Dexterity Assesment for Salsa Dancers Through the Time-delay Embedded Phase Space Representation

author 1
Affiliation
Address
e-mail address
Optional phone number

author 2
Affiliation
Address
e-mail address
Optional phone number

author 3
Affiliation
Address
e-mail address
Optional phone number

ABSTRACT

The work's aim is to understand how dexterity can be described in terms of the consistency and variability of human activity. This paper presents a description of the use of time-delay embedding to analyse data from Inertial Measurement Units mounted on people performing Salsa dance steps. Alternatively, approaches which rely on the definition of discrete events or states might not capture dexterity in the same manner. The paper shows the application to distinguish expert, intermediate and novice dancers from the patterns of data the approach produces. The paper concludes with a discussion of the potential uses of time-delay embedding for Human Activity Recognition from wearable sensor data IMUs.

Author Keywords

Activity Recognition; Dexterity Assesment; Nonlinear Dynamics; Time-series analysis;

ACM Classification Keywords

I.5.4. Pattern Recognition: Applications

INTRODUCTION

The use of data from wearable sensors to identify human activity is a staple of wearable computer research [5]. A core challenge arises from the need to partition these data into segments which represent specific actions. Such an approach can be used to recognise sequences of events drawing on signal processing techniques in the frequency domain. As Hammerla et al. [13] note "[t]herefore information about what subjects are doing is readily available, rendering activity segmentation a straight-forward follow up task". In previous work, we have shown that it is possible to distinguish between dexterity levels for jewellery students performing simple tasks, using inertial sensors embedded in their tools [25]. Using Principal Component Analysis of inertial sensors to define clusters of variables that form classes representing dexterity level. In their study of the dynamics of tennis serves, Ahmadi et al. [1], show that motion of tennis player making serves can identify the dexterity level. They show that dexterity level corresponds to peak values in velocity for shoulder rotation, wrist flexion and upper arm internal rotation prior to a tennis serve. Such studies suggest that the objective classification of dexterity can be made from data acquired from on-body sensors. This accords well with the view of expertise as the definition of a motor schema [14]. However, dexterity can also be explained as the optimal control of specific parameters and, from this perspective, recognition of specific events might not be sufficient.

When it comes to studying skilled or dextrous performance, recognition of event sequences might not be sufficient. Identifying how *well* an action is performed is more challenging than identifying action type. There are two potential reasons for this: (i) The raw data from sensors, in their original, canonical basis, contain no information regarding the structure of the activity. Variability in this data arises from at least three sources: inherent properties of the activity itself; discrepances of expertise, or between different steps; inherent noise in the sensors. (ii) Dexterity in human activity is seldom an exclusive matter of performing events faster or sequencing the events in a more consistent and defined manner.

DEXTERITY IN HUMAN PERFORMANCE AND HUMAN ACTIVITY RECOGNITION

Studies of skilled psychomotor performance indicate that expertise is not simply a matter of performing actions in a more consistent manner than novices [14]. Often the expert is able to produce different but contextually appropriate actions in a manner that the novice is unable to perform. This highlights a paradox in human motor control: in order to act consistently, people need to produce stable patterns of movement which can be repeated efficiently, but these movements also need to exhibit sufficient variability to cope with changes in contextual demand. Biomechanics research explains this control of movement in two broad approaches: a common approach is to assume that a movement is specified in a hierarchy of commands, with a high-level description of a goal defined in terms of location of end-point of that movement, from which it is possible to calculate optimal paths. For these approaches, consistency is explained through the definition of "motor schema" which specifies the neural commands required to enervate the musculoskeletal system to perform a specific action. In such a system, variability in movement arises from noise and interference in the translation of motor

ISWC'15, September 7–11, 2015,Osaka, Japan.

DOI string from ACM form confirmation

command to the performance of the movement. This means that variability is seen as something which needs to be either ignored or dismissed. For Human Activity Recognition, the motor schema view could lead to the assumption that it is beneficial to either filter out such noise or to define averaged patterns which capture the underlying consistency in movement and recognise activity against these patterns.

