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Capture Database through Symbolization, Recognition and Generation of Motion Patterns

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***Abstract*— Motion capture systems are used to obtain motion data such that humanoid robots or computer graphics (CG) characters can behave naturally. However, it has proven to be hard not only to modify the capture data without losing its reality but also to search for the required capture data in a lot of capture data. In this paper, we provide a solution to these problems based on our previous work on symbolization of motion patterns for developing humanoid intelligence. Similar motion sequences in the database are abstracted as a symbol, which will be applied to searching motion patterns in the database similar to a given motion. This paper also introduces a method for building a stochastic symbol-word mapping model utilizing the word labels provided by the operator during motion capture sessions. This model converts a input sequence of words into a sequence of symbols, and then allows the capture database both to be searched for capture data corresponding to the input (a sequence of words) and to provide the users with new motion data generated by the symbols. Finally, we apply analogy of symbols to establishing the database in order to provide an appropriate motion data in response to an unsupervised sequence of words and then demonstrate the validity of analogy theory.**

I. INTRODUCTION

In the fields of animation or robotics, CG characters or humanoid robots are required to perform human-like motion. Creating realistic motions is still a challenging task. One common solution to this problem is the use of motion capture system [1]-[3]. Although the motion capture system is a reliable tool to obtain realistic human motion, it is difficult to modify motion capture data. Moreover the capture data are difficult to search in their archives, because the search depends on only the recording date labels or motion pattern labels given by the designer. The difficulty of modification and search limits the reuse of motion capture.

As a tool for editing motion capture data, Motion Graph is a notable research topic. The motion graph finds the motion capture data that can be used in transition periods [4]-[7]. Witkin [8] et al. present an approach to motion generation by using a capture data as motion seed. The Witkin's method called "motion-warping" provides realistic motion patterns. This method depends on motion interpolation with time constraints and space constraints of key frames. Pullen et al. [9] utilize motion capture data to make a motion pattern from key frames look realistic. In this method, motion patterns based on key frames and motion capture data are segmented by detecting frames of zero speed. The segmented motion capture data are mixed with segmented motion patterns based on key frames, where segmented motion capture data are improving the quality of the synthesized motions. In addition to research for reusing capture data, Ren et al. [10] developed a method for quantifying human-likeliness of motion patterns synthesized from motion capture data. Thus various approaches to motion generation by using motion capture data have been presented.

The above survey of previous work indicates that it would be useful if a motion capture database is capable of searching and synthesizing desired motion patterns with simple input. We have developed mathematical methods for symbolization and classification of motion patterns by using Hidden Markov Models (HMMs) [13][14]. Each HMM abstracts several motion patterns that are similar to one another, and forms a proto symbol. We apply these techniques to establish a structure in the motion capture database (Fig.1). We first present a search system for the desired capture data. The database includes motion capture data being labelled automatically by the proto symbols. We then propose to introduce another structure into the database. It is common that a motion capture data is accompanied by a description or a series of keywords about it. We propose to use them as labels and form additional structure to the database. The structure associating proto symbol labels with the descriptions or keywords also provides a useful interface when we search a motion data.

II. AUTOMATIC LABELLING MOTION CAPTURE DATA WITH PROTO SYMBOLS

A. Search for Motion Capture Data Based on Proto Symbol Labels

We propose a new approach to search for the desired motion capture data based on symbol labels. We first describe how to construct the capture database. Proto symbols emerge through automatic motion segmentation and competitive learning [15]. Following the acquisition of proto symbols, motion capture data is labeled. The i-th sequence of motion capture data $\boldsymbol{O}^{(i)}$ is segmented by the segmentation strategy automatically. The capture data segment $\boldsymbol{o}^{(i)}[k]$ is obtained. Each capture data segment is recognized by proto symbols. Let us denote the motion recognition result for each capture data segment $\boldsymbol{o}^{(i)}[k]$ as the proto symbol $\lambda_{\mathcal{R}}^{(i)}[k]$, which outputs the largest likelihood against the capture data segment

