Technical Note

Low-dimensional Feature Vector Extraction from Motion Capture Data by Phase Plane Analysis

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Abstract: This paper proposes a method to obtain a low-dimensional feature vector appropriately representing the characteristics of a given motion-capture data stream. The feature vector is derived based on the concept of phase plane analysis. A set of phase plane trajectories are obtained from the temporal variation of the state variables representing the body-segment arrangement. The information on six motion-characteristic properties is extracted from the shapes of the trajectories, and used as the components of a six-dimensional feature vector. The experimental results showed the effectiveness and limitation of the proposed method.

Keywords: motion capture, motion characteristic, feature vector, phase plane analysis

1. Introduction

Nowadays, motion-capture (Mocap) data are frequently used for motion analysis. A Mocap data stream is often marked by its high dimensionality and variable length. This makes it difficult to compare the characteristics of multiple data streams. Summarizing the characteristics of each data stream as a feature vector having a specified dimensionality is a typical approach to overcome this issue. Singular value decomposition (SVD) or principal component analysis (PCA) is often used to form the feature vector [1], [2]. In these cases, the dimensionality of the feature vector generally exceeds that of a Mocap data stream (typically several tens to over a hundred), due to the use of the eigenvectors of a Mocap-data matrix. Although a high-dimensional feature vector may be effective in, for example, high-accuracy classification of Mocap data streams, it causes difficulty in intuitively and easily grasping motion characteristics from its component values.

This paper proposes a method to obtain a useful low-dimensional feature vector. We adopt the concept of phase plane analysis [3]. A phase plane consists of two axes corresponding to a state variable and its time derivative. Analyzing a phase plane trajectory, obtained from the temporal variation of a state variable, allows us to extract information on different properties from its shape. We use a set of state variables representing the spatial arrangement of the body segments, and extract the information on six motion-characteristic properties, i.e., derive a six-dimensional feature vector, from their phase plane trajectories.

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2. Method

2.1 Quantification of Body-segment Arrangement

First, we quantify the spatial arrangement of the body segments at each instant of time. The distribution of the body segments is evaluated in each of the directions in the three-dimensional space. According to Ref. [4], the above distribution can be quantified by using the statistics of the coordinate values of principal joints. Here, we calculate the following standard deviation of the coordinate values of the nineteen joints shown in **Fig. 1** (shoulders, elbows, wrists, fingers, hips, knees, ankles, toes, waist, neck and head, including end effectors) at every axis of the three-dimensional space:

$$\sigma_\alpha(n) = \sqrt{\frac{1}{J}\sum_{j=1}^{J}\{p_{j,\alpha}(n) - \bar{p}_\alpha(n)\}^2} \qquad (1)$$

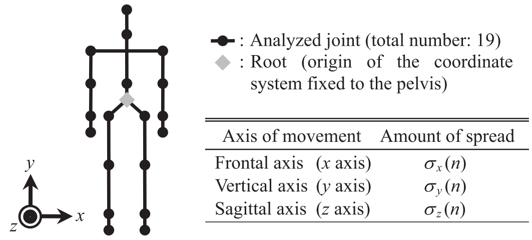
$$\bar{p}_\alpha(n) = \frac{1}{J}\sum_{j=1}^{J} p_{j,\alpha}(n) \qquad (\alpha\text{: } x, y, \text{or } z)$$

where $p_{j,\alpha}(n)$ (α: x, y or z) is the α-coordinate of the jth joint at the nth frame (coordinate system: fixed to the pelvis) and J is the number of the joints used in the analysis ($J = 19$), respectively. The value of $\sigma_\alpha(n)$ becomes large when the body segments spread widely in the α-direction. The correspondence of the obtained state variables $\sigma_x(n)$, $\sigma_y(n)$ and $\sigma_z(n)$ to the axes of movement (frontal, vertical and sagittal axes [5]) is shown in Fig. 1.

In actual calculations, the coordinate values are normalized by the body height to reduce the influence of difference in physical constitution. The obtained time-series data stream of $\sigma_\alpha(n)$ is filtered by a Gaussian filter (cut-off frequency: 10 Hz) to eliminate noise that adversely affects the calculation of time derivative shown in the next section.