Yamamoto and Gohara [26] define dexterity as "... the capacity of goal-directed movement to adapt itself to changes in the external environment..." This raises the "degrees of freedom", or "motor equivalence", problem [4]. The motor equivalence problem notes that each joint in the human body has several degrees of freedom in the postural angles that it can adopt, and that combining several joint angles in a given movement can result in a great many alternative postures, particularly when actions are performed dynamically. While people might appear to be making consistent motions in repetitive actions, there is sufficient variability to make it difficult to define a single solution to the motor equivalence problem. The challenge here is to reconstruct the originating system in such a way to compute the minimal parameters which are being optimised in the performance of the movement. From this perspective, dexterity could arise from the use of specific parameters in the control of movement and the assumption is that experts seek to optimise different parameters to novices.

Previous work on the application of dynamical systems approaches to the study of human activity sought to reconcile Bernsteins [4] 'degrees of freedom' problem with the mathematics of dynamical systems [15]. Viewing human motor control in terms of dynamical systems allows researchers to consider how dexterity capitalises on the inherent "noisiness" of the human movement system. This approach has been particularly fruitful in the field of skill in sports [9] and we believe that it offers an interesting perspective for activity recognition. Applying this assumption to Human Activity Recognition, the goal would be to identify the nonlinear dynamical system parameters that are being optimised in a data stream produced when activity is performed, rather than identifying discrete events within that data stream.

RECOGNISING DEXTERITY IN DANCE

As Miura et al. [17] point out "... how the human motor system produces dance movements in still poorly understood." A key issue concerns the manner in which experienced dancers solve the 'degrees of freedom' problem in the face of changing contextual demands. Miura et al. [18] measured muscle activation using electromyography (EMG) 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 synchronizing 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 [8] , and show superior ability in position matching of upper limbs [21].

Capturing dance activity through sensors has tended to rely on motion capture [2] or sensors mounted on the person [16] or in their shoes [19] or from their smartphones [24]. Much of this work has been concerned with using the dancers motion to work with multimedia presentations that augment and complement the dance [11, 20] or as interfacing to a game [7] or commercial games, such as Dance Dance Revolution. While the range of sensing technology used in these papers is diverse and the result of the activity recognition is varied, it is fair to say that few of the papers have considered variability or dexterity in how well dance is performed. In their work, Aristidou et al. [3] have considered the manner in which dance steps conform to a set of defined templates that describe steps in terms of three-dimensional rotation (described using quaternions). The implication is that a goodness-of-fit can be ascertained to determine how well a dancer performs a step, and how any deviation from good can be modified through practice.

For this paper, we are interested in the question of how time-delay embedding techniques can provide insight into the dexterity of dancers. To this end, we consider the performance of a set of steps from Salsa dance and compare untrained, inexperienced or non-dancers in one cohort with experienced dancers in another. Before explaining how the data is collected, the next section outlines the approach to time-series time-delay embedding and the resulting phase space representation used in this paper. It should be noted that dynamical systems research offers a range of techniques for the study of human activity (see [12] for an overview of alternative techniques). However, this paper focuses on a specific technique which utilises time-delay embedding.

PHASE SPACE REPRESENTATION OF THE TIME-DELAY EMBEDDED SERIES DATA

In this work we follow the notation employed in [23]. The purpose of time-delay embedding, also known as Takens's Theorem, is to reconstruct a $D-$dimensional manifold $\mathbf{M}$ $s(t)$ of an unknown dynamical system from time series $x(t)$ of that system. Thus, we assume that the signal we are observing has been produced by some time-varying system rather than been generated entirely at random. The assumption that the source of the signal exhibits systematic variation leads to the assumption that this signal should, over some time period, exhibit a repeated pattern and a meta-stability. What we do not know is what this time period might be or what this repeated pattern might look like. Thus, time-delay embedding assumes that the time series is a sequence $x(t) = h(s(t))$, where $h : M \to \mathbb{R}^D$ is a measurement function on the unknown dynamical system, being $x(t)$ observable (Figure 1). The time delay reconstruction in m dimensions with time delay τ is defined as: $\overline{x}(t) = (x(t), x(t-\tau), ..., x(t-(m-1)\tau))$ which defines a map $\Phi : M \to \mathbb{R}^m$ such that $\overline{x}(t) = \Phi(s)$. $\Psi : \mathbb{R}^m \to \mathbb{R}^n$ is a further transformation that is considered as a more general transformation. In order to reduce the dimensionality of the time-delay embedding sensor data we apply Principal Component Analyis (PCA) to it.

