Automatic Non-linear Analysis of the Variability of Human Activities

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Abstract—A number of studies in Human Activity Recognition using body-worn sensors have been done for the last 20 years; however, little work has been done to assess the variability of human activities. Rather than simple identifying whether an action is being performed, the core question for this PhD is how *well* an action is being performed? In this report methods of time-delay embedding and PCA are described to analyse the variability of human activity, the activity recognition chain is reviewed and an algorithm is presented to create artificial variability of human activities. Preliminary experiments of Salsa dance steps showed that

Index Terms—Activity Recognition; On-Body Inertial Sensors; Motor Skill Assessment;

1 Introduction

Human Activity Recognition (HAR) using body-worn sensors has been a topic of research for the last 20 years [1], [2]. This is due to three factors: (i) technology advances in sensors, (ii) longer battery lifetimes and (iii) different application-oriented scenarios. The challenges of HAR are based on the complexity and diversity of human activities (e.g. ambulation, transportation, phone usage, daily activities, exercise, military); the selection of different sensors to use (e.g. inertial, light, temperature or audio sensors) [2] and different bodily locations for sensor placement (e.g. chest, wrist, lower back, hip, thigh, foot) [3]. This complexity and diversity results in a large number of options for configurations [4].

According to Bulling *et al.* [1] the common challenges in HAR using body-worn sensors are: (i) *intraclass variability* which occurs when an activity is performed differently either by a single person or several people. For example, gait patterns may be more dynamic in the morning after sleep than in the evening after a day full of activities. (ii) *Interclass similarity* occurs when the sensor data is very similar. For example, recognising dietary activity, drinking water or coffee would entail the same arm movements [5]. (iii) *The NULL class problem* occurs when ambiguous activities are irrelevant for the recognition methods which leads to wrong classification of the activities [6]. Additionally, Bulling *et al.* [1] reviewed advances in the Activity Recognition Chain (ARC) using body-worn sensors. The general ARC comprises five stages (data acquisition, signal processing, segmentation, feature extraction, and selection training and classification) of which the applied technique in each stage depends on the activity to recognise.

Activity recognition often seeks to treat variability and similarity as variations of the same problem, i.e., defining an ambiguous model of the activity to enable consistent classification and recognition. By defining the model with sufficient clarity, it should be possible to reliably spot instances of the activity and to distinguish this from others similar activities. The challenge faced by this PhD project is that identifying a specific instance will not be sufficient to address the core question of how well is an action being performed? Thus, rather than asking whether a dance step is being performed, the question is whether this step is being made by an expert or a novice, and more importantly, is the novice showing improvement from previous attempts. This also means that, rather than trying to reduce or design out variability in the signal that is used for activity recognition, this PhD is looking for ways to model and work with such variability.

Therefore, the variability of dance activities is a very rich case of study to explore and investigate human movement variability. Variability is presented in either dance features (e.g. fluency of motion, coordination, steadiness of the rhythm, adding erratic or additional movements [7], [8]) or some biological and demographic features of dancers (e.g. gender, age, home country [7], [9]).

Hammerla *et al.* [10] have examined the effects of variability of motor performance using artificial signals so as to create motion structures (strategy of the motion activity) and motion noise (the precision of the motion) of human activities. To quantify the variability of motion activities, Hammerla *et al.* [10] proposed the use of PCA to compute the area underneath the curve of the cumulative principal components which is used as a metric for motor skill assessment. The variability in human activities has therefore a relation to quantitative assessment of motion structures and motion noise of human activities. Velloso *et al.* [11], [12], for example, assessed automatically the quality of weightlifting activity to quantify how *good* the repetition of weightlifting activity is in terms of angles variation of each bone in relation to reference planes.

The understanding of human behaviour using non-linear analysis has proven to make good advances since the early 1980s [13], [14]. For instance, concepts such as fractal dimensionality, the Lyapunov exponent or time-delay embedding have been applied to better understand the variability of human activities. Yamamoto *et al.* [15], [16] used the fractal dimensionality of an attractor (i.e. values that are close enough in the time-delay embedding) to model repeated forehand and backhand tennis strokes. Gouwanda *et al.* [17] showed that the variability in walking speed has a linear relationship with the Lyapunov exponent. This exponent is an average of the natural logarithm of all the distances from the time-delay embedding and its nearest neighbour state space. Lyapunov exponent therefore is suitable for analysing the temporal variation in gait stability. The time-delay embedding has been used as a feature for general gait recognition [18] as well as for recognition of cycling, running, walking upstairs and downstairs activities [19]. Recently, Caballero *et al.* [20] reviewed further non-linear analysis tools (e.g. local dynamic stability, recurrent quantification analysis, entropy measurements, detrended fluctuation analysis) to measure human movement variability. However, the questions to ask, as pointed out by Caballero *et al.* [20], are: "...do these tools actually measure variability?" and "what kind of variability?". It should be noted that non-linear analysis offers a range of techniques for the study of human activity (see [21] for an overview of alternative techniques).

