DANCE EVALUATION SYSTEM BASED ON MOTION ANALYSIS

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Abstract: We are conducting research on computer-aided edutainment with a view to creating learning environments where anybody can acquire advanced skills. In this paper, we focus on dance actions as a part of edutainment research and propose a method to evaluate dance skills through motion analysis. Our method consists of wavelet multi-resolution analysis and correlation analysis. Firstly, by using wavelet multi-resolution analysis, we decompose complex dance motion data acquired from a motion-capture system into different frequency components. And by applying correlation analysis to the decomposed data, we extract motion features that play a dominant role in evaluating sense of rhythm and harmony of movement of each body part. By comparing the extracted features of amateurs to those of experts, we have achieved a quantitative evaluation method for dance skills. Through experiments, we confirmed that there is a strong correlation amongst extracted motion features and subjective evaluation results of dance skills. Using the proposed method, we have developed a computer-aided edutainment system for dance. By mapping motion-captured dance data and its evaluation results onto the 3-D CG figure, our system enables users to visually know bad points of their dance and acquire more advanced dance skills.

1 INTRODUCTION

We are conducting research on computer-aided edutainment with a view to creating learning environments where anybody can acquire advanced skills (Naemura, 2005, Oshima, 2004). In order to make good use of computer technology in edutainment, it is important to identify the basic factors that characterize the performance difference between an amateur and an expert and to computationally analyse the difference. In this paper, we focus on dance actions as a part of edutainment research.

We can roughly classify dance into two categories: formal dance and rhythmical dance. Formal dance (e.g. ballet) has precise and highly formalized set steps and gestures, whereas rhythmical dance (e.g. jazz dance, hip-hop dance) emphasizes improvisation.

There are many works that focus on formal dance; e.g. classic ballet (Soga, 2001), traditional folk dance (Shiratori, 2004, Hachimura, 2005). Most aim to digitally archive the dance of experts as intangible cultural heritage, and do not consider amateur dance at all.

Compared to formal dance, there are few works on rhythmical dance. However, in recent years, popularity of rhythmical dance (especially hip-hop dance) is rapidly increasing. Therefore, in this paper, we focus on hip-hop dance.

As a dance analysis method, Laban Movement Analysis (LMA, Bartenieff, 1980) is widely used (Naugle, 1999, Camurri, 1999, Hachimura, 2005). LMA is a methodology classifying dynamical and geometrical features of body motions in detail. Nevertheless, LMA does not deal with rhythm that is an essential factor of hip-hop dance.

Our goal is to develop an evaluation method for rhythmical dance and help amateurs acquire advanced dance skills. In this paper, we propose an evaluation method for rhythmical dance based on wavelet multi-resolution analysis and motion correlation analysis.

2 MOTION CAPTURE SYSTEM

A motion capture system is one of the most effective methods for digitalizing human motions. Therefore, in order to acquire dance action movements, we use

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an optical motion capture system (Vicon612). Vicon612 uses 12 infrared cameras to detect reflective markers (small balls) attached to a dancer. Spatial resolution of Vicon612 is about 2mm, and sampling interval is set at 1/60 second. The number of markers attached to a dancer is 30. Based on acquired three-dimensional coordinate positions of markers, we calculate joints angles shown in Table 1 and Fig.1.

Table 1: Adopted joints angles.

ID	Joints	ID	Joints
0	Right Elbow	5	Left Knee
1	Left Elbow	6	Right Thigh
2	Right Upper Arm	7	Left Thigh
3	Left Upper Arm	8	Body Angle
4	Right Knee		

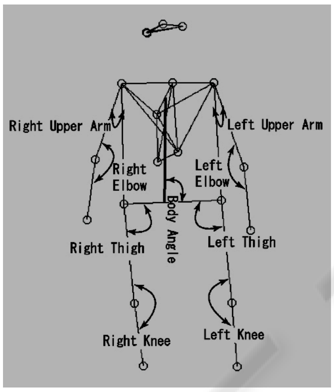

Figure 1: Adopted joints angles.

3 MULTI-RESOLUTION ANALYSIS

In human motions, there are many correlations among joint actions. Nakata (2005) proposed a behaviour recognition method based on motion correlation analysis. However, dance motion is very complex. It is a mixture of various kinds of motions, each having a different period. This complexity would give a negative effect to motion correlation analysis. Therefore, firstly, by using a multi-resolution discrete wavelet transform (DWT), we decompose complex dance motion data acquired from a motion-capture system into different frequency components.

