Analysis the Movement Variability in Dance Activities using Wearable Sensors

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***Abstract*— Variability is an inherent feature of human movement, but little research has been done in order to measure such a characteristic using inertial sensors attached to person's body (wearable sensors). Therefore the aim of this preliminary study is to investigate the assessment of human movement variability for dance activities. We asked thirteen participants to repeatedly dance two salsa steps (simple and complex) for 20 seconds. We then used a technique from nonlinear dynamics (time-delay embedding) to obtain the reconstructed state space for visual assessment of the variability of dancers. Such reconstructed state space is graphically linked with their level of skillfulness of the participants.**

I. Introduction

VARIABILITY is an inherent feature that occurs not only within individual but also between individual systems of movement. Newell and Corcos stated that the movement variability (MV) increases or decreases as a function of practice which is linked with the diminution or increment of skill [1]. In sport biomechanics, for instance, Preatoni *et al.* stated two important facts about the MV: i) MV should not be treated as a noise that needs to be removed and ii) conventional approaches can only quantify the overall variability. Hence, Preatoni *et al.* examined non-linear methodologies (entropy measures, dynamical systems theory approaches, and principal component analysis) that are able to deal with and measure variability. This research concluded that the choice of analysis to be used for a particular movement is dependent on the movement in question [2]. Despite the previous efforts of researchers in biomechanics and sport science in measuring the MV, little research has been done with wearable sensors to both quantify the MV and link the MV with the skill assessment of users. For instance, Velloso *et al.* [3] automatically assessed the quality of weight-lifting activity. Further examples of skill assessment using wearable sensors were investigated on music violin players [4] or medical students doing surgical activities [5].

Little work has been done regarding the use of nonlinear tools using wearable sensors. For instance, Liao *et al.* used the Empirical Mode Decomposition for activity recognition using accelerometer data [6]. The works of Sama *et al.* [7] and Frank *et al.* [8] used the time-delay embedding technique for gait recognition using inertial sensors. We therefore believe that the use of nonlinear tools will provide better measurements and expand the understanding of the variability and skill assessment of activities using wearable sensors. For the current work, we are interested in the question of how the time-delay embedding and PCA techniques can provide insights into the variability and dexterity of dancers. To this end, we consider the performance of a set of steps from Salsa dance and visually compare the variability across dancers.

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II. Methods

A. Time-delay embedding

The aim of the time-delay embedding is to reconstruct a D-dimensional manifold M of an unknown dynamical system $s(t)$ from a time series $x(t)$. The time-delay reconstruction, time delayed copies of the available time series $x(t)$, is define as: $\bar{x}(t) = \big(x(t), x(t-\tau), x(t-2\tau), \ldots, x(t-(m-1)\tau)\big)$ where m is the embedding dimension and τ is the embedding time-delay. We follow a modified version of the False Nearest Neighbors and the mutual information algorithms to respectively determine the embedded values of m and τ [9].

B. Framework for the experiment

The raw data is collected from triaxial accelerometer, gyroscope and magnetometer sensors. For instance, the time series, a_x, with a length of N samples is used to obtain the time-delay embedded matrix, $E\{a_x\}$, with m rows and $N-(m-1)\tau$ columns. Then, the PCA is applied to obtain, via eigenvalues $(\lambda_1, \ldots, \lambda_m)$ of eigenvectors $(v_1, \ldots, v_m)$, the principal components $(PC_1, \ldots, PC_m)$ of the time-delay embedded phase space which also provide the percentage of variance (POV) per component.

C. Participants

Thirteen participants with different years of experience in dancing were invited to dance basic salsa steps: eleven novice dancers (4 female, 7 male), one intermediate (male) dancer (4 years of experience) and one (male) expert dancer (14 years of experience). The design of the experiment was approved by the University of Birmingham ethics approval process. All participants provided informed consent prior to participation.