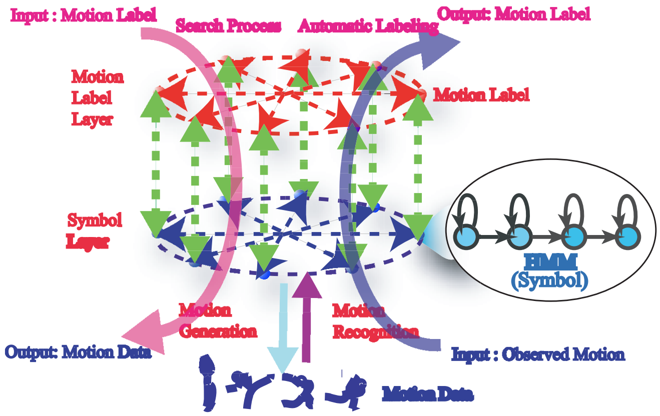

Fig. 1. The motion database includes captured data, HMMs and word labels. Each HMM (proto symbol) abstracts several motion patterns. the word labels are given to capture data manually. The stochastic connection between the symbols and word labels allows the easy search of capture data in a lot of data.

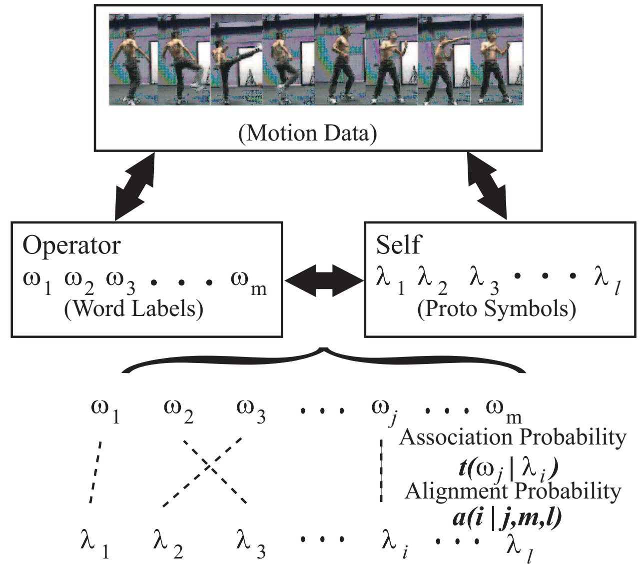

Fig. 2. Triadic relations among motion data, word labels and proto symbols. The parameters of the symbol-word model can be estimated such that mappings between symbols and word labels are optimized

$\boldsymbol{o}^{(i)}[k]$.

$$\boldsymbol{O}^{(i)} = \left\{\boldsymbol{o}^{(i)}[1], \boldsymbol{o}^{(i)}[2], \cdots, \boldsymbol{o}^{(i)}[l]\right\} \tag{1}$$

$$\Lambda^{(i)} = \left\{\lambda_{\mathcal{R}}^{(i)}[1], \lambda_{\mathcal{R}}^{(i)}[2], \cdots, \lambda_{\mathcal{R}}^{(i)}[l]\right\} \tag{2}$$

$$\lambda_{\mathcal{R}}^{(i)}[k] = \arg\max_{\lambda_j} P(\boldsymbol{o}^{(i)}[k] \mid \lambda_j) \tag{3}$$

Motion segmentation and motion recognition allow the capture data $\boldsymbol{O}^{(i)}$ to be transformed to a sequence of proto symbols $\Lambda^{(i)}$. This sequence is also stored with the capture data in the database.

The database can find capture data similar to the desired motion patterns. The desired sample data $\hat{\boldsymbol{O}}$ can be converted to a specified sequence of proto symbols $\hat{\Lambda} = \left\{\hat{\lambda}[1], \hat{\lambda}[2], \cdots\right\}$. The capture data $\boldsymbol{O}_{candidate}$ whose sequence of symbol labels includes the symbolic sequence $\hat{\Lambda}$ is detected, since the selected capture data ought to be similar to the desired motion. In this way, capture data similar to the desired motion can be searched. This approach enables the users to obtain motion capture data similar to the desired one. The detected capture data may have different word-labels from the input one. It means that the search does not rely only on manual labelling of motion patterns, and that it implements the search for capture data based only on the similarity between the capture data and the sample data $\hat{\boldsymbol{O}}$.

III. Database with Word-Labels

A. Symbols-Words Model

In the previous section, users input a sample motion to find desired capture data. However the users do not necessarily have a sample motion. Therefore we propose a new strategy, where the database can be searched for capture data corresponding to the input of a sequence of word-labels. This provides the users with a simple interface.