3.1 Discrete Wavelet Transform

Multi-resolution DWT can provide information of signals both in the time domain and in the frequency domain. A wavelet transform can be obtained by projecting the signal onto a scaled and translated version of a basic function. This function is known as mother wavelet, $\Psi(t)$. A mother wavelet must satisfy following conditions.

$$\int_{-\infty}^{\infty} \psi(t)\, dt = 0, \quad \int_{-\infty}^{\infty} \psi(t)^2\, dt = 1. \tag{1}$$

A scaled and translated mother wavelet $\Psi_{j,k}(t)$ forms basis of functions. By discretizing scaling parameters and translating parameters, $\Psi_{j,k}(t)$ is represented as

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k). \tag{2}$$

The variables j and k are integers that scale and translate the mother wavelet $\Psi(t)$ to generate wavelets. The scaling index j indicates the wavelet's width, and the translating index k gives its position. By using (2), wavelet coefficient $d_{j,k}$ is represented as follows.

$$d_{j,k} = \int_{-\infty}^{\infty} \psi_{j,k}(t)\, x(t)\, dt, \tag{3}$$

where $x(t)$ is time-series joint-angle data. The wavelet coefficient $d_{j,k}$ represents information at a particular resolution (2^{-j}) at a particular spatial location ($2^{j}k$) of $x(t)$. Therefore, a frequency component of $x(t)$ corresponding to resolution 2^{-j} can be represented as follows.

$$x_j(t) = \sum_k d_{j,k}\, \psi_{j,k}(t). \tag{4}$$

$x_j(t)$ is called as level-j wavelet detail. High-level wavelet details represent low frequency components.

Fig.2 shows time-series right-elbow angle data acquired from motion capture system and its wavelet details.

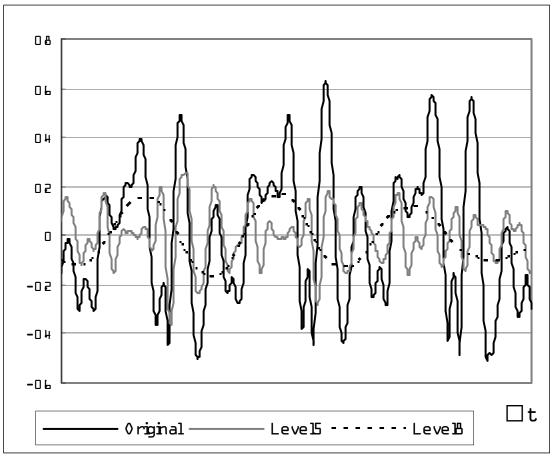

Figure 2: Right-elbow angle data of a dancer and its wavelet details.

3.2 Energy Analysis

By using multi-resolution DWT, we can decompose complex dance motion data into different frequency components (wavelet details). However, not all the components are important for evaluation of dance skills; high frequency components (low-level wavelet details) may contain only noise, whereas low frequency components (high-level wavelet details) may contain only too little and coarse information.

Since a multi-resolution DWT conserves signal energy (Walker, 1999), by comparing each frequency component's energy, we can select components having enough information for evaluation of dance skills.

Based on energy analysis, we define the contribution ratio of the level-*j* wavelet detail as

$$c_j = \frac{\|\mathbf{d}_j\|}{\|\mathbf{x}-\bar{x}\|}, \tag{5}$$

where $\boldsymbol{x}$ is time-series angle data and $\boldsymbol{d}_j$ is level-*j* wavelet coefficient vector of $\boldsymbol{x}$.

In this paper, wavelet details whose contribution ratios exceed particular criteria are selected. Using the selected wavelet details, we evaluate dance skills.

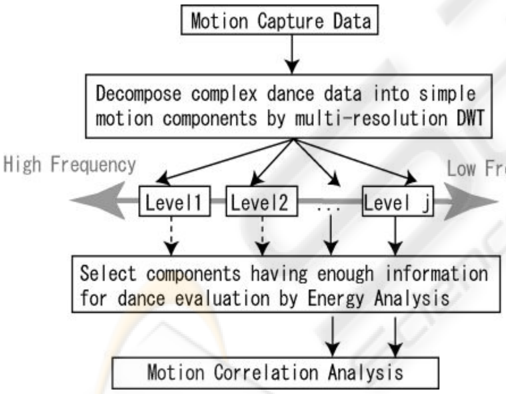

Figure 3: Overview of Multi-Resolution Analysis.