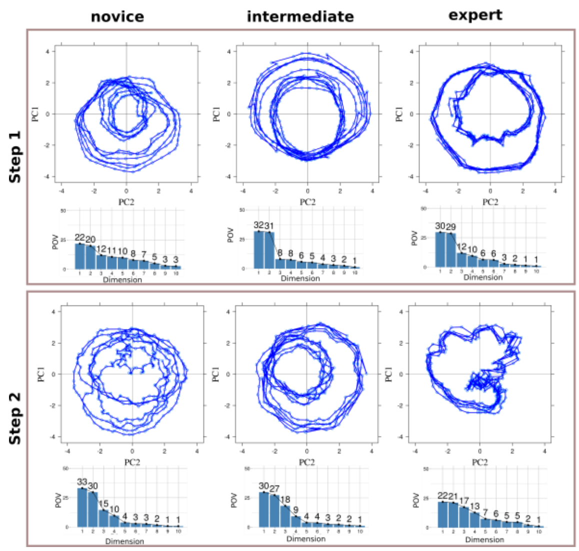

Fig. 2. 2-D reconstructed state spaces and percentage of variance using bar plots from the PCA for both participants' experience and steps.

D. Experiment design

Each participant was shown a series of video clips (recorded by the expert dancer) demonstrating basic salsa steps. Each video clip showed one step repeated several times for 20 seconds. For the analysis in this work, we reported two Salsa step patterns: step 1 which is mambo and step 2 which is side crossover. Participants watched the video clip and were then asked to copy the steps in time to music. The video was played during the data collection (so that participants did not have to rely on their memory of the steps). Data were collected from the IMUs and recorded. The analysis reported will focus on data from particular axis of the magnetometer (m_z for step 1 and m_y for step 2) taken from the sensor mounted on the left ankle.

E. Data collection

Data from triaxial accelerometer, gyroscope and magnetometer sensors were collected at a sampling rate of 50Hz using a Razor 9DOF IMU with Bluetooth (BlueSMiRF Silver). The IMUs were attached to custom-made bracelets worn by participants.

III. Results

Fig. 2 illustrates the 2-D reconstructed state space for the novice, intermediate and expert dancers. For the time-delay embedding algorithm, we used $m = 10$ and $\tau = 6$ [9]. The reconstructed state spaces visually helped us to distinguish different levels of dexterity. It is immediately noticeable that the shape of the state spaces for each level (novice, intermediate, expert) appears visually similar across step 1. As the participants are meant to be performing the same action, this similarity is to be expected. The state spaces also show a tighter and less varied pattern for the expert than for the other dexterity levels. This suggests that the expert is producing more repeatable and more consistent actions than the other dexterity levels. While this is to be expected, the reconstructed state spaces provide interesting illustrations of this phenomenon. For step 2, which is a more complicated sequence of movements, one can see a marked contrast across dexterity levels. Again, the expert is showing a consistent and repeatable action. The intermediate participant is showing a consistent action but this is different to that of the expert, and the novice is showing a pattern which appears disjointed and noisy. Indeed, for the novice dancer, the state space reconstruction of step 2 seems to have more in common with their state space for step 1 than it does with the other dancers performing step 2. On the other hand, for step 2 the percentage of variance values (bar charts) present a decreasing tendency for the components as the expertise level increased. However, for step 1 we can only say that the first two components have the highest values across the remained components and no evident tendency is shown as the expertise of the participants goes from novice to expert.

IV. Conclusion and Future work

Although the time-delay embedding is subject to the embedded parameters (m and τ), the technique is useful to visually present the differences among levels of skillfulness. We believe that movement variability (MV) is an ongoing trend towards extending the understanding of human movement with potentially promising applications in the field of human-robot interaction. From this, there are three areas that we are going to investigate: i) collect data from a wider range of individuals (gender and age) and from additional sensors, ii) undertake a wider review of nonlinear techniques that can be used for the assessment of MV using wearable sensors, and iii) explore the use of Hidden Markov Models and Deep Neural Networks for automatic recognition of the variability.

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