Given the case of the variability in dance activities, it is hypothesised that there are three possible reasons for variation: (i) inherent noise in body-worn sensors, (ii) inherent properties of the activity itself and (iii) differences in the people performing the activity, e.g., gender, anthropometry or level of skills.

1.1 Research Questions

For this PhD, the time-delay embedding and PCA methods have proven to be a reliable method for feature extraction in HAR [17], [18], [19]. It this therefore hypothesised that these methods might be suitable to learn the variability of human activities. Therefore, the following research questions will be addressed:

1) How can the time-delay embedding and PCA methods quantify the possible reasons of the variability of dance activities ?
2) In the light of limitations of time-delay embedding and PCA, which other non-linear analysis tools would be suitable to explore the variability in different human activities and use them as a features for machine learning algorithms?
3) What is the best set of features that can yield the best recognition rate of particular type of activity?
4) How does the sensor positioning influence the outcomes?
5) How can the expertise of the dancer be employed as a tool to empower the design strategy?

2 Recognising Dexterity In Dance

As Miura *et al.* [22] point out: . . . how the human motor system produces dance movements is still poorly understood. Miura et al. [23] measured muscle activation using electromyographic (EMG) data collected from muscles in the lower limb, for a task requiring participants to bounce up and down in time to a metronome beat. They demonstrated that experienced dancers show much better precision in synchronising movements to beat than non-dancers, i.e., dancers maintained much lower standard deviation in temporal deviation against the beat than non-dancers. This result is consistent with work which shows that, compared with inexperienced- or non-dancers, trained ballet dancers exhibit superior postural stability [24], and show superior ability in position matching of upper limbs [25].

Capturing dance activity through sensors has tended to rely on motion capture [26] or sensors mounted on the person [27] or in their shoes [28] or data recorded from their smart phones [29]. Much of this work has been concerned with using the dancers' motion to work with multimedia presentations that augment and complement the dance [30], [31] or as interfacing with a game [32] or commercial games, such as Dance Revolution. While the range of sensing technology used in these papers is diverse and the results of the activity recognition are varied, it is fair to say that few of the papers have considered variability or dexterity in how a dance is performed. In their work, Aristidou *et al.* [8] have considered the manner in which dance steps conform to a set of defined templates that describe steps in terms of a three-dimensional rotation (described using quaternions). The implication is that a goodness-of-fit can be ascertained to determine how good a dancer performs a step, and how any deviation from good can be modified and improved through practice.

For this report, we are interested in the question of how time-delay embedding and PCA techniques can provide insight into the variability and dexterity of dancers. To this end, we consider the performance of a set of steps from Salsa dance as well as other dance styles in future and compare untrained, inexperienced or non-dancers in one cohort with experienced dancers in another.

Before explaining how the activity recognition chain, the next section outlines the approach to time-delay embedding and the resulting phase space representation used in this report.

3 Time-delay Embedding

The aim of time-delay embedding, also known as Takens's Theorem, is to reconstruct a $k-$dimensional manifold M of an unknown dynamical system $s(t)$ from a time series $x(t)$ with discrete observations at given time points t. Time-delay embedding assumes that the time series is a sequence $x(t) = h[s(t)]$, where $h : M \to \mathbb{R}$ is a measurement function in the unknown dynamical system, being $x(t)$ measurable.

Thus, the time delay reconstruction is defined as: $\overline{x}(t) = (x(t), x(t-\tau), ..., x(t-(m-1)\tau))$ where m is the embedding dimension and τ is the embedding time-delay. $\overline{x}(t)$ defines a map $\Phi : M \to \mathbb{R}^m$ such that $\overline{x}(t) = \Phi(s)$. Similarly, $y(t) = \Psi[\overline{x}(t)]$ is a n-dimensional vector where $\Psi : \mathbb{R}^m \to \mathbb{R}^n$ is a further transformation (e.g., PCA [33], Nonlinear PCA [34], Locally Linear Embedding [35]). Figure 1 illustrates the time-delay reconstruction process. For details, see the work of Uzal *et al.* [36].

3.1 Embedding Parameters m and τ

Given any time series $x(t)$, the time delay reconstruction system, $\overline{x}(t)$, is easy to implement. For this work, Cao's method [37], a modification of the False Nearest Neighbours (FNN) algorithm, and mutual information algorithm by Fraser *et al.* [38] have been used to calculate minimum embedding parameters (m_{min}, τ_{min}).

