隠れマルコフモデルを用いたダンスモーションの自己組織化

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あらまし: CGアニメーションに動作生成の方法として、モーションキャプチャで得たデータの周波数解析を用いて特徴的な動きを抽出し、データの信号処理を用いて加工している。人体動作の再生成は、動き間の相関関係を考慮する必要がある。本稿では、時系列パターン認識のための新たな確率モデルとして、隠れマルコフモデルを提案し、舞踊符によって分類した動きの方向を用いて、ダンス動作のパターンを認識した。認識したパターンを出現頻度順に並べることにより、ダンスモーションの特徴、相関関係を解析し、べき乗則、すなわち、Zipfの法則に従うかどうかを調べた。現在まで開発されている複雑系理論を利用することにより、新たなマルチメディア情報解析手法が試した。

Self-Organized Criticality in Some Dance Motion Using Hidden Markov Model

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Abstract: Although people recorded the motion using Labanotation, the difference between the specialist of a dance and of a beginner cannot be expressed. If we can find the feature of a human body dance motion well, we can recognize the specialist of a dance, and a beginner's dance analytically, can save the culture of a dance, and then reconstruct it. Recently, much effort has addressed the problem of editing and reuse of existing animation, including dance. A common approach is using Hidden Markov Models (HMMs) to recognize and analyze motion from video sequence. We are studying a new method, which is extracting some characteristics or features of human motion, to analyze and reconstruct human motions. That is a self-organized criticality (SOC) in dance motion using the developing complexity theory. Firstly, using Labanotation, we classify every one movement toward a dance exactly, and classify severely motion in the different state, and structure the HMMs to carry out for our classification of motion having been right for a check. At the end, classified motion is ranked with frequency of appearance, and it verify whether it is conformity to the power's law in quest of the logarithm of the order of a rank, and the logarithm of the number of frequency of appearance.

Keywords-Hidden Markov Models (HMMs), Labanotation, self-organized criticality (SOC).

I INTRODUCTION

In the past few years, complex system attract more and more people's attentions in the most exciting and ambitious fields in physics. It is realized that many complex systems advance to minimally stable state[1]. Some systems consisting of many interacting constituent may exhibit some general characteristic behaviors. The seductive claim is that, under very general conditions, dynamical systems organize themselves into a minimally stable state, which is called self-organized criticality (SOC), with a complex but rather general structure. A self-organized criticality is the term generically applied to the system that are driven to a critical state that is robust to perturbations and whose macroscopic behavior is predictable to the extent that it follows power laws with exponents depending on geometry and spatial structure [2].

It has been suggested that biological populations are typically in a self-organized state. They are evidenced for example by a power law distribution of extinction events.

While this is a very appealing idea, especially, in view of the robustness of living systems, it has suffered from being somewhat vague, mainly because of the difficulty involved in modeling living system. Specifically, there is as yet neither a clear identification of the self-organized criticality state of life or the agent that caused self-organization, nor a definition of a critical or threshold variable whose disturbance causes the ubiquitous avalanches giving rise to power-law distributions [2 4].

Human, as the highest living thing of the nature, keeps the natural order. Does the moving from the correlative motion of a human body, and the movement toward a dance, that is to say, the movement toward the present dance to the next dance, protect the rule of a nature? We debate in this paper.

We use Labanotation to classify every one movement toward a dance exactly, and classify severely motion in the different state at first, then, use the model of Hidden Markov to estimate the classified state of the dance pattern from the motion capture data. HMMs is the usual estimation of dynamical models from examples, and style and content separation. Finally, we rank emergencies of classified dance motion patterns. We examine the logarithm of the order of rank and emergencies, check if it fits the power law or Zipf's law that is the necessary condition for the self-organized criticality (SOC) state.

Ⅱ RELATED WORK

In the field of computer graphics, many people address the problem of editing and reuse of existing animation. Brand et al.[5] propose the problem of stylistic motion synthesis by learning motion patterns from a highly varied set of motion capture sequences [5]. Gleicher [6] provides a low-level interactive motion editing tool that searches for a new motion that meets some new constraints while minimizing the distance to the old motion. Howe et al. [7] analyze motion from video using a mixture of Gaussians model. With regard to styles, Wilson and Bobick [8] use parametric HMMs, in which motion recognition models are learned from user-labeled styles. These models provide a method for classifying and estimating animation; we use HMMs to analyze and estimate the classified human motion capture data by Labanotation, and then extract the characteristics of human motion like multi-fractality or SOC to survey the power law of dance motion.

