic Operations

We choose roulette wheel selection algorithm [16] for our system. This selection algorithm calculates probabilities that individuals are selected by GA. We define f_i is a fitness value. The probability p_i of the individual i selected by GA is calculated by

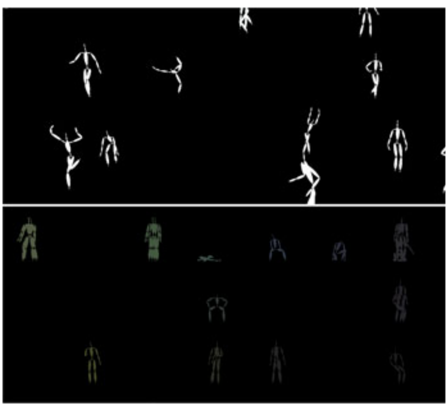
$$p_i = \frac{f_i}{\sum_{k=1}^{N} f_k} \ . \tag{9}$$



(a) SOM layout of motion database colored by *Effort* feature: Red assigned to the Weight feature value and green assigned to the Space feature value and blue assigned to the Time feature value.



(b) SOM layout of motion database colored by *Shape* feature: Red assigned to the TablePlane feature value and green assigned to the DoorPlane feature value and blue assigned to the WheelPlane feature value.



(c) Zoom-in figures of the two regions within rectangular lines in (a).

(d) Zoom-in figures of the two regions within rectangular lines in (b).

Fig. 2. SOM layout of motion database colored by *Effort* (a) and *Shape* (b) feature values. (c) and (d) are zoom-in figures of the regions within rectangular lines in (a) and (b).

In addition, this expression assumes that a fitness value is positive. When the fitness value of an individual is higher, the probability of it becomes higher. If some fitness values are too high rather than others, it causes early convergence which the search settles in the early stages.

There are some crossover operators for real-coded GA such as BLX-α [17] [18], UNDX [19], SPX [20] and so on. In this study, we employ BLX-α because of its simplicity and fast convergence. Let $C_1 = (c_1^1, ..., c_n^1)$ and $C_2 = (c_1^2, ..., c_n^2)$ be parents chromosomes. Then, BLX-α uniformly picks new individuals with a number of the interval $[c_{min} - I \cdot \alpha, c_{max} - I \cdot \alpha]$, where $c_{max} = max(c_i^1, c_i^2)$, $c_{min} = min(c_i^1, c_i^2)$, and $I = c_{max} - c_{min}$.

For a mutation operator, we choose the random mutation operator [18] [21]. Let $C = (c_1, ..., c_i, ..., c_n)$ be a chromosome and $c_i \in [a_i, b_i]$ be a gene to be mutated. Then, c_i' is an uniform number picked from the domain $[a_i, b_i]$.

5 Motion Retrieval System

In this section, we explain our proposed IEC-based motion retrieval system and we also present experimental results of motion retrievals actually performed using the system by several subjects.

5.1 System Overview

There are some typical motion data formats. For example, BVH file format is employed by Biovision Co., Ltd. and ASF-AMC file format is employed by Acclaim Co., Ltd. In our system, we use BVH file format because it is supported by a lot of commercial 3D-CG animation software such as Alias Motion Builder, 3dsMAX Character studio, Poser and so on. This file format consists of two sections: the HIERARCHY section for skeleton information and the MOTION section for motion information. The HIERARCHY section defines an initial pose of a skeleton that includes bone lengths as offset values. The MOTION section defines time series data about sequential poses of a skeleton in a motion.

Fig.3 and Fig.4 show the overview and a screen snapshot of the motion retrieval system, respectively. As the preprocessing, the system creates LMA-based features as a database from the motion database. In this process, index numbers of motions are assigned to each LMA-based feature and the gene is represented as a combination of index numbers. The allele is represented as an index number of a motion. When the user runs the system, it randomly generates genes and retrieves the corresponding twelve motions appeared on a screen. The user evaluates each of these motions by three stage scoring, i.e., good, normal and bad. This evaluation is performed only by mouse clicks on thumbnails of motions. After the evaluation, the system automatically applies GA operations, i.e., selection, crossover and mutation to the genes in order to generate the next generation. And then, the system searches motion data having LMA-based features similar to the features of the newly generated genes to presents them to the user as his/her more desirable motions. After several trials of the evaluation