4 EVALUATION METHOD OF DANCE SKILL

In order to evaluate dance skill, we employ (1) sense of rhythm and (2) harmony of movement of all body parts as evaluation criteria.

4.1 Evaluation Method of Sense of Rhythm

Dancing to the rhythm of music is very important for rhythmical dance. When a dancer moves his/her limbs to the rhythm of music, each limb will draw a periodic (proportion to beat-to-beat period) trajectory.

In this paper, we propose an evaluation method of sense of rhythm based on the autocorrelation function and beat-to-beat interval information of music.

Autocorrelation function of level-*j* wavelet detail is defined as

$$R_{xx,j}(\tau) = \lim_{T\to 0}\frac{1}{T}\int_{-T/2}^{T/2} x_j(t)\, x_j(t+\tau)\, dt, \tag{6}$$

where $x_j(t)$ is level-*j* wavelet detail. $R_{xx,j}(\tau)$ takes its maximum at τ=0, and if $x_j(t)$ is periodic, $R_{xx,j}(\tau)$ attains its peak at $\tau = nT_j$, where T_j is a period of $x_j(t)$ and *n* is an integer.

Let us assume that beat-to-beat interval of music is τ_b, then autocorrelation function of motion data moving perfectly to the rhythm of music will attain its peak at $\tau = n\,\tau_b$, where *n* is an integer. Therefore, as a criterion for evaluating dancer's sense of rhythm, we employ the peak value of $R_{xx,j}(\tau)$ and difference between T_j and τ_b.

4.2 Evaluation Method of Harmony of Movement of Each Body Part

Since dance is a gesture of the whole body, harmony of movement of all body parts is essential. Therefore, in this paper, we propose a method to evaluate harmony of movement of each body part based on the mutual-correlation function and beat-to-beat interval information of music.

Let $x_j(t)$ and $y_j(t)$ be the level-*j* wavelet detail of time-series angle data $x(t)$, $y(t)$ respectively. Then, mutual-correlation function of $x_j(t)$ and $y_j(t)$ is defined as follows.

$$R_{xy,j}(\tau) = \lim_{T\to 0}\frac{1}{T}\int_{-T/2}^{T/2} x_j(t)\, y_j(t+\tau)\, dt. \tag{7}$$

If $x_j(t)$ and $y_j(t)$ are periodic, and move in harmony with each other, $R_{xy,j}(\tau)$ attains its peak at $\tau = nT_j$, where T_j is a period of $x_j(t)$, $y_j(t)$. Therefore, as a criterion for evaluating harmony of movement of body parts, we employ the peak value of $R_{xy,j}(\tau)$ and difference between T_j and τ_b.

Although there are many combinations of body parts to calculate mutual-correlation functions, we adopted 24 pairs of body parts shown in Table 2 under consideration of dance motion's characteristics.

Table 2: Pairs of Body Parts for Evaluation of Harmony of Movements.

Harmony of Arm Parts

ID	Body Part A	Body Part B
0	Right Elbow	Right Upper Arm
1	Left Elbow	Left Upper Arm

Harmony of Leg Parts

ID	Body Part A	Body Part B
2	Right Knee	Right Thigh
3	Left Knee	Left Thigh

Harmony of top and bottom Parts

ID	Body Part A	Body Part B
4	Right Upper Arm	Right Thigh
5	Left Upper Arm	Left Thigh
6	Right Elbow	Right Knee
7	Left Elbow	Left Knee

Harmony of right and left Parts

ID	Body Part A	Body Part B
8	Right Upper Arm	Left Upper Arm
9	Right Elbow	Left Elbow
10	Right Thigh	Left Thigh
11	Right Knee	Left Knee

Harmony of Diagonal Parts

ID	Body Part A	Body Part B
12	Right Upper Arm	Left Thigh
13	Left Upper Arm	Right Thigh
14	Right Elbow	Left Knee
15	Left Elbow	Right Knee

Harmony of Body-Angle and Limbs

ID	Body Part A	Body Part B
16	Right Elbow	Body Angle
17	Left Elbow	
18	Right Upper Arm	
19	Left Upper Arm	
20	Right Thigh	
21	Left Thigh	
22	Right Knee	
23	Left Knee	

5 EXPERIMENTS

In our experiment, we let 4 dancers (1 expert and 3 amateurs) dance (7 kinds of hip-hop dance) to the rhythm of music, and acquired their dance motions using Vicon612.