We next describe a symbols-words model (Fig.2). The symbols-words model represents a stochastic mapping between a proto symbol and word-label. The designer subjectively segments the motion capture data $\boldsymbol{O}^{(i)}$ and gives a sequence of word-labels $\Omega^{(i)} = \left\{\omega^{(i)}[1], \omega^{(i)}[2], \cdots, \omega^{(i)}[m]\right\}$ to the data. The capture data is also converted to a sequence of symbols as shown in equation 3. Note that segmentation by the designer is different from the automatic segmentation method. This means that the number of capture data segments generated by the designer is not always equal to the number generated by the automatic segmentation method ($l \neq m$). The stochastic mapping between a sequence of proto symbols Λ and a sequence of word-labels Ω are calculated by the IBM translation model [11]. Five IBM translation models are presented. These models are numbered in order of increasing complexity. In this paper, we adopt the second model. This model consists of variables for translation probabilities and alignment probabilities. The translation probability $t(f|e)$ denotes the probability that the word e is translated to into the word f. The alignment probability $a(i|j, m, l)$ denotes the probability that position i in the source sentence $\boldsymbol{e}$ can align to position j in the target sentence $\boldsymbol{f}$, where l and m are the length of the source sentence and the target sentence respectively. The translation probability $t(\omega|\lambda)$ is the probability that the symbol λ is associated with the word ω. Let the translation probability be the association probability. The symbols-words model is optimized such that the likelihood Ψ that a sequence of symbols $\Lambda^{(i)}$ generates a sequence of words $\Omega^{(i)}$ becomes the largest

$$\Psi = \sum_{\boldsymbol{O}^{(i)}} P(\Omega^{(i)} | \Lambda^{(i)}) \tag{4}$$

where $\Lambda^{(i)}$ and $\Omega^{(i)}$ expresses the motion capture data $\boldsymbol{O}^{(i)}$ symbolically and linguistically. The optimum values can be computed by the EM algorithm.

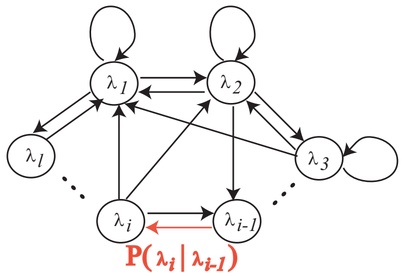

Fig. 3. Symbol emergence is represented by a bigram model.

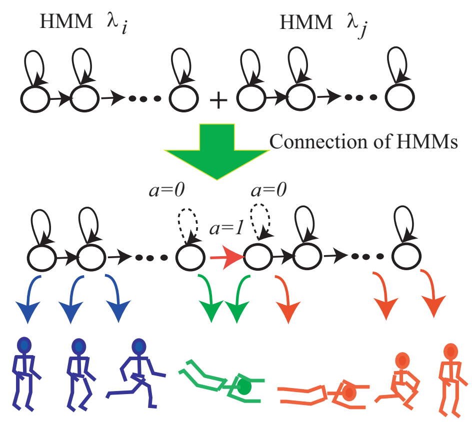

Fig. 4. HMMs is connected to other HMMs by assuming that transition probability from an end node in a precedent HMM to first node in the following HMM has the value of 1. The cofigured HMM generates motion data consisting of some motion patterns stochastically.

B. Search for motion capture data based on symbols-words model

We describe the mapping from a sequence of words, Ω, to a sequence of symbols $\hat{\Lambda}$, where Ω generates $\hat{\Lambda}$ with the largest likelihood. However, direct computing for a sequence of symbols provides us with a sequence of symbols in an inadequate order, because the symbols-words model is insufficient in terms of symbolic order. We therefore establish a symbols-emergence model which learns the symbolic transitions stochastically. We adopt the N-gram model based on the assumption that the current event depends on only $N-1$ previous events. Specifically in this work we use bigram ($N=2$) as illustrated in Fig.3. The probability that a sequence of symbols $\Lambda = \{\lambda[1], \lambda[2], \cdots, \lambda[l]\}$ emerges can be computed by equation 5.

$$P(\Lambda) = \prod_{i=2}^{l} P(\lambda[i]|\lambda[i-1]) \tag{5}$$

The conditional probability on the right hand side of equation (5), $P(\lambda[i-1]|\lambda[i])$, can be optimized by using relative frequency as follows.

$$P(\lambda[i]|\lambda[i-1]) = \frac{C(\lambda[i-1], \lambda[i])}{C(\lambda[i-1])} \tag{6}$$

where $C(*)$ denotes the frequency for event $*$.