Ⅲ HIDDEN MARKOV MODELS (HMMs)

An HMM is a probability distribution over time-series. It is specified by $\theta = \{S, P_{i,}, P_{j\to i,}, p_i(x)\}$, where

1. $S=\{s_1, \ldots, s_N\}$ is the set of discrete states;
2. stochastic matrix $P_{j\to i}$ gives the probability of transitioning from state j to state i;
3. stochastic vector P_i is the probability of a sequence beginning in state i;
4. emission probability $p_i(x)$ is the probability of observing x while in state i, typically a Gaussian probability.

For some essentials, please see a more detailed tutorial [9].

Ⅳ POWER'S LAW IN SELF-ORGANIZED CRITICALITY (SOC)

Now let's propose the definition of Power law behavior in spectrum, which is a necessary, but not a sufficient, condition for SOC, and is seen in many physical systems. First, we have the power spectral density distribution (such as $1/f$ noise) [2]:

$$p(f) \sim 1/f^{\alpha} \qquad (1)$$

Another kind of power law appears in size distribution [2]:

$$N(s) \sim 1/s^{\beta} \qquad (2)$$

This kind of distribution is observed as the Gutenberg-Richter [2] law in geophysics. Finally, we distinguish a power law in the temporal distribution of events [2]:

$$N(\tau) \sim 1/\tau^{\gamma} \qquad (3)$$

Particularly, when t is the rank of the event r, we call it Zipf's law [2].

$$N(r) \sim 1/r^{\gamma} \qquad (4)$$

Power law reveals that no periodic dynamics in the population, but does not rule out certain random process that have a power law frequent spectrum but show no signs of self-organized critical behavior [2].

V METHOD

Our learning data is shown in Fig. 1 that shows the sequences of motion dance.

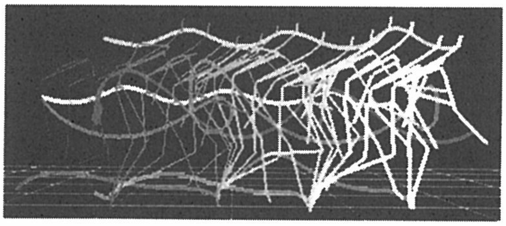

Fig.1: stick figure of motion

Samples are classified using Labanotation rule [10], which is a standard system for analyzing and recording human motion. In Labanotation, it is possible to record every king of human motion. The basis of the notation is some natural human motions. Every deviation from this natural human motion has to be specifically written down in the notation.

We write our Labanotation of motion capture data referencing [10].

Using our motion data, lower case we calculate the entropy and estimate the states of HMMs. Fig.4 shows HMMs estimated from our samples.

In figure 4, there is the sequence of observations, and x axis means observation vector, y axis means state vector; "x" means the sequence of observations, and green is state 1; red is state 2; magenta is state 3; the color is the label of the state attached to the observation, the red plots are the given 2D Gaussian on the current plot by parameters of the real ni and lambda of HMM [9]; the white plots are also the given 2D Gaussian by the estimated parameters of ni and lambda of HMM [9]; ni and lambda are estimated parameters by HMMs using Baum-Welch Algorithm [9]; and the squares in fig.2 are the incorrectly estimated states. If there are too many mistakes, the relabeling procedure fails and the squares are no meaningful any longer [9].

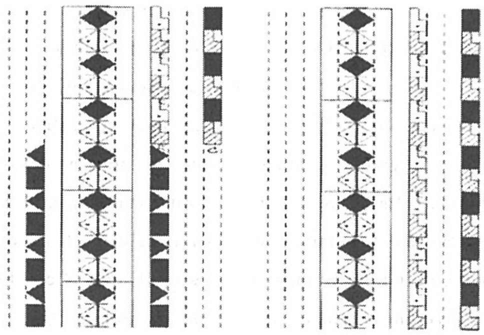

Figure 2: Labanotation of motion capture data

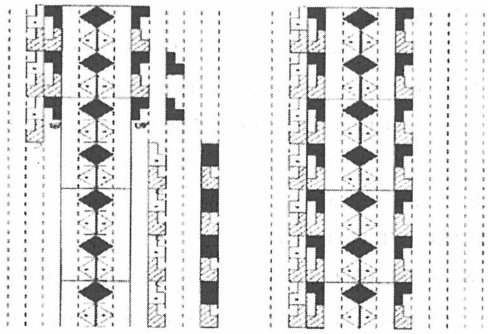

Figure 3: Labanotation of motion capture data

Then we get the Richardson graph [11] of movement from the estimated states. From Fig.5, we compute one regression line at the left of the break point as:

$$y-1.17=-0.602(x-0.26) \qquad (5)$$

where the slope of the line is 0.602. The regression line at the right of the break point can be expressed as:

$$y-0.688=-3.56(x-0.639) \qquad (6)$$

where the slope of the line is 3.56. These values of slope can be considered as the fractal dimensions of this system as HMM [11].