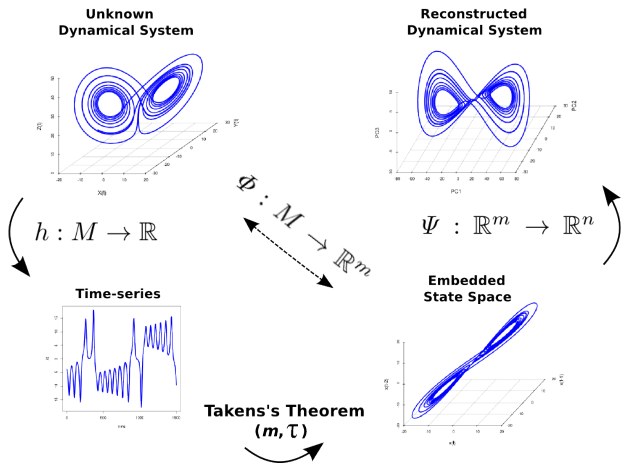

Figure 1. The reconstruction problem

In our work the sequence $x(t)$ is the raw data collected from an (IMU) for triaxial data for accelerometer ($a_{\{x,y,z\}}$), gyroscope ($g_{\{x,y,z\}}$) and magnetometer($m_{\{x,y,z\}}$) sensors. Then, for instance, the time-series a_x with a length of N samples is 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 is applied so as to obtain via eigenvalues $(\lambda_1, \ldots, \lambda_m)$, eigenvectors $(v_1, \ldots, v_m)$ and the principal components $(PC_1, \ldots, PC_m)$ of the time-delay embedded phase space (Figure 2).

Determining the minimal dimension parameters

Although Takens's Theorem has been used extensively in gait recognition [22] and walking, running and cycling activities [10] some problems still remain to be solved. Sama et al. [22] estimated that the minimal embedded dimension (m_{min}) with False Nearest Neighbours (FNN) method. However, Cao [6] pointed out that 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. [10] proposed a grid search method to find the minimal embedded parameters, but there are no details about their approach. Additionally, Sama et al. [22] states that the minimal embedding parameters largely depend on the application at hand. Thus, there is still research to be done to find the minimal dimension parameters (m_{min} and τ_{min}).

$E1(d)$ and $E2(d)$ values

Cao's method for computing the minimal embedding dimension is based on the mean values $E1(d)$ and $E2(d)$ in which d is the range of evaluation of the embedding dimension. $E1(d)$ is used to obtain the minimal dimension m_{min}. $E1(d)$ stops changing when d comes from an attractor. $E2(d)$ 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. 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 [6]. Figures 3 illustrate our application of this approach, which is described in more detail in the Estimation of the Minimal Embedded Parameters section.

DATA COLLECTION

Data from 3-axis accelerometer, gyroscope and magnetometer were collected at a sampling rate of 50 Hz 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 the front part of the right and left ankle, one in the back of the hip and another in back of the neck.

Participants

Thirteen participants with different years of experience in dancing salsa were invited, one (male) expert dancer (14 years of experience), one intermediary (male) dancer (4 years of experience) and eleven non-dancers. The non-dancers are students of engineering (mean age 22 years; 4 female and 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 paper, we focus on the data from 3 individual dancers –an expert, intermediate and non-dancer, respectively.

Experimental Conditions

The design of the experiment met the University of XXX 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 comforable 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 4). 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 paper, the analysis reported will focus on data taken from the sensor mounted on the left ankle.

ESTIMATION OF THE MINIMAL TIME-DELAY EMBEDDING PARAMETERS

Data from the inertial sensor for left ankle of the expert dancer were used to compute $E1(d)$ and $E2(d)$. $E1(d)$ and $E2(d)$ values are computed using a time-series, for instance, m_x so as to optain 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 3) one can notice that the minimal value for the embedded dimmension is approximately equal to $m_{min} \approx 10$.