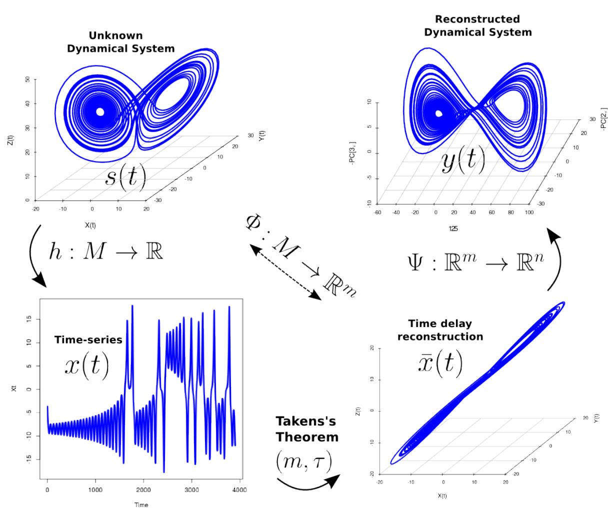

Fig. 1. The reconstruction problem. The figure is based on the work of Uzal *et al.* [36].

3.1.1 Minimum Embedding Dimension m_{min}

Cao's method [37] for computing the minimal embedding dimension is based on the mean values $E1(d)$ and $E2(d)$ where d is for the embedding dimension values.

$E1(d)$ is used to obtain the minimal dimension m_{min} and stops changing when the time series comes from an attractor (Figure 2 B). We computed $E1(d)$ values for $1 \leq \tau \leq 10$ to exemplify the minor dependency of τ given periodic, chaotic and random time series (Figures 2 (A,B,C)).

The second of these values, $E2(d)$, is used to distinguish deterministic signals from random signals in which case the $E2(d)$ values will be approximately equal to 1 for any d (Figure 2 F). Similarly, we computed $E2(d)$ values for periodic, chaotic and random time series, to exemplify the no significative dependency on τ, where $1 \leq \tau \leq 10$ (Figures 2 (D,E,F)).

Cao's method is a modified version of the FNN method, and $E1(d)$ and $E2(d)$ values are only dependant on m and τ [37].

3.1.2 Minimum Time-delay Embedding τ_{min}

The method of choosing the minimum time-delay embedding, τ_{min}, was proposed by Fraser *et al.* [38] in which the first minimum of the mutual information graph is chosen to estimate the minimal time-delay embedding parameter. For instance, Figure 3 illustrates the mutual information from periodic, chaotic and random time series. The local minimum for the Chaotic series in Figure 3 is $\tau_{min} = 18$. On the other hand, for the random time series, the mutual information plot has no local minimum and values are monotonically decreasing which means that $\tau_{min} = 1$ [38]. However, further research has to be done when data comes from a periodic time series since its minimum appears at $\tau_{min} = 3$.

3.1.3 Embedding Parameters Setbacks

Although the time-delay embedding method using inertial sensors has been used in gait recognition [18], gait stability

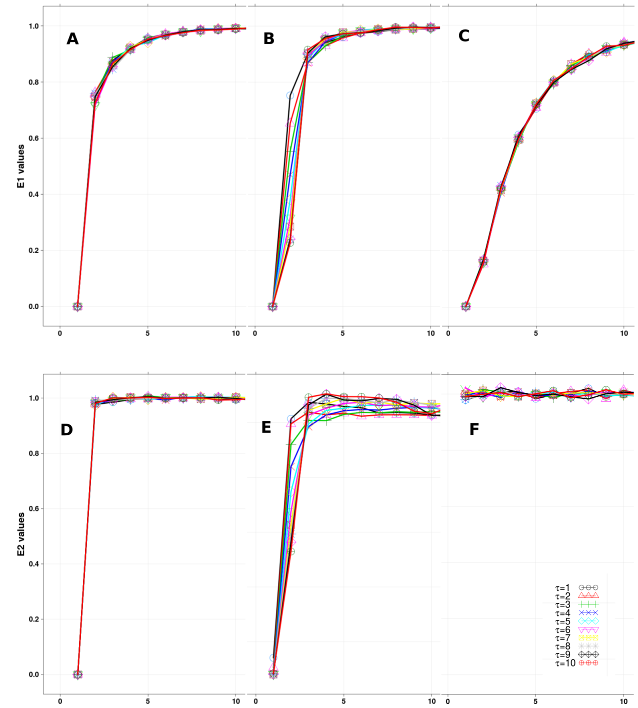

Fig. 2. The values of $E1(d)$ and $E2(d)$ with different time-delay embedding parameters from periodic (A,D), chaotic (B,E) and random (C,F) time series.

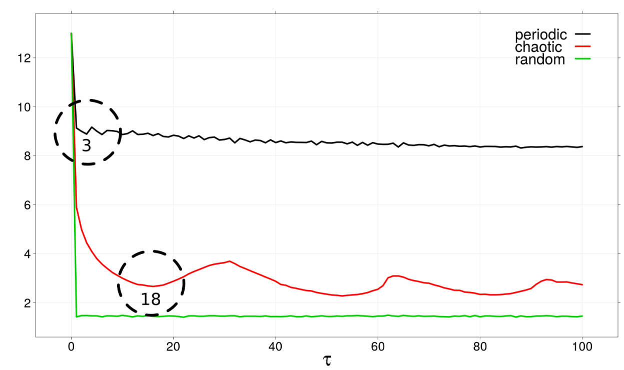

Fig. 3. Mutual information plots from periodic, chaotic and random time series.

