Dance Motion Analysis and Editing using Hilbert-Huang Transform

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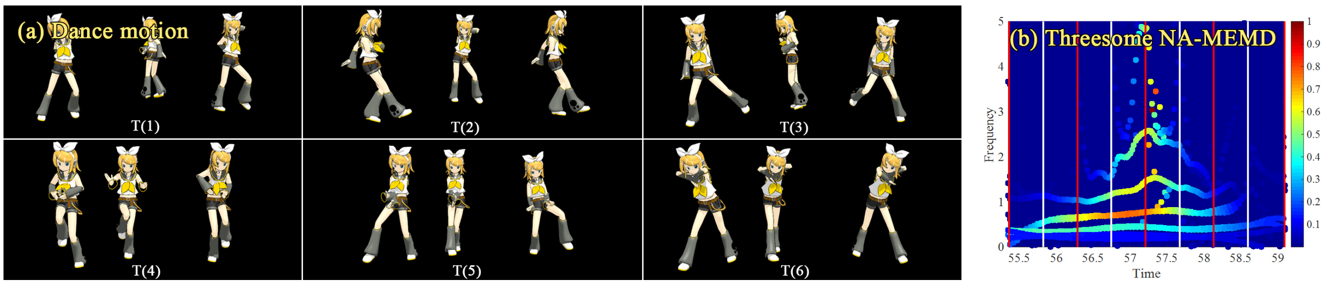

Figure 1: (a) Six-time shots of 4-second Japanese threesome pop unit "Perfume" dance motions. (b) Hilbert spectral (Energy(color)-Frequency(y)-Time(x)) of three dancer motion data. The white and red line in (b), respectively, corresponds to the strong and weak beat.

Figure 2: Japanese threesome pop unit "Perfume" dance motion blended with Salsa motion. Decomposing Perfume and Salsa dance into different distinct modes (IMFs) using NA-MEMD, Perfume hip motion IMFs can easily be replaced with Salsa motion IMFs, and, thus, the dance can be converted into "new" dance motion with Salsa tastes.

ABSTRACT

Human motions (especially, dance motions) are very noisy and it is difficult to analyze the motions. To resolve this problem, we propose a new method to decompose and edit the motions using the Hilbert-Huang transform (HHT). The HHT decomposes a chromatic signal into "monochromatic" signals that are the so-called Intrinsic Mode Functions (IMFs) using an Empirical Mode Decomposition (EMD)[Huang 2014]. The HHT has the advantage to analyze non-stationary and nonlinear signals like human joint motions over the FFT or Wavelet transform. In the present research, we propose a new framework to analyze a famous Japanese threesome pop singer group "Perfume". Then using the NA-MEMD, we decompose dance motions into motion (choreographic) primitives or IMFs, which can be scaled, combined, subtracted, exchanged, and modified self-consistently.

CCS CONCEPTS

• **Computing methodologies** → **Motion capture**; *Motion processing*; • **Mathematics of computing** → *Mathematical analysis*;

KEYWORDS

Dance motion, Motion analysis, Motion editing and blending, Motion Synthesis

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1 HILBERT-HUANG TRANSFORM

Analytical signal varies $z(t) = z_r(t) + iz_i(t)$ in time. The instantaneous amplitude and frequency can be expressed as follows:

$$A(t) = \sqrt{z_r^2(t) + z_i^2(t)} \qquad \omega_0(t) = \frac{d}{dt} tan^{-1} \frac{z_i(t)}{z_r(t)} \tag{1}$$

It is known that the Hilbert Transform (HT) converts the real part of the analytical function into its imaginary part. However, the Hilbert Transform assumes the signal is a monochromatic wave and the real part of the analytical function can be expressed as $x(t) = A(t)cos(\omega_0(t)t)$. Thus, Hilbert Transform can be defined as follows[Bracewell and Bracewell 1986]:

$$z_i(t) = y(t) = \frac{1}{\pi} PV \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau = \frac{1}{\pi t} * x(t) \qquad (2)$$

In Eq. (2), the integration means the Cauchy principal value (PV) integration.