We define the minimal value as the point on the graph where the line appears to asymptote (or, at least, where the increase becomes very slight). It is therefore important to note that neither the axis of the IMU sensor nor the time-delay values

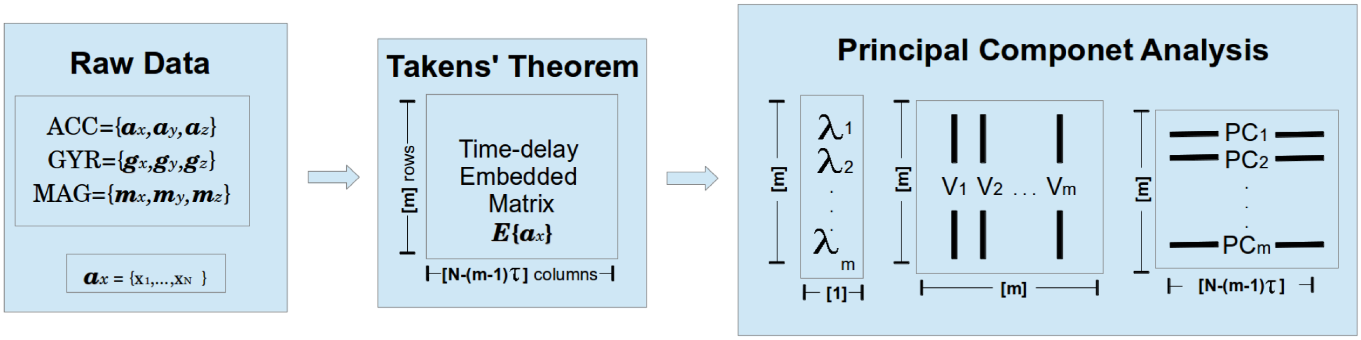

Figure 2. Diagram for the Phase Space Reconstruction.

