Motion Texture: Motion analysis by self-organization to criticality

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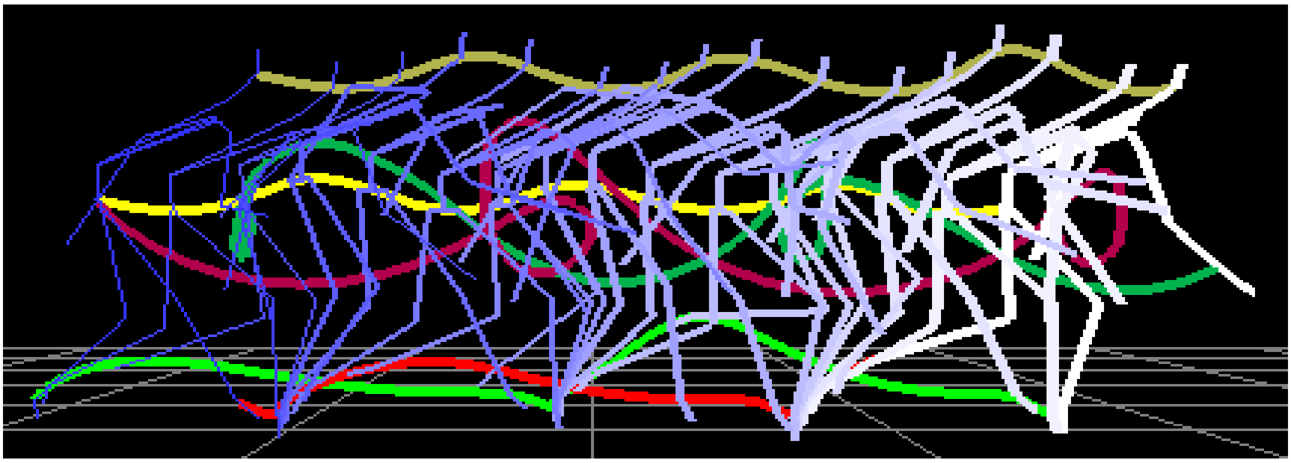

Figure 1. stick figure of motion

Ⅰ INTRODUCTION

At first, Let us think about this question: Can we explain such phenomenon as you certainly recognize your friends from faraway, or even if you are apart from a long time?

We seek the answer from "Motion Texture". Like from your born, you take features that the nature, or your mother, or DNA gives you, such as finger mark, voice, birthmark, "Motion Texture" is also your personal property. Following your age increased, your "Motion Texture" will have little changes too, just like your finger mark, your voice or your birthmark will have, but it always is your feature, your mother and friends will recognize you from 64 hundred million persons by it! "Motion Texture" is people's motion features. Then, how can we distinguish your "Motion Texture" from 64 hundred million persons, as say, recognize your motion features from other motion? Furthermore, if we can analyze people's "Motion Texture", to recognize motion features, like as voice recognition, recognize person, and then reuse recognized "Motion Texture" to the field of entertainment, pattern recognition, multimedia? Even if it seems interesting about "Motion Texture", then how do we analyze the new direction of computer graphics sicence?

Recently, people analyze the living system that is around us everyday and everywhere from the view of complexity. 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 [1, 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.

As the highest living thing of the nature, does the human's "Motion Texture" keeps the natural order? Instead, we ask the other question: Does the moving from the correlative motion of somebody's "Motion Texture", and the movement toward a motion, (in this paper, we are concerned about dance motion) that is to say, the movement toward the present dance to the next dance, protects the rule of a nature? We debate this problem in this paper.

Ⅱ RELATED WORK

In the field of computer graphics, many people address the problem of editing and reuse of existing animation. Brand et al.[3] propose the problem of stylistic motion synthesis by learning motion patterns from a highly varied set of motion capture sequences. Gleicher [4] 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. [5] analyze motion from video using a mixture of Gaussians model. With regard to styles, Wilson and

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Bobick [6] use parametric HMMs, in which motion recognition models are learned from user-labeled styles. These models provide a method for classifying and estimating animation; Based on the observation that these repetitive patterns of life-like motion exhibit inherent randomness, Pullen and Bregler [7] proposed a multi-level sampling approach to synthesize new motions that are statistically similar to the original, similar to multi-resolution representations of texture and movie texture. Bruderlin et al. [8] introduce motion signal processing from multisolution motion filtering, multitarget motion interpolation with dynamic time-warping, waveshaping and motion displacement mapping. As an exercise or for comparison with our proposal, we have raw-data of walk circle1 and walk circle2, and warp walk circle1 to walk circle2.