Based on the acquired three-dimensional coordinate positions of markers, we calculate joint angles (Fig.1, Table 1), and decompose the data into different frequency components (wavelet details) using multi-resolution DWT. After selecting important wavelet details by contribution ratios, we evaluate each dancer's skill.

5.1 Subjective Evaluation of Dance

Firstly, in order to confirm the subjective difference in dance skill between an expert and an amateur, we carried out a subjective evaluation experiment using 20 evaluators. We showed captured dances to evaluators at random, and let them select the best dance. As a result, all evaluators selected the expert's dance as the best one. This result shows that there is a significant difference between the expert's dance and amateurs' dance from the subjective viewpoint. In the following sections, we try to quantitatively evaluate this difference.

5.2 Evaluation Result of Sense of Rhythm

Fig.4, 5 show the expert's autocorrelation functions (level-4, 6). X axis represents joints (numbers on x axis correspond to ID in Table 1) and y axis is τ. Colour of pixels in the figure represents the value of autocorrelation functions. White pixels represent strong positive correlation, black pixels represent strong negative correlation, and gray pixels represent week correlation. Dashed lines in the figure represent beat-to-beat interval of the music.

Level-4 wavelet details capture short-period motions (i.e. subtle motions), whereas level-6 wavelet details capture long-period motions (i.e. general motions). As shown in Fig.4, 5, each autocorrelation function peaks at the same time, and the period of each joint's motion is almost equal to beat-to-beat interval of the music; i.e. the expert moves her body parts completely to the rhythm of music. These results show that the expert pays conscious attention to subtle dance motions as well as general dance motions.

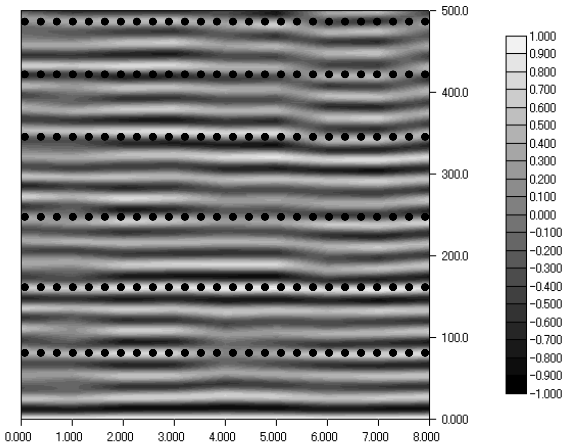
Figure 4: Expert's autocorrelation functions (Level-4).

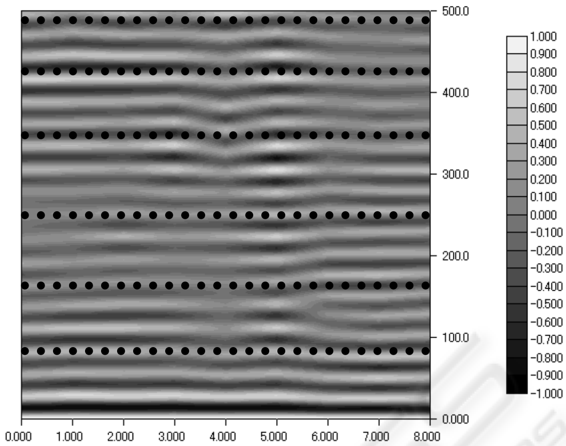
Figure 6: Amateur's autocorrelation functions (Level-4).

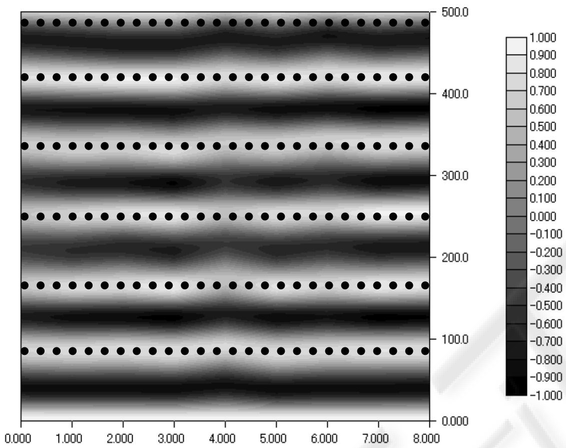
Figure 5: Expert's autocorrelation functions (Level-6).