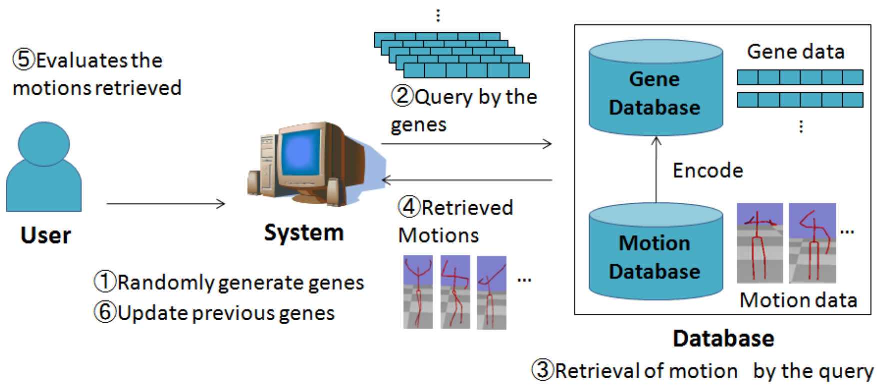


Fig. 3. Overview of motion retrieval system.

process, the user can obtain his/her most desirable motion without any difficult operations.

5.2 Experimental Results

We present experimental results of motion retrievals performed using the proposed system by several subjects. Five students in Graduate School of ISEE, Kyushu University volunteered to participate in the experiment. The experiment is performed on a standard PC with Windows XP Professional, a 2.66 GHz Core 2 Quad processor and 4.0 GB memory.

As a motion database for the experiment, we employed CMU Graphics Lab Motion Capture Database [22]. It contains about 2500 motion data created by recording real human motions using a motion capture system. As for the GA operators, we employed roulette wheel selection operator for the selection, BLX-α crossover operator for the crossover and random mutation operator for the mutation. The value of α is 0.5, crossover rate is 1.0 and mutation rate is 0.01. The fitness values of three stage scoring are 0.8 for good, 0.5 for normal and 0.2 for bad.

For the obtaining the optimum population, we asked the five participants to try to use the system with a different population, i.e., 9, 12 and 16 as shown in Fig.5, and also asked them the question "Which population is preferable for you ?". From the answers to the question, the case of 9 is supported by the two participants, 12 is supported by the three participants and 16 is not supported by any participants. This result means that the case of 16 is obviously too many for the user to scoring them. However, a large number of the population makes it possible to present many motions at once to the user and to reduce a total number of generations. Therefore, we fixed the population is 12. Furthermore, we asked the five participants and found out that users regard the overall movement of a motion as an important factor rather than its detail.

In the experiment for evaluating the usefulness of our proposed system, the participants searched randomly presented target motions using the system. Each

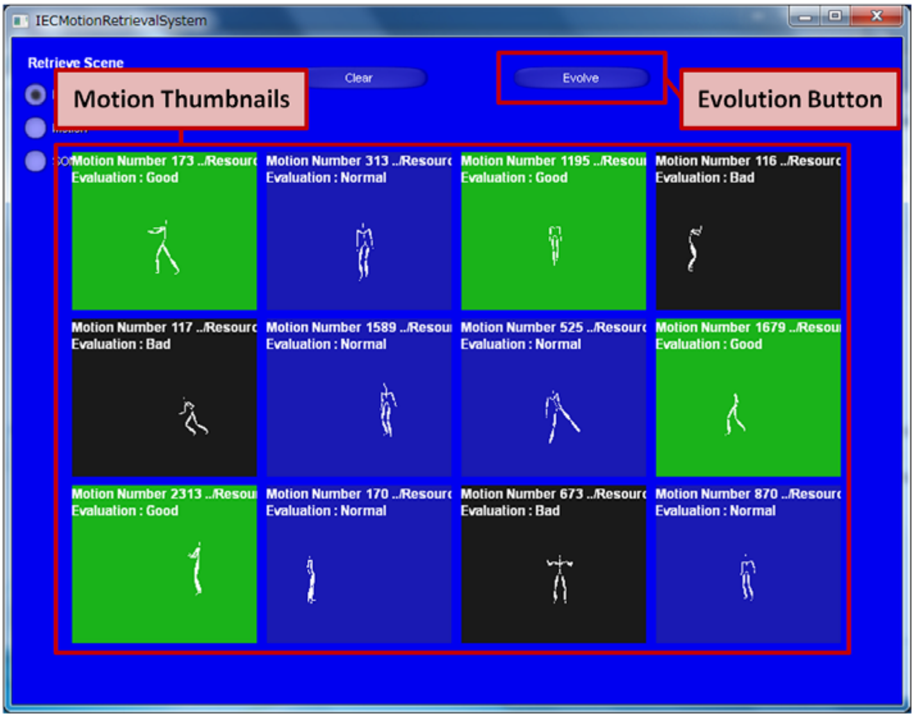


Fig. 4. Screenshot of motion retrieval system.

participant tried to search each of five target motions until 20 generations, and then, we obtained 25 trial results totally. We measured computation and operation times, and we explored retrieved motions. These trials are performed according to the following procedure.