The symbols-words model and symbols-emergence model are applied to mapping from a sequence of words Ω to a sequence of symbols $\hat{\Lambda}$ as indicated in equation 7.

$$\begin{aligned} \hat{\Lambda} &= \arg\max_{\Lambda} P(\Lambda|\Omega) \\ &= \arg\max_{\Lambda} P(\Lambda)P(\Omega|\Lambda) \end{aligned} \tag{7}$$

The symbols-emergence model allows us to pick up a sequence of symbols in an appropriate order.

We describe how a sequence of symbols $\hat{\Lambda}$ is calculated in equation 7. The calculation employs A^* search method [12]. A^* search method is one of the most efficient graph search algorithm in computer science. The graph search has a tree structure of nodes and edges, and finds a path from a given initial node to a given goal node. The A^* search method employs a heuristic estimation that ranks each node by estimating the best path that goes through that node. The node with the largest heuristic estimate is visited first such that the best path is found in a short time.

The sequence of symbols calculated by equation 7 allows the search of capture data as described in the precedent section. Moreover, the sequence of symbols $\hat{\Lambda} = \left\{\hat{\lambda}_1, \hat{\lambda}_2, \cdots, \hat{\lambda}_l\right\}$ can generate motion data as illustrated by Fig.4. Each symbol is represented by a left-to-right HMM. The symbols in $\hat{\Lambda}$ are connected in series by setting the transition probability from the node at the end in the precedent HMM λ_i to the node at the head in the following HMM λ_{i+1} to 1. This connection constructs one left-to-right HMM. Motion can then be generated by this HMM stochastically [16].

C. Motion Generation Using Analogy from Clustering Proto Symbols

The symbols-words model and the symbols-emergence model described in the previous subsections represent the mapping between symbols and words, and transition of symbols in supervised data stochastically, which means that this strategy may not be useful for unlearned sequences of words or symbols. This problem is often called poverty of the stimulus. However human can adapt to unknown situations by using some knowledge acquired in experienced situations similar to the current one. This estimation based on similarity is analogy. We think that analogy is one of the solutions to this problem. Therefore, we propose a new symbols-emergence model that represents the stochastic transition among clusters of symbols. The similarities among symbols which belong to the same cluster can supports the database's adaptability to unknown input patterns. We call this strategy analogy in the viewpoint that the database can use knowledge about similarity among symbols.

The clustering for proto symbols employs the proto symbol space and the mixture probability density function (Fig.5). The proto symbol space can be constructed by using multidimensional scaling based on Kullback Leibler information which defines the dissimilarity among HMMs.

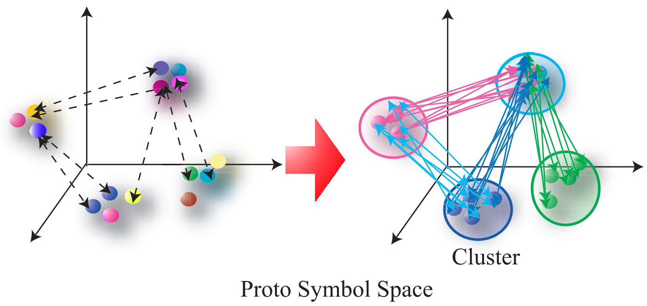

Fig. 5. Symbols are located in a multidimensional space such that the ditance between the symbols in the space become as close as possible to their dissimilarities. The symbols are classified based on the their locations. Each cluster is assumed to correspond to a node in the symbol emergence model (bigram). Even if two symbols λ_a and λ_b do not have relation of emergence with each other, they has strong relation when λ'_a and λ'_b have emergent correlation, where λ'_a is one of the symbols belonging to the same cluster as λ_a, and λ'_b belong to the cluster of λ_b.