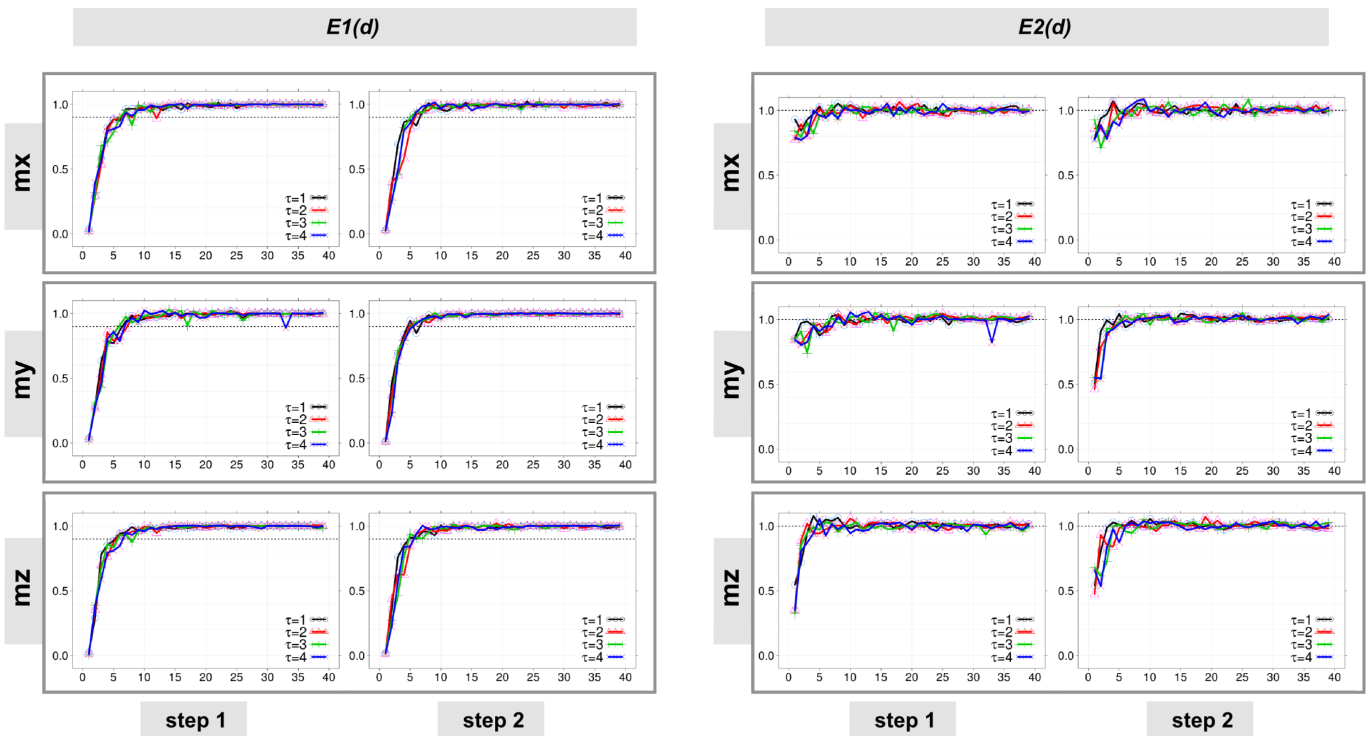

Figure 3. $E1(d)$ **and** $E2(d)$ **values for** $\tau = 1, 2, 3, 4$ **with** $0 \leq d \leq 40$ **from magnetometer sensor (**$Em_{\{x,y,z\}}$**) of the expert dancer for two steps. The dashed straight line for** $E1(d)$ **and** $E1(d)$ **corresponds to the value 0.9 and 1, respectively.**

are a factor for having different embedded dimension parameters.

Independently of the sensors' axis or dance steps, different τ values provide approximately the same minimal embeding dimension ($m = 10$) in $E1(d)$ values (Figures 3). We therefore computed time-delay embedded matrix with $m = 10$ and $\tau = 1$ for each axis of the IMU as depicted in Figure 2. Table 1 illustrates the first two components and its addition values of the PCA (C_1, C_2, $C_1 + C_2$) using all embedded matrix axis ($Em_{\{x,y,z\}}$) for step 1 and step 2 from expert, intermediate and non-dancer participants. Table 1 also help us to select the sensor and the axis that provides the highest variance in the data. We therefore choose the magnetometer sensor in the z-axis since it has the highest variance for step 1 and the magnetometer sensor in the y-axis in the case of the step 2.

Additionally, we illustrate the problem of the minimal embedded parameters since different pairs of embedded parameters might be used to reconstruct the state space (Figure 5).

METHODOLOGY OF THE EXPERIMENT

Our methodology consist of five parts: 1. Collect the raw data from inertial sensors; 2. Estimate mininum value for m and τ using $E1(d)$ and $E2(d)$ values (Figures 3); 3. Select an axis for each step based on the highest variation of the PCA (Table 1); 4. Show Hammerla's approach vs time-delay embedding for dexterity assessment (Figures 6 and Table 2); 5. Finally, present the state space represenatation for the variation of m and τ (Figure 5) and the dexterity levels (Figure 7).

RESULTS

Skills assessment using only PCA

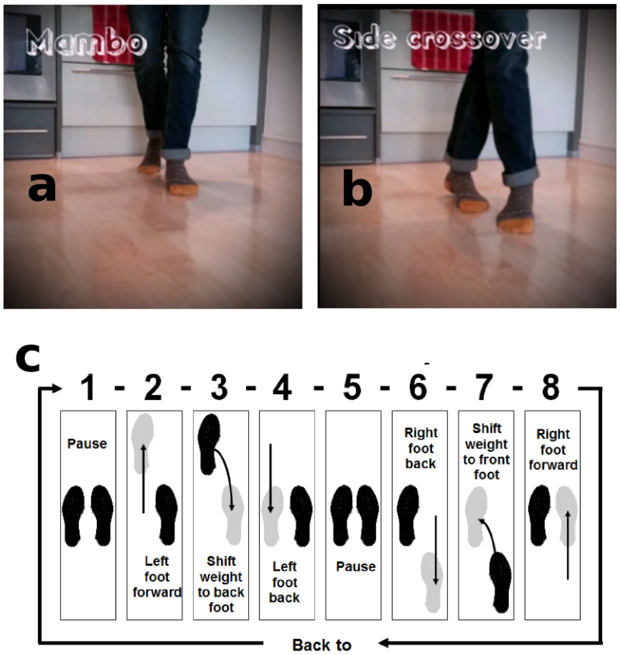

Figure 4. Salsa step patterns: (a) mambo (step 1) and (b) side crossover (step 2). (c) Foot pattern for the mambo style.