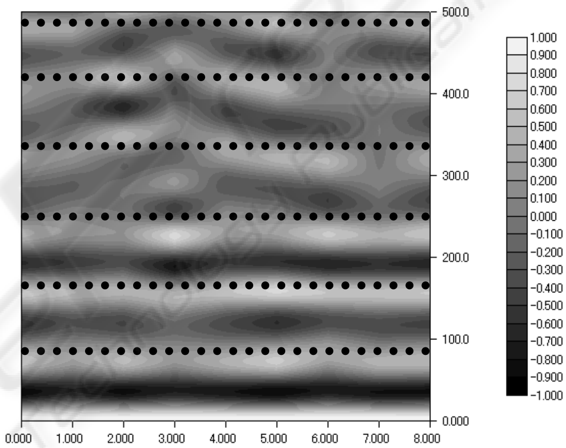
Figure 7: Amateur's autocorrelation functions (Level-6).

Fig.6, 7 show an amateur's autocorrelation function (level-4, 6). Most pixels in Fig.7 are gray; i.e. most of level-6 wavelet details of amateur's dance motion data are not periodic. However, as shown in Fig.6, when focusing on short-period motions, most of autocorrelation functions attain their peaks at the same timing that corresponds to the beat-to-beat interval. These results show that whereas the amateur can move her limbs at each moment, she can't pay conscious attention to long-period dance motions.

5.3 Evaluation Result of Harmony of Movement of Each Body Parts

Fig.8, 9 show expert's mutual-correlation functions (level-4, 6). X axis represents pairs of body parts (numbers on x axis correspond to ID in Table 2) and y axis is τ.

As shown in Fig.8, 9, each mutual-correlation function peaks (bottoms) at almost the same time; i.e. in expert's dance, each body part moves to make a good harmony with the other body parts.

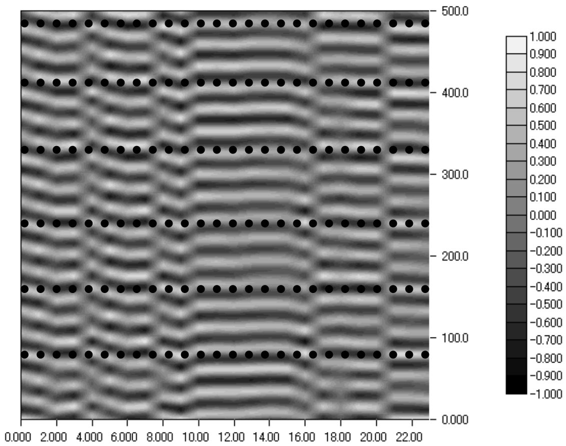

Figure 8: Expert's mutual-correlation function (Level-4).

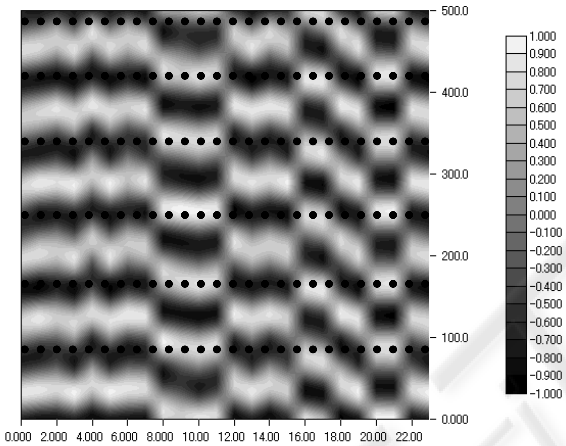

Figure 9: Expert's mutual-correlation functions (Level-6).

Fig.10, 11 show the amateur's mutual-correlation functions (level-4, 6). Most pixels in Fig.10, 11 are gray; i.e. in the amateur's dance, most of body parts move separately without considering harmony.

As shown above, the proposed evaluation method shows that whereas the expert pays conscious attention to subtle dance motions and to the harmony of whole body parts, the amateur only moves her limbs separately as an approximation of dance.