[17] and walking, running and cycling activities [19], some problems with the minimal embedding parameter estimation (m_{min} and τ_{min}) still remain to be solved.

Sama *et al.* [18] and Gouwanda *et al.* [17] estimated the minimal embedded dimension (m_{min}) with the False Nearest Neighbours (FNN) method. However, Cao [37] pointed out that the FNN algorithm introduces new parameters (R_{tol} and A_{tol}) that lead to different results and cannot differentiate random series from deterministic series. Frank *et al.* [19] proposed a grid search method to find the minimal embedded parameters, but there are no details about their approach.

In the case of the minimal time delay embedding value, τ_{min}, Fojt *et al.* [39] mentioned a method in which the chosen τ is made in function of filling the space of the reconstructed system; however, Fojt *et al.* [39] mentioned that "it is a rough estimation based on a graphical procedure." Although, Sama *et al.* [18] computed τ_{min} using the method proposed by Fraser *et al.* [38], they pointed that the chosen τ_{min} largely depend on the application.

4 THE ACTIVITY RECOGNITION CHAIN

Bulling *et al.* [1] reviewed the state of the art of HAR using body-worn inertial sensors. Figure 4 illustrates the typical activity recognition chain (ARC) to identify activities with body-worn sensors.

The first stage of the ARC is the raw data collection from several sensors attached to different parts of the body. Data from sensors over a given time, s_i, provide multiple time series d_n, (e.g. d_1, d_2, d_3 for 3-D acceleration referred to as x, y and z direction)

$$s_i = (d_1, d_2, \ldots, d_n), \quad \text{for } i = 1, \ldots, k \tag{1}$$

where k denotes the number of sensors and n the number of degrees of freedom of the inertial sensor.

In the preprocessing stage of the ARC, raw multivariable time series are transformed into a pre-processed time series $D' = (d'_1, \ldots, d'_n)^T$, where d'_i is one dimension of the data for the preprocessed time series and n is the number of total data dimensions. Different methods for the preprocessing tasks may be applied to the raw data (e.g. synchronisation, calibration, unit conversion, normalisation, resampling, denoising or baseline drift removal [1]).

The stage of data segmentation identifies segments within the continuous data stream that are likely to have information about activities. The segmentation stage creates a set of segments w_m such that

$$W = \{w_1, \ldots, w_m\}, \tag{2}$$

where m corresponds to the number of segments. Since the segmentation of the data is a difficult problem, there are various methods in the literature to solve this problem: sliding window, energy-based segmentation, rest-position segmentation, additional sensors and external context sources.

In the feature extraction stage, a feature extraction function F reduces the signals D' into segmented signals W. The total number of features X_i is the feature space.

$$X_i = F(D', w_i) \tag{3}$$

In the literature on activity recognition, different methods for feature extraction can be found including signal-based features, body model features, event-based features, multilevel features or automatic feature ranking and selection.

Machine learning tools have been used in HAR over the last 15 years so as to describe, analyse and predict human activities [1]. However, the chosen approach is subject to computational complexity, recognition performance or latency. Generally for the learning stage, a training data set $T = \{X_i, y_i\}_{i=1}^{N}$ is computed prior to the classification with N pairs of feature vectors X_i and ground truth labels y^i (possible activities to recognise). For this stage, model parameters θ can be learned to decrease the classification error on T. Then, with the trained model T, each feature vector X_i is mapped to a set of class labels $Y = \{y^1, \ldots, y^c\}$ with scores $P_i = \{p_i^1, \ldots, p_i^c\}$:

$$p_i(y \mid X_i, \theta) = I(X_i, \theta), \quad \text{for } y \in Y \tag{4}$$

and inference method I. Finally, the classification output y_i is computed with the maximum score P_i

$$y_i = \underset{y \in Y, p \in P_i}{\operatorname{argmax}} \, p(y|X_i, \theta) \tag{5}$$

The most common classification algorithms are: decision trees, Bayesian models, domain transform, fuzzy logic, Markov models, support vector machines (SVM), artificial neural networks (ANN) and ensembles of classifiers [2].

Similarly, when the recognition of activities can miss, confuse or falsely recognise activities that did occur, several metrics can be used to optimise the classification. Some of the metrics are confusion matrices, accuracy, precision, recall, and F-scores, decision-independent Precision-Recall or receiver operating characteristic curves (ROC curves) [1].