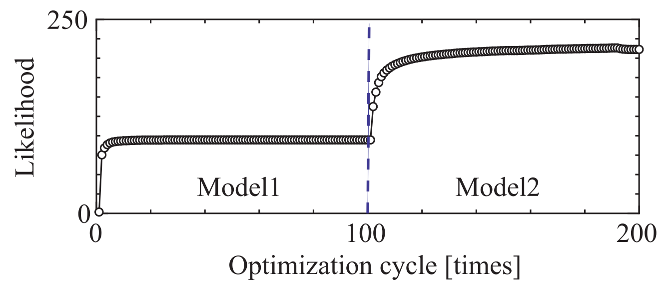

Fig. 8. Likelihood over the iterative computation for optimizing parameters of symbols-words model.

The mixture probability density function approximates the distribution of proto symbols in the proto symbol space. Each probability density function is defined as a cluster. From cluster analysis, transition probability among these clusters can be computed. We can then obtain a new symbols-emergence model from assumption that each cluster corresponds to each node in the bigram illustrated in Fig.3.

$$P(\Lambda) = \prod_{i=1}^{l} P(\lambda[i] \mid \lambda[i-1]) \tag{8}$$

$$P(\lambda[i] \mid \lambda[i-1]) = \frac{C\big(\mathcal{S}(\lambda[i-1]), \mathcal{S}(\lambda[i])\big)}{C\big(\mathcal{S}\left(\lambda[i-1]\right)\big)} \tag{9}$$

$\mathcal{S}(\lambda)$ indicates the cluster where the proto symbol λ is categorized. In the symbol-emergence model without clustering, the transition probability from the proto symbol λ_i to λ_j becomes zero if the symbolic transitional patterns that the proto symbol λ_j follows the proto symbol λ_i are not included in the supervised data. However in this model, this transition probability can have a nonzero value if a proto symbol in the cluster $\mathcal{S}(\lambda_i)$ precedes a proto symbol in the cluster $\mathcal{S}(\lambda_j)$ in the learning phase. The information of proto symbols near to the proto symbols λ_i and λ_j in the space makes it possible to generate motion data appropriate for unlearned input patterns.

IV. Experiment for Validity of Motion Capture Database

A. Search for Capture Data based on Symbol Labels

We performed some experiments to verify the validity of the motion capture database. We are given 537 motion capture data related to baseball. The total time period of the capture data is 4088 seconds. The original capture data consists of a sequence of Cartesian coordinates for 34 markers attached to some performers. Inverse kinematics using 20 DOF human character model converts original capture data into 30 dimensional data of the two horizontal velocities, height, roll, pitch, and yaw velocity of the body, Cartesian coordinates of both elbow joints, knee joints, wrists joints and ankle joints in the local coordinate system of the body. The capture sampling time is 30 milliseconds. Each sequence of 30 dimensional data $\left\{\boldsymbol{O}^{(i)} : i = 1, 2, 3, \cdots, 537\right\}$ is stored in the database.

The 99 proto symbols $\{\lambda_j : j = 1, 2, 3, \cdots, 99\}$ are acquired automatically through observing the capture data. Using these proto symbols, each capture data $\boldsymbol{O}^{(i)}$ is given a sequence of symbols. The sequence of symbols is also stored as symbol label for each capture data in the database. The database is searched for capture data similar to the desired motion based on the symbol label. For example, we searched for motion capture data using an input of motion data corresponding to "dash". In this experiment, the database picked up several capture data whose symbol labels include the proto symbol signifying motion data of "dash". Fig.6 shows two examples of capture data output by the database. Each capture data partially includes motion pattern of "dash". Therefore we can confirm that the database can find various capture data similar to the desired motion through matching proto symbols of the desired motion with the symbol label of each capture data in the database.

B. Search for Capture Data and Motion Generation based on Symbols-Words Model

Each capture data $\boldsymbol{O_i}$ is given a sequence of words $\Omega^{(i)}$ manually. For example, capture data for a lefty's swinging and then running is labeled with "left_swing run". Note that 64 words $\{\omega_k : k = 1, 2, 3, \cdots, 64\}$ are required to express all the capture data. The symbol labels for the capture data are the same as the previous subsection. We calculate the stochastic mapping between a sequence of symbols $\Lambda^{(i)}$ and a sequence of words $\Omega^{(i)}$ for capture data $\boldsymbol{O^{(i)}}$. Fig.8 indicates the likelihood computed by equation 4 against times of iterative estimation for parameters of the symbols-words model. Note that the parameters are first optimized through convergent calculations of 100 times, on the assumption that the symbols-words models is the model 1. The parameters are then estimated by using an optimization algorithm for the model 2 in order to improve the accuracy of the optimization. Fig.8 shows that the stochastic mapping between sequences of symbols and words is optimized since the likelihood gets