We propose to analyze motion capture data, specifically, analyze the quantified or discrete angles of each D.O.Fs of human model, and distinguish the postures, or “Motion Texture” from minimum state. Then, we estimate the distinguished motion capture data by quantified angle, and extract the characteristics of human motion like multi-fractality or SOC to survey the power law of motion. We use some dance motion specifically, and would find the similar characteristics in other motion without doubt.

So, what is SOC, and what are it’s necessary conditions? In section III, we introduce the theory about SOC.

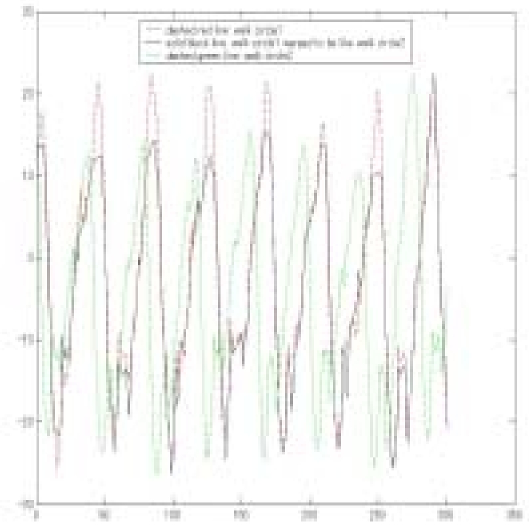

Fig.2 angles curves of two walks and warped curve

Ⅲ Power’s law in Self-Organized Criticality (SOC)

As of yet, there is no universal theory of SOC, we try to summarize the main requirements that must be met in order to observe a self-organized critical system.

- A dissipative dynamical system with (locally) interacting degrees of freedom.
- Propagation of fluctuations described by a dissipative transport equation.
- Noise that can propagate through the entire system.
- An infinitesimal driving rate.

The paradigm for the self-organized critical state is the sandpile that Bak, Tang, and Wiesenfeld (BTW) introduced [2].

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 τ 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].

Ⅳ Our Proposal of analyze “Motion Texture” by quantify joint angles.

Because the dance are completed in one rhythm companying the music, we analyze the frequency of joint motion by FFT, for example the root hip in the skeleton model. Then, we can watch some keyframe appearance in the signal.

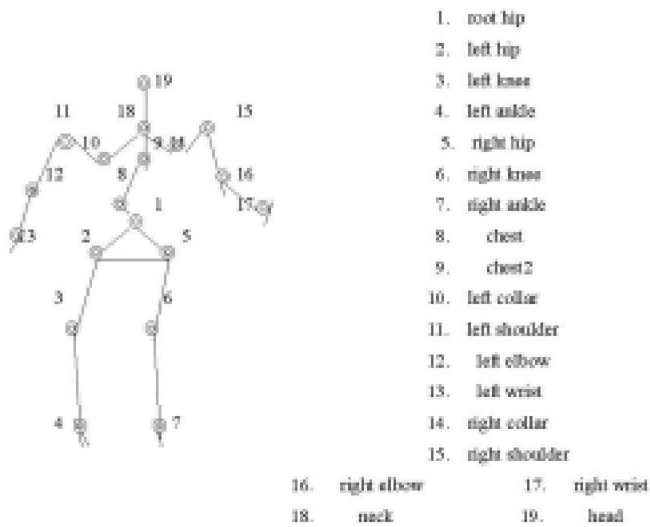

Fig.3 the model of skeleton

Assuming the keyframes and postures are specified, we have to identify each postures, as to say, identify “Motion Texture” of each dance postures or pattern. First step, we convert signal data into joint angles. We use only joint angle to classify the key posture, analyze the involving information about joint angles, which articulately cause greatest changes in dance pose. Fig.4 shows the signal of our dance motion data.