The state-of-the-art on ARC framework is far from quantifying the repeatability and consistency of human activities. The reason for this are: i) ARC frameworks have only been applied to identify the activities; and ii) once the activities have been identified, further analysis has to be done to learn the variability of the activities. The quantification of the skillfulness in terms of the variability and consistency of the human activities is an example. However, little work has been done in this area. Tessendorf *et al.* [40], for instance, proposed an ARC framework in which only the raw data collection and indicators of the rowing technique are used to quantify the rowing techniques of ambitious amateurs and world-class rowers. Velloso *et al.* [11], [12] presented a framework that is more related to the ARC; this framework includes data collection (angle joints from kinect sensor), preprocessing (converting the joints' position coordinates), segmentation (specific intervals of time or every repetition of the activity), feature extraction (performing statistical analysis when the event is triggered) and classification (threshold operations).

5 ARTIFICIAL SIGNALS

To understand the possible sources of variability in dance activities, I followed the method of Hammerla *et al.* [10] which can be useful to model: i) noise in sensors, ii) properties of activities and iii) properties of people.

The proposal of Hammerla *et al.* [10] is aimed at examining the effects of variability in the precision of motion (additive noise) and in the strategy of motion (structural noise) of activities using artificial signals.

Additive noise is normalised noise with σ_a^2 added to the sinusoidal signal S:

$$S^a = S + \mathbf{N}(0, \sigma_a^2) \tag{6}$$

Structural noise is a sinusoidal signal distorted with different variance in frequency σ_u^2, amplitude σ_s^2 and window length w_s. Algorithm 1 describes the creation of structural noise. To make the data less redundant for possible variations of environmental conditions or body-worn sensor mobility in users, the data is whitened (i.e. data is normalised to have zero mean and unit variance)

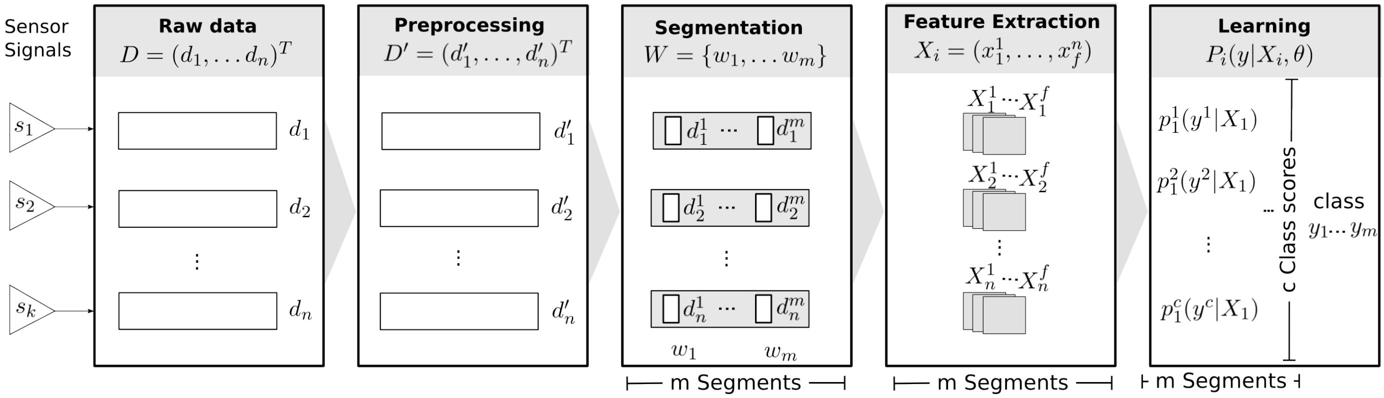

Fig. 4. Typical activity recognition chain (ARC) to identify activities or gestures from body-worn inertial sensors. Diagram is replicated from the work of Bulling *et al.* [1].

Algorithm 1 Structural Noise

Input: time-series S^a, variance σ_s^2, window length w_s
Output: Structurally distorted signal S^s

1: **for** $j = 1$ to L, $j = j + w_s$ **do**
2: $\quad \mathbf{u'} \leftarrow \mathbf{N}(0, \sigma_s^2)$
3: $\quad S^a =$ sinusoid with frequency $|\mathbf{u'}|$ and variance σ_a^2 of length w_s
4: $\quad S^s_{j\to j+w_s} = S^s_{j\to j+w_s} + S^a \times \sigma_s^2$
5: **end for**
$\quad S^s = whiten(S^s)$
6: **return** S^s

By varying both σ_a^2 and σ_s^2 is possible to simulate and control the additive noise and the structural noise in the structure of the human activity. For example, low values of σ_a^2 are associated with precise movements while low values of σ_s^2 correspond to a well chosen strategy for a movement (Figure 5).

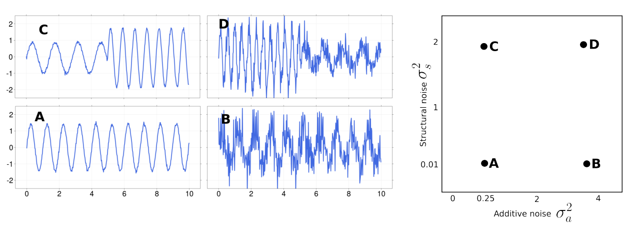

Fig. 5. Graphs (A, B, C and D) present the variability of additive noise (σ_a^2) and structural noise (σ_s^2) on the sinusoid signals with $w_s = 500$ according to the parameters indicated on the left plot.