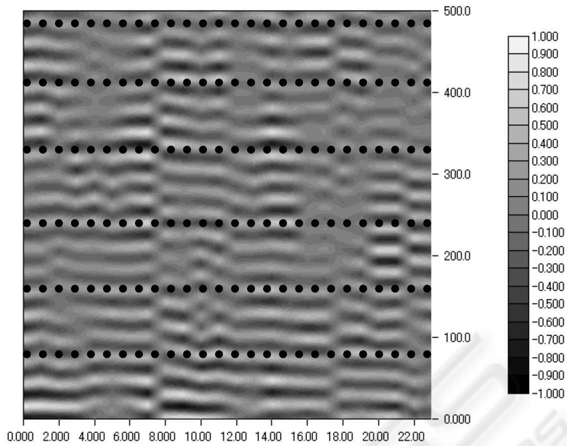

Figure 10: Amateur's mutual-correlation functions (Level4).

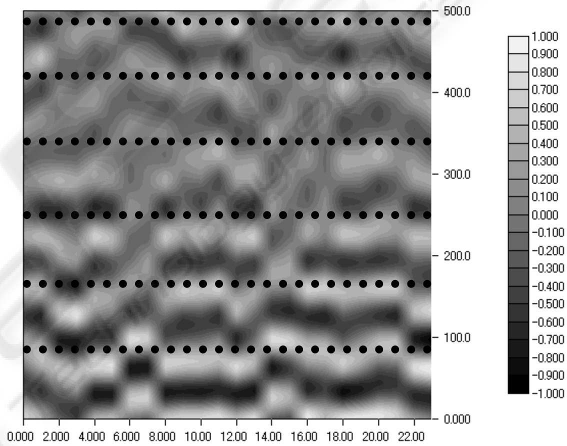

Figure 11: Amateur's mutual-correlation functions (Level6).

5.4 Comparison: Evaluation Result WITHOUT Multi-Resolution DWT

To evaluate efficiency of multi-resolution DWT, we also evaluate harmony of movement of all body parts using "normal (without DWT)" mutual-correlation functions as a comparison.

Fig.12 shows the expert's mutual-correlation functions (without DWT), and Fig.13 shows the amateur's. Whereas we can see clear difference between Fig.8, 10 and Fig.9, 11, there is little difference between Fig.12 and Fig.13. Most pixels in Fig.12, 13 are gray; without multi-resolution DWT, no strong motion correlation has appeared on dance motion data.

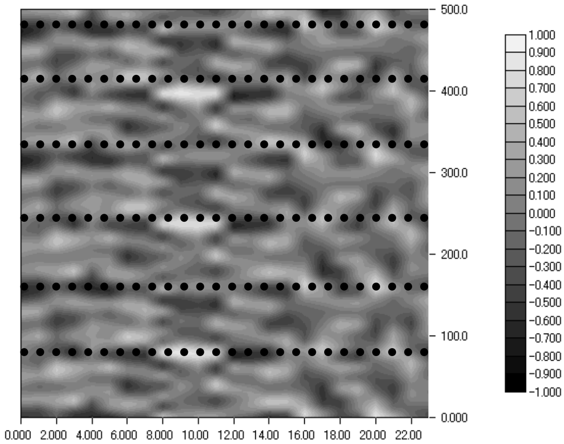
Figure 12: Expert's mutual-correlation functions WITHOUT DWT.

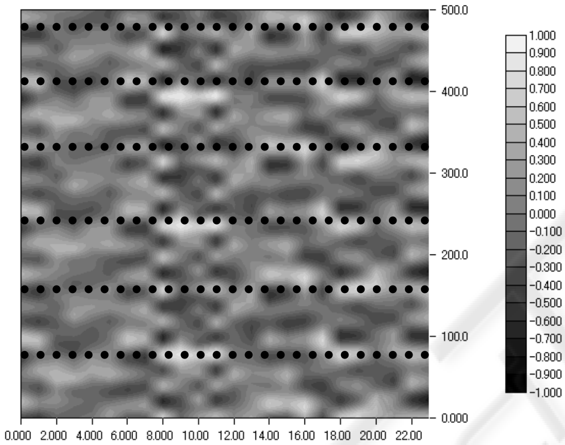
Figure 13: Amateur's mutual-correlation functions WITHOUT DWT.