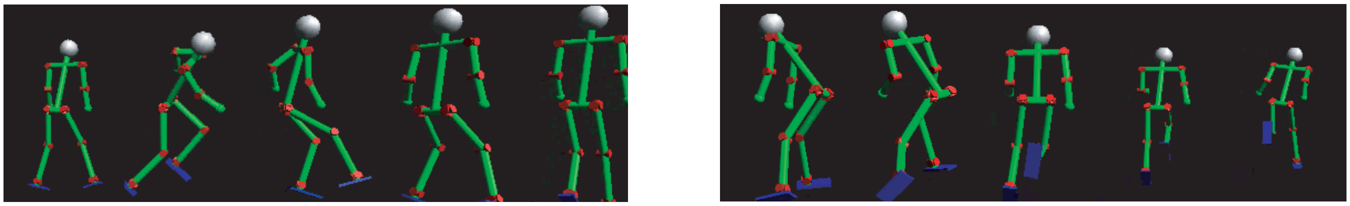

Fig. 6. Some captured data are detected based on symbol labels on the each captured data. Animations show two examples of captured data detected from an input "dash" motion data.

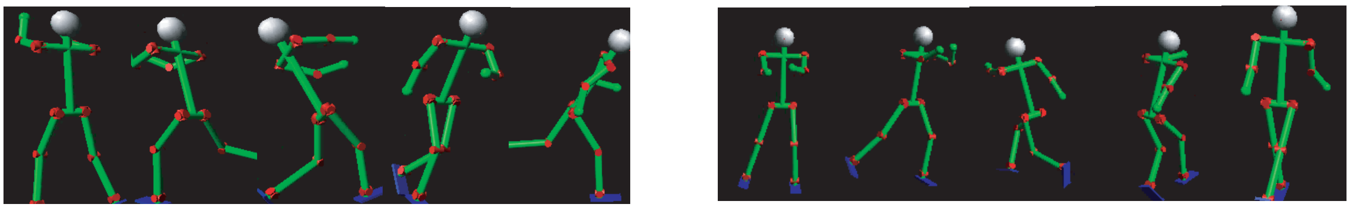

Fig. 7. Some captured data are picked out from input of sequences of words. Animations show two examples of captured data found from a sequence of word labels "left_swing run"

larger as the convergent calculation proceeds.

We perform an experiment by searching for capture data from a sequence of words using the optimized symbols-words model and symbols-emergence model. We input "left_swing run" to the database. Fig.7 shows two examples of the detected capture data. The search based on a sequence of symbols is the same as in the previous subsection. The motion data on the left side of Fig.7is adequate for the input "left_swing run". However the other capture data in Fig.7 reveals that the performer swings his bat and then walks. We are sure that output data "walk" are different from the input "run". However these motion patterns are similar to each other. We do not necessarily think that the database makes mistakes in searching the capture data. The database provides the users with capture data which can not be found by conventional search methods such as "text matching". This experiment clarifies that we can easily find motion capture data similar to desired one by using this database.

In addition to searching for the desired capture data, we aim to construct a database which can generate new motion data in response to an input of words. The same input "left_swing run" used in the search experiment was employed for the experiment, where the database yields motions through a sequence of symbols from an input sequence of words. Fig.9 shows the motion generated by the database through sequences of symbols from sequences of words. It demonstrates that the lefty swings the bat and then runs. The snapshots on the right side in Fig.9 shows that a small humanoid with 20 joints behaves using the generated motion data as motion reference. The database can generate a new motion suitable for the input of "left_swing run", which can be used for CG characters or real humanoid robots. We verify that the database can not only detect capture data similar to the desired one but also generate appropriate motion data in response to a sequence of words based on the symbols-words model, symbols-emergence models.