2.2 Phase Plane Analysis

Here, we introduce the concept of phase plane analysis [3]. An



Axis of movement	Amount of spread
Frontal axis (x axis)	$\sigma_x(n)$
Vertical axis (y axis)	$\sigma_y(n)$
Sagittal axis (z axis)	$\sigma_z(n)$

Fig. 1 Principal joints used to evaluate the body-segment arrangement.

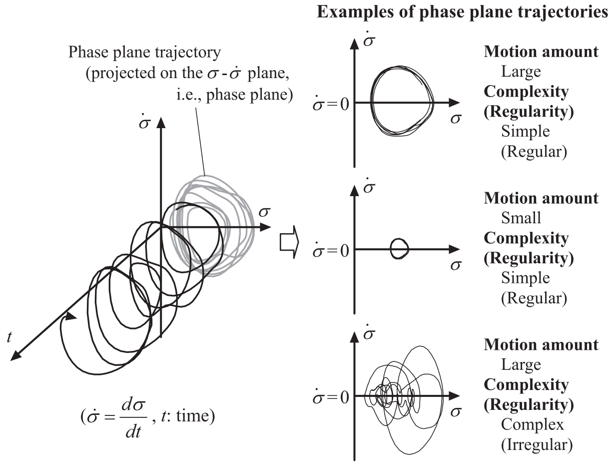


Fig. 2 Concept of phase plane analysis.

example is shown in **Fig. 2**. In this case, the horizontal axis corresponds to σ being any of $\sigma_x(n)$, $\sigma_y(n)$ and $\sigma_z(n)$ and the vertical axis to its time derivative $\dot{\sigma}$. The shape of a phase plane trajectory shows the characteristics of a given σ. When an area surrounded by a trajectory is large (top and bottom of Fig. 2), the motion amount in a given axis-of-movement direction is regarded as large. In the case that a trajectory is given as a set of overlapped loops (top and middle of Fig. 2), σ has a highly simple and regular motion sequence, whereas a complex and irregular characteristic is shown when a trajectory has a complex and complicated shape (bottom of Fig. 2). We quantify the above properties as follows.

First, the time-series data stream of the time derivative of $\sigma_\alpha(n)$ is obtained by the following difference calculation:

$$\dot{\sigma}_\alpha(n) = \{\sigma_\alpha(n+1) - \sigma_\alpha(n)\}/\Delta t \qquad (2)$$

where Δt is the sampling time. Next, the tendency of motion amount in each axis-of-movement direction is quantified. The mean value of all the areas of single loops included in a given trajectory is used. Here, we define a locus from a negative-direction zero-cross point of $\dot{\sigma}_\alpha(n)$ to the next point as a single loop, as shown in **Fig. 3**. The area of the lth α-direction single loop is obtained as follows:

$$S_\alpha(l) = \sum_{n=n_{S\alpha}(l)}^{n_{E\alpha}(l)-1} s_\alpha(n) \qquad (3)$$

$$s_\alpha(n) = \begin{cases} \dfrac{|\dot{\sigma}_\alpha(n)| + |\dot{\sigma}_\alpha(n+1)|}{2}|\sigma_\alpha(n+1) - \sigma_\alpha(n)| \\ \quad (\text{when } \mathrm{sgn}(\dot{\sigma}_\alpha(n)) = \mathrm{sgn}(\dot{\sigma}_\alpha(n+1))) \\ 0 \quad (\text{otherwise}) \end{cases}$$

where $n_{S\alpha}(l)$ and $n_{E\alpha}(l)$ are the start and end frames of the lth α-direction single loop, respectively. The feature quantity representing the motion amount in the α-direction throughout the whole trajectory is obtained as follows:

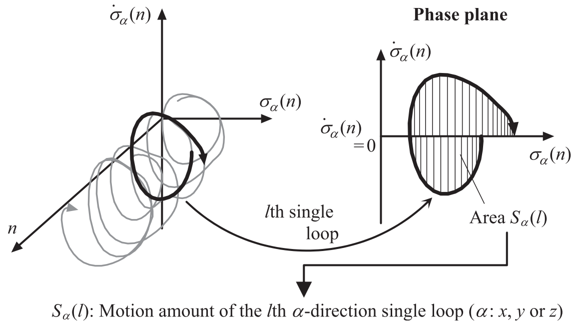


Fig. 3 Extraction of motion amount from a phase plane trajectory.

$$q_{\mathrm{MA}\alpha} = \log\left\{\frac{1}{L}\sum_{l=1}^{L} S_\alpha(l) + C\right\} \qquad (4)$$

where L is the number of the single loops included in the whole trajectory and C is a small constant introduced to avoid log(0) (we set $C = e^{-10}$), respectively. A logarithm transform is used since the mean value of $S_\alpha(l)$ throughout the whole trajectory varies in a wide range depending on motion style.