These results show that complexity of dance motion would give a negative effect to motion correlation analysis. By decomposing complex dance motions into simple motion components using multi-resolution DWT, we can cancel the negative effect to motion correlation analysis.

Fig.14 shows the expert's mutual-correlation function with DWT between left-thigh and body angle, and Fig.15 shows the amateur's. X axis represents level of wavelet details, and y axis is τ. As shown in Fig.14, by decomposing complex dance motions into simple motions, strong correlations have appeared on the expert's dance. In contrast, as shown in Fig.15, no strong correlation has appeared on the amateur's dance. These results show that decomposition of complex dance motions by DWT is indispensable to evaluate dance skills.

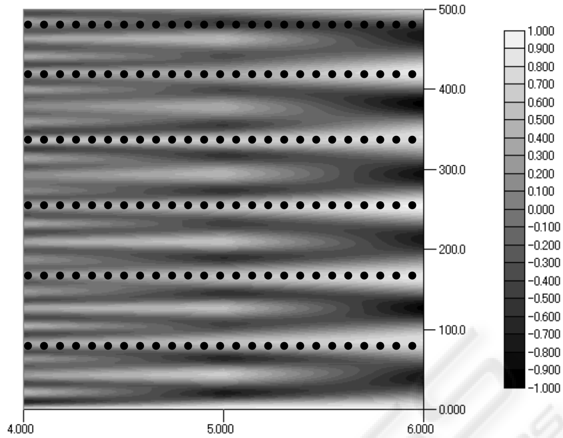
Figure 14: Expert's mutual-correlation functions between left-thigh and body angle with DWT (Level 4-6).

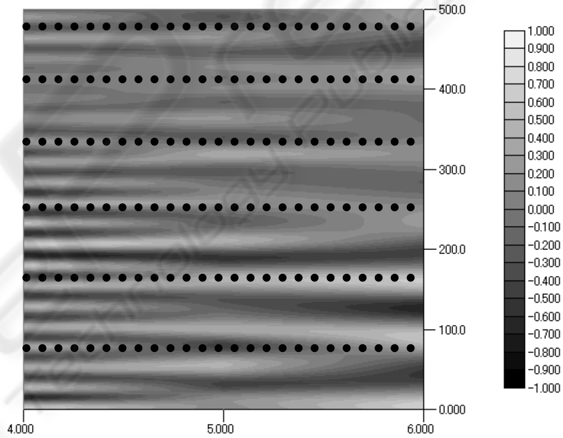
Figure 15: Amateur's mutual-correlation functions between left-thigh and body angle with DWT (Level 4-6).

6 DANCE EVALUATION SYSTEM

As discussed in Sec.5, by using the proposed method, we can evaluate dance skills. However, it is difficult to instinctively know bad points of a dance from patterns like Fig.10. Therefore, in this paper, we score an amateur's dance skill by comparing evaluation results of the amateur (e.g. Fig.10) to those of the expert (e.g. Fig.8) by DP matching (Cormen, 2001). By mapping motion-captured dance data and its scoring result onto the 3-D CG figure, we have developed a computer-aided edutainment system for dance (Fig.16). Colour of balls attached to each joint of 3D CG figure shows evaluation result; blue balls represent a good score, and red balls represent a bad score. By using our system, amateurs are able to visually know the bad point of their dance, and to check their dance from any viewpoint in a 3D CG space.

7 CONCLUSION

In this paper, we have developed an evaluation method for rhythmical dance based on wavelet multi-resolution analysis and motion correlation analysis. A dance motion is a mixture of various kinds of motions, each having a different period. This complexity would give a negative effect to motion correlation analysis. Therefore, by using wavelet multi-resolution analysis, we decompose complex dance motion data acquired from a motion-capture system into different frequency components. And by applying correlation analysis to the decomposed data, we extract motion features that play a dominant role in evaluating sense of rhythm and harmony of movement of each body part. By comparing the extracted features of amateurs to those of experts, we have achieved a quantitative evaluation method for dance skills.

Using the proposed method, we have developed a computer-aided edutainment system for dance. By mapping motion-captured dance data and its evaluation results onto the 3-D CG figure, our system enables users to visually know bad points of their dance.

Figure 16: Screen shot of computer-aided edutainment system for dance.

Expert Amateur

Figure 17: Expert's Dance and Amateur's Dance.

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