1. Introduction of the motion retrieval system (1 minute).
2. Try to use the system for answering preparation questions (3 minutes).
3. Actual searches for target motions using the system.
4. Answering good points, bad points and comments.

Performance Evaluation. We tried to measure an actual computation time spent for one GA operation and an average user operation time. First, the time spent for one GA operation is less than ten milliseconds and the retrieval time to present next generation is around 1.5 seconds in the case of about 2500 motion data of a database. So, the user manipulates the system without feeling any impatience. Second, the average user operation time until 10, 15 and 20 generations is 6.6 minutes, 9.7 minutes and 12.4 minutes, respectively. As discussed later, it is enough if the user search until around 10 generations or until 15 generations at most. Therefore, it is said that our system allows the user to search his/her desirable motions in a reasonable time.

Fig. 5. Screenshots of three motion retrieval systems which have the different population 9 (left), 12 (center) and 16 (right).

Search Results. Next, we explored retrieved motions and classified the results of trials into three types: 1) Retrieval of the same motion as a target motion, 2) Retrieval of the same class motion as a target motion, 3) Retrieval failure. Table. 2 shows the classification of retrieved motion results. Result 1) can be judged from a corresponding file name. Result 2) and 3) are judged from descriptions of CMU Graphics Lab Motion Capture Database and the participants' subjective evaluations.

Table 2. Classification of retrieved motion results.

	Number of Results
1) Retrieval of the same motion as a target motion	4
2) Retrieval of the same class motion as a target motion	17
3) Retrieval failure	4
Sum	25

The motion descriptions of result 3) are *opening a box*, *putting on a skirt*, *story* and *nursery rhyme - "I'm a little teapot..."*. These motions are consisted as the combination of several different motions so the motions are difficult to classify using LMA features and also difficult for users to continue remembering while search operations using the system. These are reasons for the failure of retrieving such target motions.

Fig.6 shows two charts of the average and maximum similarity values to each of the corresponding target motions among motions retrieved as individuals of each generation until 20 generations in the case of result 1). From these charts, it is said that the system appropriately presents various motions according to the user's selection because peaks of the both charts appear before around 10th generation. Therefore, in this case, around 10 generations are enough for users to search his/her desirable motions.

These experimental results indicate that our proposed system is practically useful for retrieving motion data even in the case of a huge database including many motions more than one thousand.

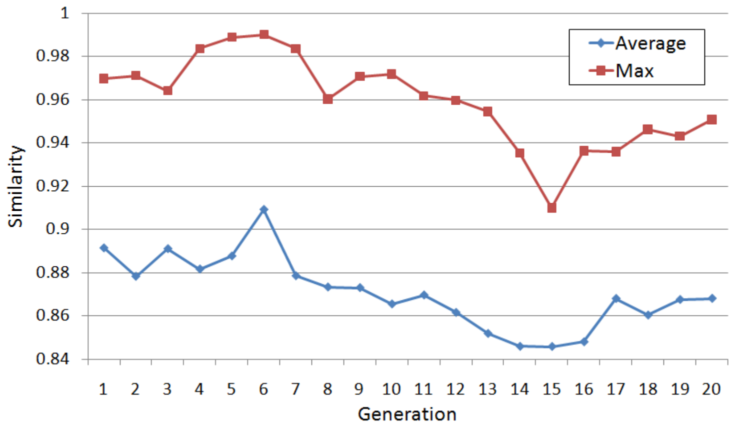


Fig. 6. Average and maximum similarities about result 1).

6 Conclusion and Remarks

In this paper, we introduced the motion retrieval system using IEC based on GA and motion features defined based on LMA which we have already proposed and developed. Our proposed IEC-based motion retrieval system allows the user to retrieve motions similar to his/her required motions easily and intuitively only through the interactive operation to evaluate retrieved motions without any difficult operations. For the motion similarity calculation of the system, we defined LMA-based motion features and clarified that those features are available as similarity features by showing results of analyzing them using SOM visualization. Furthermore, we performed user experiment for evaluating the usefulness of our proposed motion retrieval system. The results indicate that our proposed system is effective for retrieving motion data including many motions more than one thousand.

As future work, there are some improvement points in our system. We will try to find other motion features more available as similarity metrics besides the LMA-based motion features to enhance the motion retrieving accuracy. In addition, we will improve GUI of the system to make it more useful. We also have a plan to provide the proposed system as one of the web services.

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