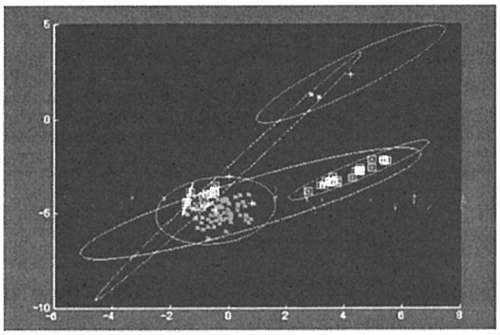

Figure 4: estimated states of HMM

VI OPEN QUESTIONS AND CONCLUSIONS

It's still a new field to analyze the motion dance from the viewpoint of self-organized criticality in computer graphics. Our final goal is producing dance motion pattern with regard of evolutionary dynamical system by the interactive characteristic of dance motion; and our framework is currently superficial to analyze the characteristic of dance motion. In the future, we want to use larger of data to analyze the characteristic. The motion data will appear some other important nature which we do not know now. It should be very interesting and developmental in the field of computer graphics, and recognize the art of dance analytically, and can save the culture of classical or realistic dance.

ACKNOWLEDGMENTS

We would like to thank Mr. Nobuyosi Ono of Visual Science Inc. Japan, who kindly for offered us the motion dance data of "DaTe KyoKo".

REFERRENCES

[1] Scientific American in Japanese, 120, N0.6, 1997.

[2] Adami Christoph, *INTRODUCTION TO ARTIFICAL LIFE*, the electronic library of science, 1998.

[3] M.F Barnsley, R.L. Devaney, B.B Mandelbrot, H.O. Peitgen, D.Saupe, R.F Voss, *The Science of FRACTAL IMAGES*, Springer-Verlag New York Inc, 1988.

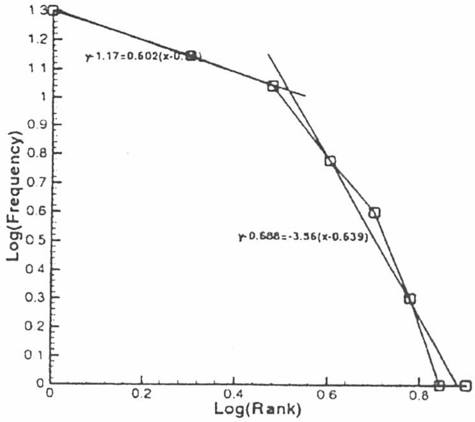

Fig.5: Richardson graph of movement by labanotation

[4] Henrik Jeldtoft Jensen, *Self-Organized Criticality, Emergent Complex Behavior in Physical and Biological Systems*, Cambridge Univ. Press, 1998.

[5] Mattew Brand, Aaron Hertzmann, *Style machines*, Proceeding of SIGGRAPH 2000, pages 183-192.

[6] M.Gleicher, *Motion editing with space-time constraints.*, 1997 Symposium on Interactive 3D Graphics, pages 139-148, April 1997.

[7] N.R. Howe, M.E. Leventon, and W.T. Freeman, *Bayesian reconstruction of 3d human motion from single-camera video.*, In S.Solla, T.Leend, and K.Muller, editors, Advances in Neural Information Processing Systems, volume 10. MIT Press, 2000.

[8] A. Wilson and A. Bobick, *Parametric hidden markov models for gesture recognition*, IEEE Irans, Pattern Analysis and Machine Intelligence, 21(9), 1999.

[9] Max Welling, *CS/CNS/EE 156B Learning Systems Spring 2000*, http://www.vision.caltech.edu/welling/class/

[10] Ann Hutchinson, *Labanotation or Kinetograph*, Theatre Arts Books, Revised Third Edition, 1977.

[11] J.C. Graf, *The importance of resolution limits to the interpretation of fractal descriptions of fine particles*, Socar system Exploration Division, NASA-Johnson Space Center Houston, TX 77058(U.S.A)(Received July 30, 1990).