We classify $\{\theta_{head;\ R,L\ UpperArm;\ R,L\ LowerArm;\ \ldots}\}$ by D.O.Fs of the human skeleton model with their angle values following the movement directions (θ><0 or $\theta_{t+\Delta t}$><0). However, human motion does not generate exactly the same angles with the same postures, thus we have to quantify or discrete the angles and distinguish the postures according to their nearest quantified angles. The question here is that how we can quantify the angles or how we can specify the angle ranges or levels of each key posture.

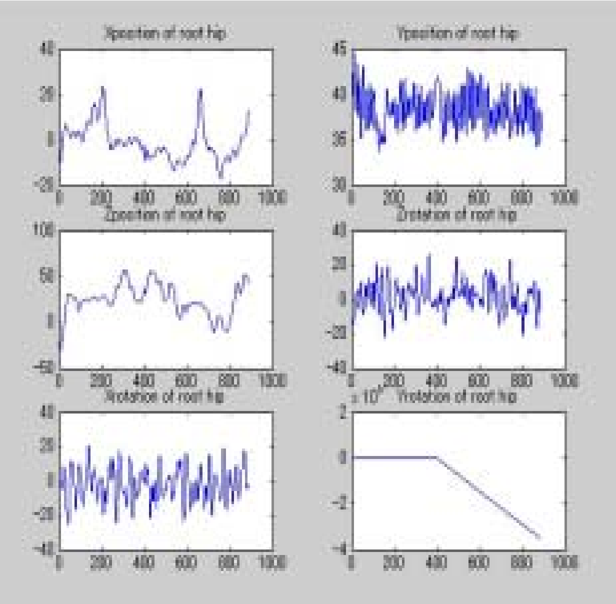

Fig.4 signal of motion capture data of our dance

Of course, in one rhythm of the music, we have 16~17 frames, then we can discrete θ 16~17 angles, like $\theta_0 + \Delta\theta * i/N$, where θ_0 is the initial angles and $\Delta\theta$ is the maximum range of the joint angles, N is the frame number in one rhythm, and i=1,…,16 or 17. We do not know if this gives the distinct key postures or not. This may gives different key posture with the same posture, at the same time; the different quantified method may give different results. In face of such adversity, we have to first estimate the theoretical distribution of SOC. This process is essentially the process to determine the dance motion D.O.Fs. Note that dance motion D.O.F is different from dynamical D.O.Fs. We use the determined theoretical distribution to determine the motion D.O.F. Thus, both the number of quantified levels and motion D.O.F can be determined.

Assuming the normal distribution, we attempt to fit the data with the smallest number of parameters, that seems reasonable to us, in the form of a power law [2]:

$$N(\tau) = A\frac{1}{\tau^{\beta}}e^{-\tau/T} \qquad (5)$$

Where T is a cut-off parameter, τ is the rank, A is const, N is the number of that key postures appeared, and β is unknown. Eq.5 is the χ^2 distribution, we assume the dance motion is based on 1st order Markov model. If "T" is larger enough, $N \propto \frac{1}{\tau^{\beta}}$ for $\tau \ll T$, thus we consider or assume for human dance motion the distribution may follow the self-organized criticality.

Note the dynamical D.O.F have 9 or 10 D.O.Fs. Eq.5 assume each joint have the same smallest quantified parameters or have the same number of quantified levels. (This may be not true). Here we consider a different $M(\tau)$, obtained from our distribution $N(\tau)$, by asking about the distribution of events with rank larger than τ.

As this distribution, we take [2]:

$$M(\tau) = \frac{1}{\tau^{\beta}}\int_{\tau}^{\infty} N(t)dt\ . \qquad (6)$$

but have much better statistics, we may have better luck fitting that distribution without the need of large bin. Fortunately the function form for the fit of $M(\tau)$ is dictated to us, can be done analytically, resulting in an incomplete Γ-function [2]:

$$M(\tau) = A'\frac{1}{\tau}\Gamma(1-\beta, \tau/T) \qquad (7)$$

Note that fitting $M(\tau)$ should give the same result as fitting $N(\tau)$. Now fitting Eq.7 we obtain "β", thus, Eq.6 is determined. Eq.6 is the χ^2 distribution and if data fits (6), we can conclude the situation is in "Self-Organized Criticality" state.