For graphs in Figure 5, the base frequency of the sinusoidal is 1 Hz sampled at 50Hz with an amplitude 1 and window length of 250 samples.

6 Data Collection and Analysis

6.1 Data Collection

Data from 3-axis accelerometer, gyroscope and magnetometer were collected at a sampling rate of 50Hz using four Razor 9DOF IMUs with Bluetooth (Adeunis ARF7044). The IMUs were attached to custom-made bracelets worn by participants: two sensors were located in front part of the right and left ankle, one in the back of the hip and another in the back of the neck.

6.2 Participants

Thirteen participants with different years of experience in dancing salsa were invited, one (male) expert dancer (14 years of experience), one intermediate (male) dancer (4 years of experience) and eleven non-dancers. The non-dancers were students of engineering (mean age 22 years; 4 female, 7 male). While 2 of these dancers (1 male and 1 female) had danced previously, none of this group has experience in Salsa dancing. For this report, we focus on the data from 3 individual dancers an expert, intermediate and non-dancer, respectively.

6.3 Experimental Conditions

The design of the experiment met the University of Birmingham ethics approval and all participants provided informed consent prior to participation. On arrival, participants were assisted in attaching the IMUs and the manner in which data were collected from these IMUs was demonstrated to them. Once they were comfortable with the fit of IMUs, the experimental task was explained to them.

Each participant was shown a series of video clips (recorded by the expert dancer) demonstrating Salsa steps. Each video clip showed one step repeated several times for 20 seconds. For the analysis in this paper, we report two Salsa step patterns: step 1 = mambo and step 2 = side crossover (Figure 6). 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. For this report, the analysis reported will focus on data taken from the sensor mounted on the left ankle.

6.4 Framework for the Experiment

The raw data was collected from accelerometer ($a_{\{x,y,z\}}$), gyroscope ($g_{\{x,y,z\}}$) and magnetometer($m_{\{x,y,z\}}$) sensors. Then, the time-series a_x with a length of N samples was used to obtain the time-delay embedded matrix, $\boldsymbol{E}a_x$, with m rows and $N - (m-1)\tau$ columns. Finally, the PCA algorithm was applied so as to obtain via eigenvalues $(\lambda_1, \dots, \lambda_m)$, eigenvectors $(v_1, \dots, v_m)$ and the principal

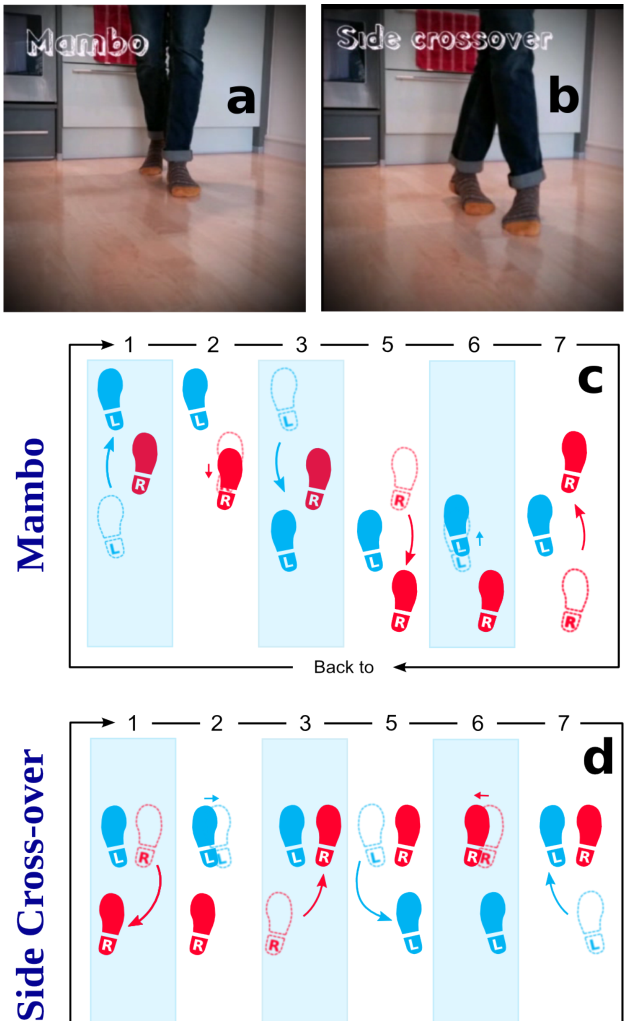

Fig. 6. Salsa step patterns: (a) mambo (step 1) and (b) side crossover (step 2). Foot patterns for (c) the mambo style and (d) the side crossover style.

components $(PC_1, \ldots, PC_m)$ of the time-delay embedded phase space (Figure 7).