In order to decompose univariate data into series of monochromatic data that the Hilbert transform can be applied, Huang proposed the Empirical Mode Decomposition (EMD) that is implemented through a sifting process that is summarized as follows[Huang 2014]:

1. Calculate residual $r(t)$ (Let $r(t) = x(t)$ in the first time) as follows:

$$r(t) = x(t) - \sum_n C_n(t) \qquad (3)$$

2. Initialize $c(t) = r(t)$ and extract the Intrinsic Mode Function (IMF)

a) Find maximum envelope $u(t)$ and minimum envelope $l(t)$ of $c(t)$

b) Subtract the average envelope from $c(t)$

$$c_{new}(t) = c_{old}(t) - \frac{u(t) + l(t)}{2} \qquad (4)$$

c) If the convergence condition SD (0.2-0.3) is satisfied, add $c(t)$ into the IMF set.

$$SD = \sum_n \frac{(c_{old}(t) - c_{new}(t))^2}{{c_{old}}^2(t)} \qquad (5)$$

3. Repeat step 1 and 2 to extracts all IMFs from a chromatic signal.

This residue $r(t)$ is called "Trend". Finally, we apply the Hilbert Transform to each IMFs ("chromatic" signals) and obtain the Hilbert Power Spectrum.

2 HILBERT SPECTRAL ANALYSES AND DANCE MOTION EDITING

In order to decompose the motion capture data, human motions are composed of many joints with three angles $\theta_{(x,y,z)}$ and are multivariate signals. To deal with these data, we generate an n-dimensional envelope by taking signal projections along different directions in n-dimensions. Using this n-dimensional sphere, we obtain the n-dimensional envelope, and, thus, the n-dimensional IMF. We call this method the multivariate empirical mode decomposition (MEMD)[Huang 2014]. Due to the MEMD filter bank function that can remove white noises of the data, in the NA-MEMD, Gaussian White Noises (GWN) are proposed to be packed into one extra data channel. Thus, the mode mixing that causes the HHT inaccurate can be reduced or eliminated significantly[Huang 2014].

Figure 1 shows the decomposed 4 seconds threesome dancer techno pop dance by Perfume using the NA-MEMD. Threesome dancers' motions are almost synchronous and occasionally asynchronous. Applying the NA-MEMD using all three dancers' joint angle data, the hip motions of one dancer are now clearly decomposed into 5 different almost harmonic IMFs as shown in Fig. 1. In the center, both the bell-shape highest two modes whose average frequencies calculated using Weighted average frequency algorithm (WAFA)[Niu et al. 2012] are, respectively, 1.8 and 3.5 Hz indicate the rotating motions of left and right legs, respectively, and now these noisy motions are clearly decomposed. The white and red lines, respectively, represent the strong and weak beats. The dance is two-beat dance. First, the slow 1.8 Hz mode left leg rotation starts at the strong beat (the red line) lifting the right leg. Second, once the right leg touches the ground, the fast 3.5 Hz mode right leg rotation starts at the weak beat (the white line) and finishes in the next weak beat. The slow 1.8 Hz mode rotation still continues and ends at the next strong beat. However, this rest slow rotation prepares for the next right leg step. Note that the two different strong and weak beat synchronized sophisticated choreographic primitive motions are clearly decomposed.

Since the choreographic primitive motions can be clearly decomposed, these distinct choreographic primitive can be extracted self-consistently. These primitives can be blended, eliminated, subtracted, added, scaled, and can be exchanged between different dance motions smoothly. As shown in Fig. 2 (bone figure model), replacing Perfume dance motion IMFs with those of Salsa can easily convert Perfume dance motions into those with Salsa tastes.

3 CONCLUSION AND FUTURE WORK

The human motions like dance motions are complicated, very noisy, and extremely difficult to analyze. The Hilbert-Huang transform using the NA-MEMD can clearly decompose the noisy dance motions into distinct "monochromatic" IMFs and may have a strong advantage over the other method like the Short-tAime Fourier and Wavelet analysis etc. We propose a dance motion analysis system based on HHT, and we find some characteristic "choreographic" primitives using our method in the Hilbert spectrum. The proposed framework can reveal the detailed "choreographic" primitives synchronized to the dance beats. Thus, the framework can lead us to understand the dance motion in detail.

The NA-MEMD can decompose dance motion into different distinct modes (IMFs). These IMFs are the more detailed motion primitives than those choreographic primitives. Thus, by editing, mixing, exchanging different dance motion IMFs, dance motions can be easily modified into new dance motions with different tastes. The HHT and our framework can be considered to be a very powerful and useful tool to decompose, blend, and edit dance motions for animators. The editing and blending methods shown here are still limited and very primitive. Further researches are required for the detailed dance motion editing and blending using the HHT in the future.

REFERENCES

Ronald Newbold Bracewell and Ronald N Bracewell. 1986. *The Fourier transform and its applications*. Vol. 31999. McGraw-Hill New York.

Norden Eh Huang. 2014. *Hilbert-Huang transform and its applications*. Vol. 16. World Scientific.

J Niu, Y Liu, W Jiang, X Li, and G Kuang. 2012. Weighted average frequency algorithm for Hilbert–Huang spectrum and its application to micro-Doppler estimation. *IET Radar, Sonar & Navigation* 6, 7 (2012), 595–602.