In summary, our procedure is:

1. Quantify all joint angle with direction and classify the key frame according to their joint angle of $\{\theta_{head;\ R,L\ UpperArm;\ R,L\ LowerArm;\ \ldots}\}$, and calculate $M(\tau)$ and fit to incomplete Γ-function and determine the β.
2. Once β is determined, we know the theoretical χ^2 distribution for this motion capture classification analysis.
$$N(\tau) = A\frac{1}{\tau^{\beta}}e^{-\tau/T}$$
3. We reduce the quantified level and try to find the best fit $N(\tau)$ to real data.
4. If we find the best fit of $N(\tau)$, the quantified level is the best quantified level l, then the motion D.O.F. is determined
5. Once the distribution and motion D.O.F are determined, we can perform χ^2 distribution fitting test to see the result are reasonable or not.

We have to check all joint one-by-one using 1~5 procedure estimates and fitting test separately.

V **Open Question**

It's still a new field to analyze the "Motion Texture" of motion capture data 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 that 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.

REFERRENCES

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

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

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

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

[5] 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.
[6] A. Wilson and A. Bobick, *Parametric hidden markov models for gesture recognition*, IEEE Irans, Pattern Analysis and Machine Intelligence, 21(9), 1999.
[7] K.Pullen and C.Bregler. *Motion capture assisted animation: Texturing and synthesis*. In Proceedings of ACM SIGGRAPH 02, 2002.
[8] Bruderlin, A., and Williams, L. 1995. *Motion signal processing*. Proc.SIGGRAPH 1995, 97-104.

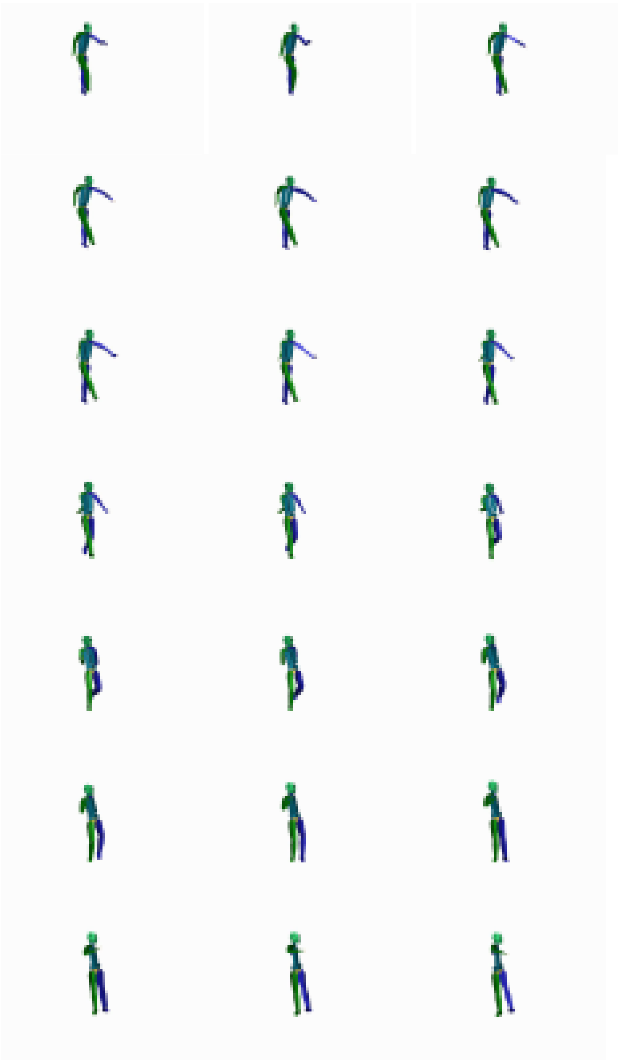

Fig. 5. sequence of dance motion