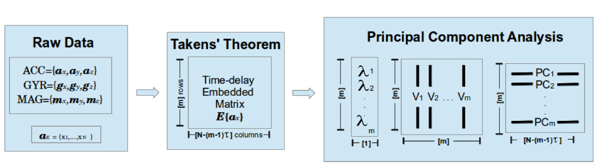

Fig. 7. Diagram for the Phase Space Reconstruction.

6.5 Estimation of the Minimal time-delay Embedding Parameters

Data from the inertial sensor for the left ankle of the expert dancer were used to compute $E1(d)$ and $E2(d)$. These values are computed using a time-series, for instance, m_x so as to obtain four curves that correspond to each delay embedding parameters ($\tau = 1, 2, 3, 4$) for dimension that are in the range $0 \leq d \leq 40$. From $E1(d)$ values (Figures 8) one can notice that the minimal value for the embedded dimension is approximately equal to $m_{min} \approx 10$. Generally, the $E2(d)$ values show that data from m_x and m_y are more noisier than that from m_z; however, $E2(d)$ values from step 2 are less noisier than that from step 1 (Figures 8). Independently of the sensors' axis or dance steps, different τ

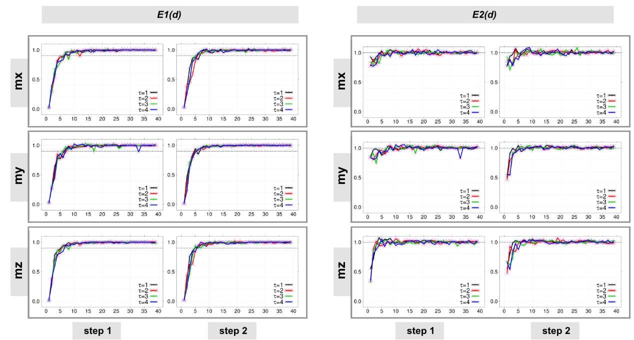

Fig. 8. $E1(d)$ and $E2(d)$ values for $\tau = 1, 2, 3, 4$ with $0 \leq d \leq 40$ from magnetometer sensor $(m_{\{x,y,z\}})$ of the expert dancer for two dance steps. The dashed straight line for $E1(d)$ and $E1(d)$ corresponds to the value 0.9 and 1, respectively.

values provide approximately the same minimal embedding dimension ($m = 10$) in $E1(d)$ values (Figures 8). For the minimum time delay embedding parameter, the mutual information plot is computed from magnetometer sensor data $(m_{\{x,y,z\}}$ and the first minimum for both plots from m_z is at $\tau = 6$ (Figure 9). We therefore computed time-

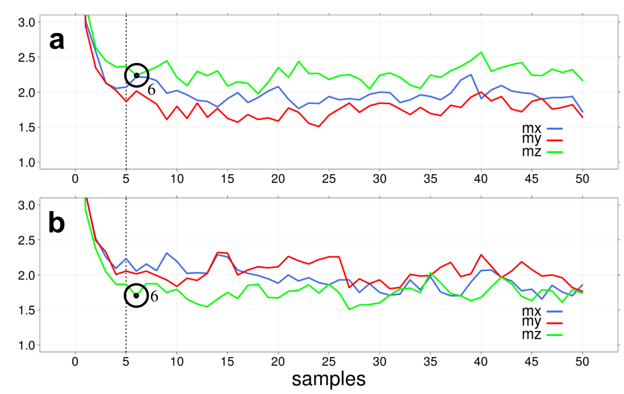

Fig. 9. Mutual information values for $0 \leq \tau \leq 50$ from magnetometer sensor $(m_{\{x,y,z\}})$ of the expert dancer for (a) step 1 and (b) step 2. The vertical dashed straight line in both plots correspond to the value $\tau = 5$. The first minimum for both plots from m_z is at $\tau = 6$.

delay embedded matrix with $m = 10$ and $\tau = 6$ for each axis from the magnetometer sensors depicted in Figure 7.

6.6 2-D Reconstructed State Spaces

Figure 10 illustrates the 2-D reconstructed state space for the non-dancer, intermediate and expert dancers which visually helps us to distinguish different levels of dexterity. It is immediately noticeable that the shape of the state space for each level (novice, intermediate, expert) appear visually similar across step 1. As the participants are meant to be performing the same action, this similarity is to be expected. However, 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, 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.