Meanwhile, the tendency of motion complexity in each axis-of-movement direction is quantified. The value of approximate entropy (ApEn) [6] is used. ApEn is known as an index representing the complexity of a time-series data stream. The ApEn value is obtained as follows:

$$\boldsymbol{\Sigma}_\alpha(n) = \begin{bmatrix} \mu_{1\alpha}(n) & \mu_{1\alpha}(n+\tau_\alpha) & \cdots & \mu_{1\alpha}(n+(m-1)\tau_\alpha) \\ \mu_{2\alpha}(n) & \mu_{2\alpha}(n+\tau_\alpha) & \cdots & \mu_{2\alpha}(n+(m-1)\tau_\alpha) \end{bmatrix}$$
$$(\mu_{1\alpha}(n) = \sigma'_\alpha(n),\ \mu_{2\alpha}(n) = \dot{\sigma}'_\alpha(n))$$
$$d(\boldsymbol{\Sigma}_\alpha(n), \boldsymbol{\Sigma}_\alpha(j)) = \max_{i=1,2,\,k=1,2,\cdots,m}(|\mu_{i\alpha}(n+(k-1)\tau_\alpha) - \mu_{i\alpha}(j+(k-1)\tau_\alpha)|)$$
$$C_n^m = \frac{\sum_{j=1}^{N-(m-1)\tau_\alpha}\theta(r - d(\boldsymbol{\Sigma}_\alpha(n), \boldsymbol{\Sigma}_\alpha(j)))}{N-(m-1)\tau_\alpha}$$
$$\Phi^m = \frac{\sum_{n=1}^{N-(m-1)\tau_\alpha}\log C_n^m}{N-(m-1)\tau_\alpha}$$
$$q_{\mathrm{ApEn}\alpha} = \Phi^m - \Phi^{m+1} \qquad (5)$$

where $\sigma'_\alpha(n)$ and $\dot{\sigma}'_\alpha(n)$ are the standardized $\sigma_\alpha(n)$ and $\dot{\sigma}_\alpha(n)$ (with zero mean and unity standard deviation), N is the total number of frames and $\theta(x)$ is the Heaviside function, respectively. We set the parameters $m = 4$ and $r = 0.5$ through trial and error. The time-delay parameter τ_α [7] is introduced since the sampling time of Mocap data is generally much smaller than the time scale of human motion. Specifically, one fifth of the weighted mean of single-loop periods is used (weight: $S_\alpha(l)$ for each single loop) as follows:

$$\tau_\alpha = \mathrm{round}\left[\frac{0.2}{\sum_{l=1}^{L} S_\alpha(l)}\sum_{l=1}^{L}\{S_\alpha(l)(n_{E\alpha}(l) - n_{S\alpha}(l) + 1)\}\right] \qquad (6)$$

The $q_{\mathrm{ApEn}\alpha}$ value becomes large when a phase plane trajectory shows a complex shape. In actual calculations, we use a fast algorithm [8] to reduce the calculation time.

To sum up, the motion characteristics of a Mocap data stream is summarized as the following six-dimensional feature vector:

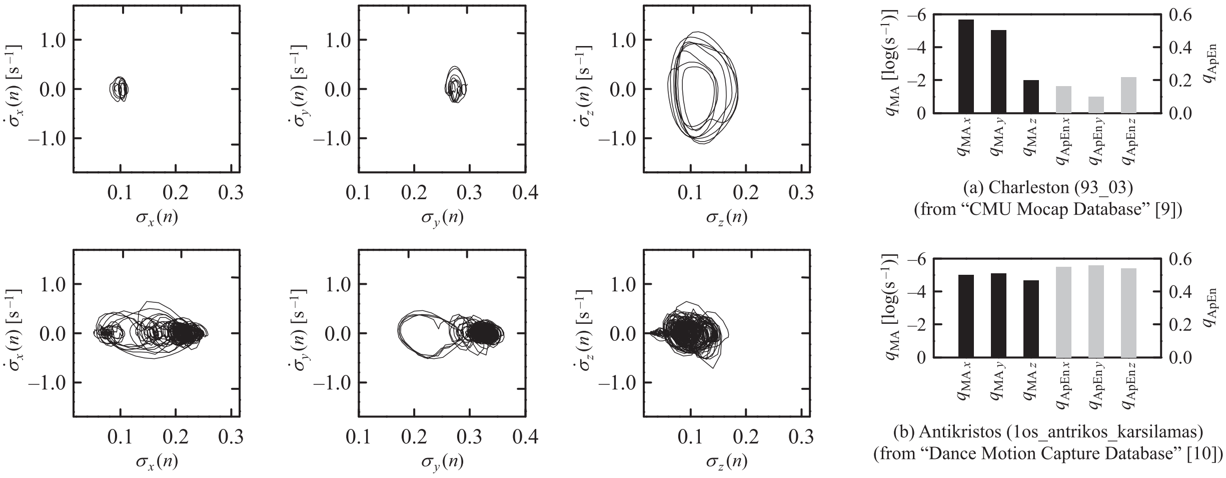


Fig. 4 Examples of phase plane analysis.

$$\boldsymbol{F} = \begin{bmatrix} q_{\mathrm{MA}x} & q_{\mathrm{MA}y} & q_{\mathrm{MA}z} & q_{\mathrm{ApEn}x} & q_{\mathrm{ApEn}y} & q_{\mathrm{ApEn}z} \end{bmatrix}^{\mathrm{T}} \tag{7}$$

Each of the former three components represents the motion amount along each axis of movement, whereas each of the latter three represents the motion complexity in each axis direction.

3. Results

This section presents the experimental results of the proposed method. We used Mocap data streams open to the public [9], [10], [11]. In some data streams, periods in which the whole body is kept in a still state are included before and after the actual performance. To remove these periods, we selected only the region sandwiched between the $(n_1 - 1)$th and $(n_2 + 1)$th frames:

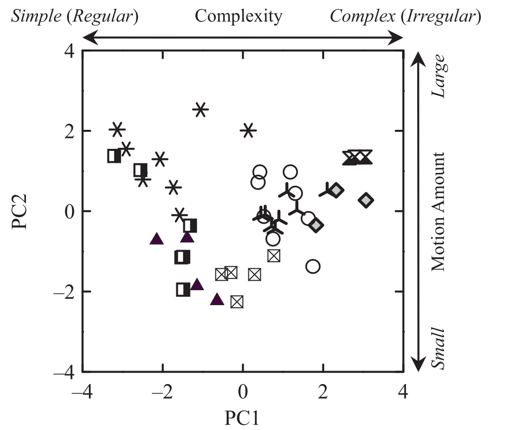
n_1: frame first satisfying $|\dot{\boldsymbol{\sigma}}(n)| \geq |\bar{\dot{\boldsymbol{\sigma}}}| - 0.25|\dot{\boldsymbol{\sigma}}|_{\mathrm{SD}}$

n_2: frame finally satisfying $|\dot{\boldsymbol{\sigma}}(n)| \geq |\bar{\dot{\boldsymbol{\sigma}}}| - 0.25|\dot{\boldsymbol{\sigma}}|_{\mathrm{SD}}$

where $|\dot{\boldsymbol{\sigma}}(n)| = \{\dot{\sigma}_x^2(n) + \dot{\sigma}_y^2(n) + \dot{\sigma}_z^2(n)\}^{1/2}$ and $|\bar{\dot{\boldsymbol{\sigma}}}|$ and $|\dot{\boldsymbol{\sigma}}|_{\mathrm{SD}}$ are the mean and standard deviation of the time series of $|\dot{\boldsymbol{\sigma}}(n)|$.

Figure 4 shows examples of phase plane analysis. In the case of Charleston (top of Fig. 4), the loops in the z-direction (i.e., sagittal-axis direction) are extremely large compared with those in the x- and y-directions, and the degree of overlapping is relatively high in all directions. The data stream “93_03” consists of the repetition of the forward-kick back-step sequence, i.e., a set of regular motions along the sagittal axis. This tendency is consistent with the shapes of the obtained trajectories and the values of the feature-vector components shown in the right of Fig. 4. On the other hand, Antikristos (bottom of Fig. 4) is one of the Cypriot folk dances characterized by complexity and a combination of complicated motions of the lower limbs [12]. The trajectories of this dance provided extremely complicated structures. This tendency is estimated to have been caused by the above complicated lower-limb motions, and its influence was well reflected in the values of the feature-vector components.