C. Motion Generation Based on Symbolic Analogy

An experiment is conducted on the generation of new motion in response to an unsupervised sequence of words by applying cluster analysis of proto symbols to the symbols-emergence model. We employed an input "run sliding stand_up dash" to the database. The supervised sequences of words do not include the sequence "stand_up dash" but the sequence "stand_up run". However words "dash" and "run" may signify motion patterns similar to each other. If a new motion suitable for the input can be generated by the database, estimation based on this similarity is a solution to the problem of analogy. Therefore we used this input as one of sequences including "stand_up dash". Fig.10 shows motion generated by the database based on the symbols-emergence model without or with clustering proto symbols. Motion on the right side in Fig.10 represents that the character swings, bends a little and then stands still. On the other hand, the character runs, slides, stands up and then tries to run on the right side in Fig.10. We can confirm that the database with symbols-emergence model based on clusters of symbols can generate motions in response to unlearned sequences of words. The database processes the estimation using similarities among proto symbols and we believe this estimation can develop into analogy.

V. Conclusion

In this paper, we describe an application for the symbolization of motion patterns, motion recognition and motion generation through the symbols to establishing the motion capture database.

The database stores the capture data, sequences of symbols which can be automatically assigned to the capture data through symbolization and classification of motion patterns, and sequences of words which can be manually given to the capture data. The database has two main functions, search for motion capture data and generation of new motion data. The

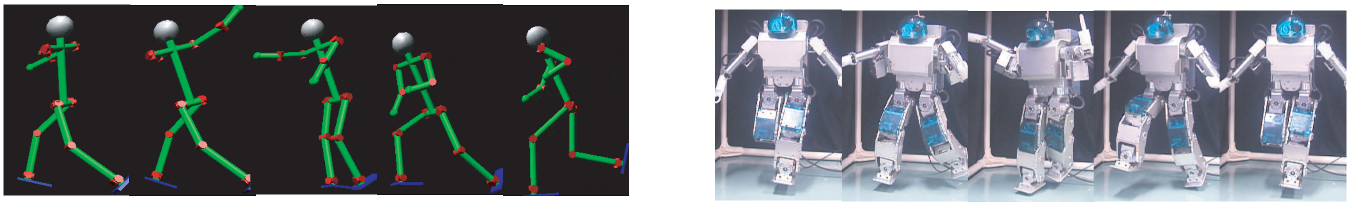

Fig. 9. A motion pattern is generated by a sequence of proto symbols corresponding to input words "left_swing run" on the right animation. The left figure indicates that the generated motion pattern can be used for a real humanoid's behavior.

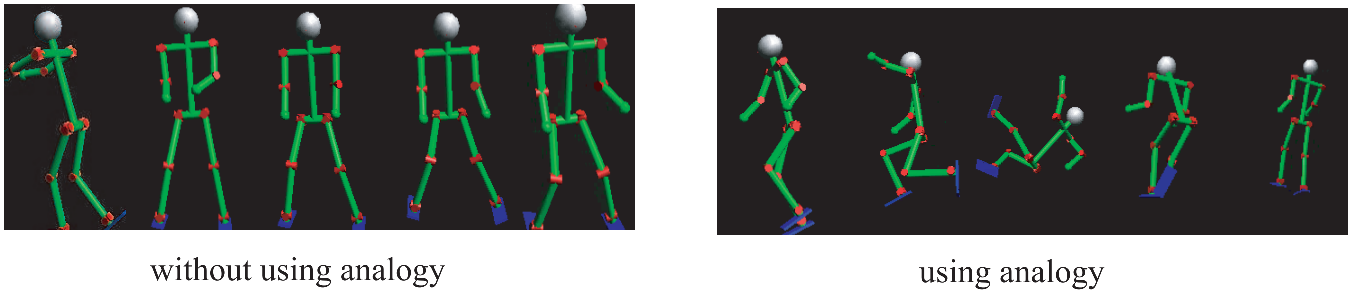

Fig. 10. Comparison between motion generation without analogy and analogical one. The right side shows the generated motion using symbol emergence model without clustering the proto symbols. The left side shows the generated motion using symbol emergence model based on clusters of the proto symbols.

search function provides capture data similar to the desired sample motion data input by the user. The database also allows the users to input a sequence of words corresponding to their desired motion and then obtain the capture data signified by the input. Additionally, the database can convert a sequence of words into a sequence of symbols and generate motion data based on these symbols. The symbolic operation enables the capture data to be modified or edited. Finally, the database with symbolic analogy can generate new motion data which is not unsupervised. This addresses the problem of "poverty of stimulus". We conclude that symbolization and classification of motion patterns can be an efficient approach to construction of the motion capture database.

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