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 having a specified dimensionality is a typical approach to oversampling the characteristics of each data stream as a feature vector, from their phase plane trajectories.

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.

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:

\[ \sigma_\alpha(n) = \frac{1}{J} \sum_{j=1}^{J} (p_{j,\alpha}(n) - \bar{p}_\alpha(n))^2 \]  \hspace{1cm} (1)

where \( p_{j,\alpha}(n) \) (\( \alpha: x, y, or z \)) is the \( \alpha \)-coordinate of the \( j \)th joint at the \( n \)th 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 \( \alpha \)-direction. The correspondence of the obtained state variables \( \sigma_\alpha(n), \sigma_y(n) \) 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
obtained as follows: (bottom of Fig. 2). We quantify the above properties as follows. The area of the zero-cross point of $\dot{\alpha}$ trajectory is used. Here, we define a locus from a negative-direction amount in each axis-of-movement direction is quantified. The feature quantity representing the complexity of a time-series data stream. The 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:

$$\Sigma_a(n) = \left\{ \begin{array}{l} \mu_a \cdot (n_t + \tau_a) \\ \mu_a \cdot (n + (m - 1)\tau_a) \\ \ldots \\ \mu_a \cdot (n + (m - 1)\tau_a) \\ \end{array} \right.$$

$$d(S_a(n), S_a(j)) = \max\{d(\mu_a(n + (k - 1)\tau_a) - \mu_a(j + (k - 1)\tau_a))\}$$

$$C_n = \sum_{i=1}^{N-(m-1)r} \theta(\tau - d(S_a(n), S_a(j)))$$

$$q_{\text{ApEn}} = \frac{q_{\text{ApEn}}}{N - (m - 1)\tau_a}$$

where $(n, j)$, $(n, m)$ are the standardized $\sigma_a(n)$ and $\tilde{\sigma}_a(n)$ (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 $\tau_a$ [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: $S_a(l)$ for each single loop) as follows:

$$\tau_a = \frac{0.2}{\sum_{l=1}^{L} S_a(l)} \sum_{l=1}^{L} \left(S_a(l)(n_{\text{lo}}(l) - n_{\text{hi}}(l) + 1)\right)$$

The $q_{\text{ApEn}}$ 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:
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 \(|\dot{\sigma}(n)| \geq |\bar{\sigma}| - 0.25|\dot{\sigma}|_{SD}\)
- \(n_2\): frame finally satisfying \(|\dot{\sigma}(n)| \geq |\bar{\sigma}| - 0.25|\dot{\sigma}|_{SD}\)

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

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 distribution 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

\[
F = \begin{bmatrix}
q_{\text{MAx}} & q_{\text{MAy}} & q_{\text{MAz}} & q_{\text{ApEnx}} & q_{\text{ApEny}} & q_{\text{ApEnc}}
\end{bmatrix}^T
\]

(7)
The nearest-neighbor classifier to the Mocap data set identical to that one-out cross validation [14] was performed by applying the 1-limitation of the low dimensionality of the feature vector. which the other methods caused no error. This may indicate the range of the proposed method will be the subject of future work. and limitation of the proposed method. To clarify the application data stream. The experimental results showed the effectiveness of Time Delay on Approximate & Sample Entropy Calculations, Physica D, Vol.237, No.23, pp.3069–3074 (2008).

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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