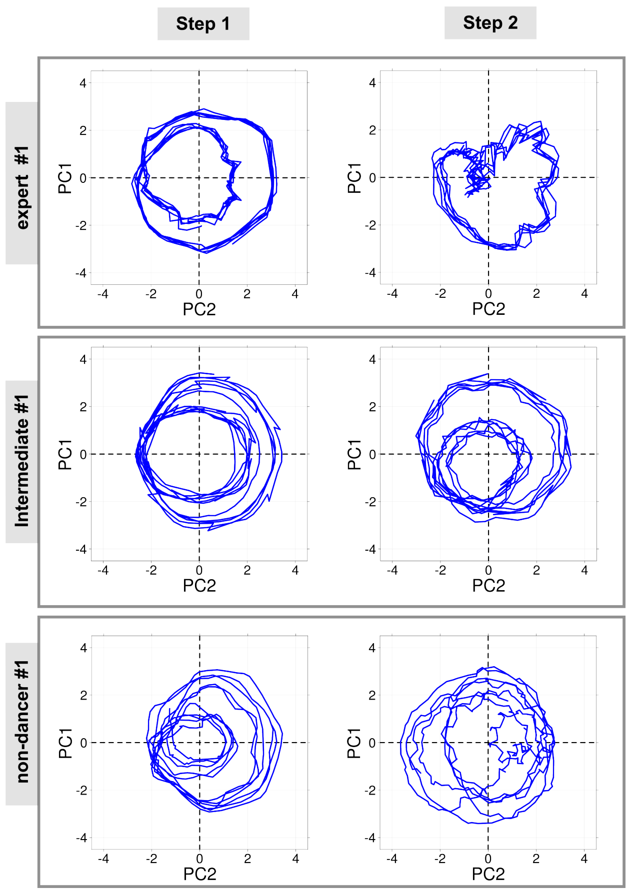

Fig. 10. 2-D reconstructed state spaces for the expert, intermediate and non-dancer participants for step 1 (m_z data) and step 2 (m_y data). First two component of the PCA with embedding parameters ($m = 10$ and $\tau = 6$).

Sama *et al.* [18] pointed out that the chosen τ_{min} largely depends on the application. In this case, the mutual information method indicates that $t_{min} = 6$; however, different values of m and τ give different reconstructed state spaces (Figure 11).

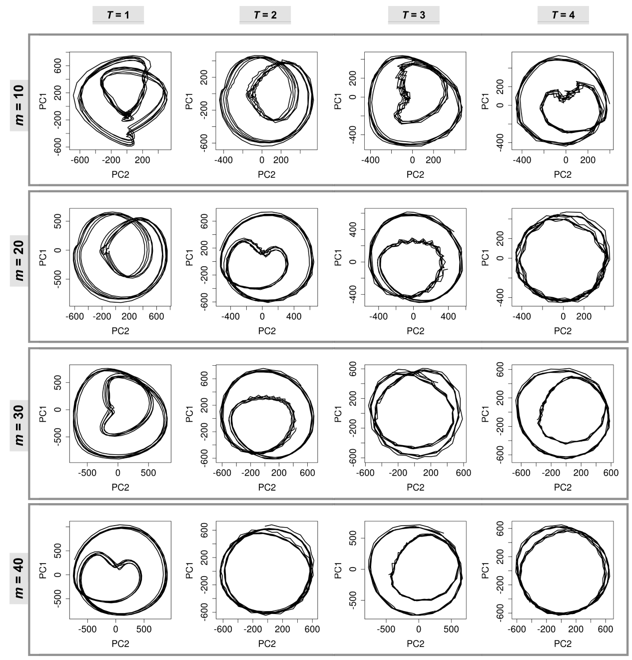

Fig. 11. 2-D reconstructed state spaces with different embedded parameters ($m = 10, 20, 30, 40$ and $\tau = 1, 2, 3, 4$) for the expert dancing step 1.

7 Publication Plan

Preliminary results were submitted to the International Symposium on Wearable Computers (ISWC) 2016; however, the submission was rejected because the reviewers argued that the method of using time-delay embedding and PCA to quantify dexterity for salsa dancers is too specific and it is not transferable to other applications. Additionally, they pointed out that data analysis were collected from 11 novices, 1 intermediate and 1 expert dancers, and no classification framework was performed. However, I am planning to revise the ISWC paper to submit it in another conference.

8 Future Work

To raise the bar in the field of human activity recognition, the plan for the next six months is:

- **Aug. 2015 (10th)** Collect more data from experts dancers so as to capture as much of the variability as possible in either different dancers as well as different dancing tasks.
- **Sep. 2015 (11th)** Using the sawing data, present the limitations of time-delay embedding and PCA and propose improvements for the method. I am also planning to investigate other non-linear analysis tools that would be suitable to explore the variability of dance activities.
- **Oct. 2015 (12th)** Work towards a submission in Measuring Behaviour 2016 and Augmented Human 2016 conferences.
- **Nov. 2015 (13th)** Submit works in the Measuring Behaviour 2016 and Augmented Human 2016 conferences.
- **Dec. 2015 (14th)** Search for an appropriate journal and work towards a submission.
- **Jan. 2016 (15th)** Submit a journal publication

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