As mentioned above, the feature vector derived from the phase plane analysis validly quantifies the characteristics of a given Mocap data stream. **Figure 5** shows an application example of the feature vector. In this example, the motion-characteristic distri-



Motion feature	Eigenvector PC1	PC2
$q_{\mathrm{MA}x}$	-0.216	0.484
$q_{\mathrm{MA}y}$	-0.191	0.686
$q_{\mathrm{MA}z}$	-0.246	0.401
$q_{\mathrm{ApEn}x}$	0.540	0.173
$q_{\mathrm{ApEn}y}$	0.537	0.206
$q_{\mathrm{ApEn}z}$	0.526	0.248
Contribution rate	49.0%	23.7%

◨ : Modern dance
⊠ : Chicken dance
⅄ : Salsa
✳ : Breaking
▲ : Charleston
○ : Indian dance
◈ : Antikristos (Cypriot folk dance)
⧗ : Perfume (Japanese electropop group)

Motion capture data used in the analysis:
From 8 dance categories, total 45 data streams.
Downloaded from “CMU Mocap Database” [9]
◨: Modern dance (05_02, 04, 05, 09, 11, 14), ⊠: Chicken dance (18_15, 19_15, 20_01, 21_01, 143_34), ⅄: Salsa (61_01 – 08), ✳: Breaking (85_01 – 04, 06 – 08, 10), ▲: Charleston (93_03 – 05, 08), ○: Indian dance (94_01 – 04, 09 – 12).
Downloaded from “Dance Motion Capture Database” [10]
◈: Antikristos (Cypriot folk dance) (1os – 3os_antrikos_karsilamas).
Downloaded from “Perfume Global Site” [11]
⧗: Perfume (Japanese electropop group) (aachan, kashiyuka, nocchi).

Fig. 5 Motion-characteristic distribution of dances (analysis method: principal component analysis of the phase-plane feature vectors).

bution of 45 Mocap data streams selected from eight dance categories (bottom of Fig. 5) was visualized. The visualization was performed by applying PCA to the feature vectors. From the eigenvector values of the obtained PCs (middle of Fig. 5), the first PC (PC1) is interpreted as corresponding to “Complexity,” whereas the second PC (PC2) to “Motion Amount.” The obtained distribution agrees with the impression of each dance category; e.g., Antikristos (characterized by complexity as already mentioned) was plotted in the *Complex* region, whereas Breaking (including various intense unit motions [13]) was plotted in the

Table 1 Results of the leave-one-out cross validation using the 1-nearest-neighbor classifier.

	Phase plane	*k*WAS	PCA Similarity Factor
Dimensionality	6	232 $((3J + 1)k)$	228 $(3Jk)$
Error	MD 1 C 2 ID 1 A 1	MD 2 S 1 B 1 ID 1	MD 2 B 1 C 2
Empirical accuracy	0.889	0.889	0.889

MD: Modern dance, S: Salsa, B: Breaking, C: Charleston,
ID: Indian dance, A: Antikristos.
J: Number of joints ($J = 19$), k: Number of SVs (or PCs) (we set $k = 4$.).

Large region, etc.

Table 1 shows the results of another example. The leave-one-out cross validation [14] was performed by applying the 1-nearest-neighbor classifier to the Mocap data set identical to that of Fig. 5. We compared the proposed method with *k*WAS [1] and PCA Similarity Factor [2]. Although the dimensionality of the proposed feature vector is extremely lower than those of *k*WAS and PCA Similarity Factor, all methods gave the same empirical-accuracy value. This suggests that the proposed feature vector extracts the characteristics of each dance extremely efficiently. However, an error occurred in the dance category Antikristos in which the other methods caused no error. This may indicate the limitation of the low dimensionality of the feature vector.

4. Conclusions

The main contribution of this paper is to provide a useful low-dimensional feature vector appropriately characterizing a Mocap data stream. The experimental results showed the effectiveness and limitation of the proposed method. To clarify the application range of the proposed method will be the subject of future work.

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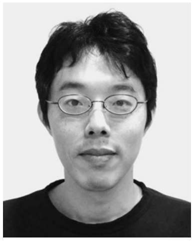

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