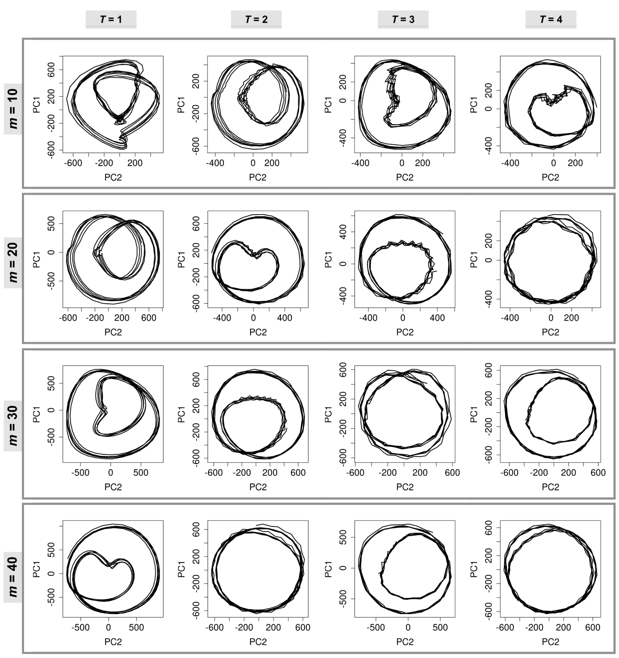

Figure 5. 2-D reconstructed state spaces with different embedded parameters ($m = 10, 20, 30, 40$ and $\tau = 1, 2, 3, 4$) for the expert dancing step 1.

Hammerla et al. [13] proposed the use of PCA with triaxial accelerometer sensor for 'skill' assesment of whisking activity. Prior to the PCA computation, raw data is whitened, i.e. each axis is normalised to have zero mean and unit variance. Then the area between the cumulative energy percentage curve (CEP) and the diagonal is used as a metric for motor skill assesment.

	Step 1			Step 2		
Expert	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$
Em_x	79.18	10.81	89.99	82.13	10.42	92.56
Em_y	67.43	9.03	76.46	73.31	21.00	94.31
Em_z	66.36	28.19	94.55	61.58	25.78	87.37
Intermedium	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$
Em_x	84.91	9.40	94.31	81.80	15.01	96.81
Em_y	64.00	28.66	92.66	77.41	18.17	95.59
Em_z	70.24	25.43	95.67	79.29	16.45	95.75
Non-dancer	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$
Em_x	64.24	23.82	88.06	83.79	12.43	96.23
Em_y	58.45	32.08	90.53	85.71	12.06	97.77
Em_z	66.58	27.88	94.46	72.99	20.96	93.96

Table 1. Percentages of variances of the first two PCA components and its addition from the time-delay embedded matrices. Colored cells represent the maxium percentange of variation of the fist two components.

	Step 1			Step 2		
Expert	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$
MAG	64.00	26.64	90.65	54.97	32.64	87.62
Intermedium	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$
MAG	62.44	33.93	96.37	72.48	25.58	98.07
Non-dancer	C_1	C_2	$C_1 + C_2$	C_1	C_2	$C_1 + C_2$
MAG	71.96	23.60	95.57	54.06	41.93	95.99

Table 2. Percentages of variances of the first two PCA components and its addition from triaxial accelerometer (ACC), gyroscope (GYR), and magnetometer (MAG) sensors. Colored cells represent the maxium percentange of variation of the fist two PCA components.

We compute the cumulative energy using the triaxial whitening data in each sensor for step 1 and 2. From Table 2 we can see that data from the magnetometer sensors has the highest variance of the $C_1 + C_2$ value for each of the users and steps with the exception of the intermediate participant in step 1. We therefore choose the magnetometer sensor for further analysis. Figures 6 (a,e) present the CEP curves of raw data in which at least two out of three cumulative energy curves are overlaped. One might expect the expert to lie farther to the straightline. However, it is not easy to determine why.

On the other hand, Figures 6 (b,d,c,f,g,h) illustrate the CEP curves using the time-delay embedding. Almost all the curves are overlaped. It is therefore hard to establish significative differences among the curves to distinguish differences among expert, intermediate and non-dancers in each of the sensors.

Phase Space Representation

Figure 7 illustrates the 2-D reconstructed state space for the non-dancer, intermediate and expert dancers which visually help us to distinguish different levels of dexterity. It is immediately noticeable that the shape of the state space for each

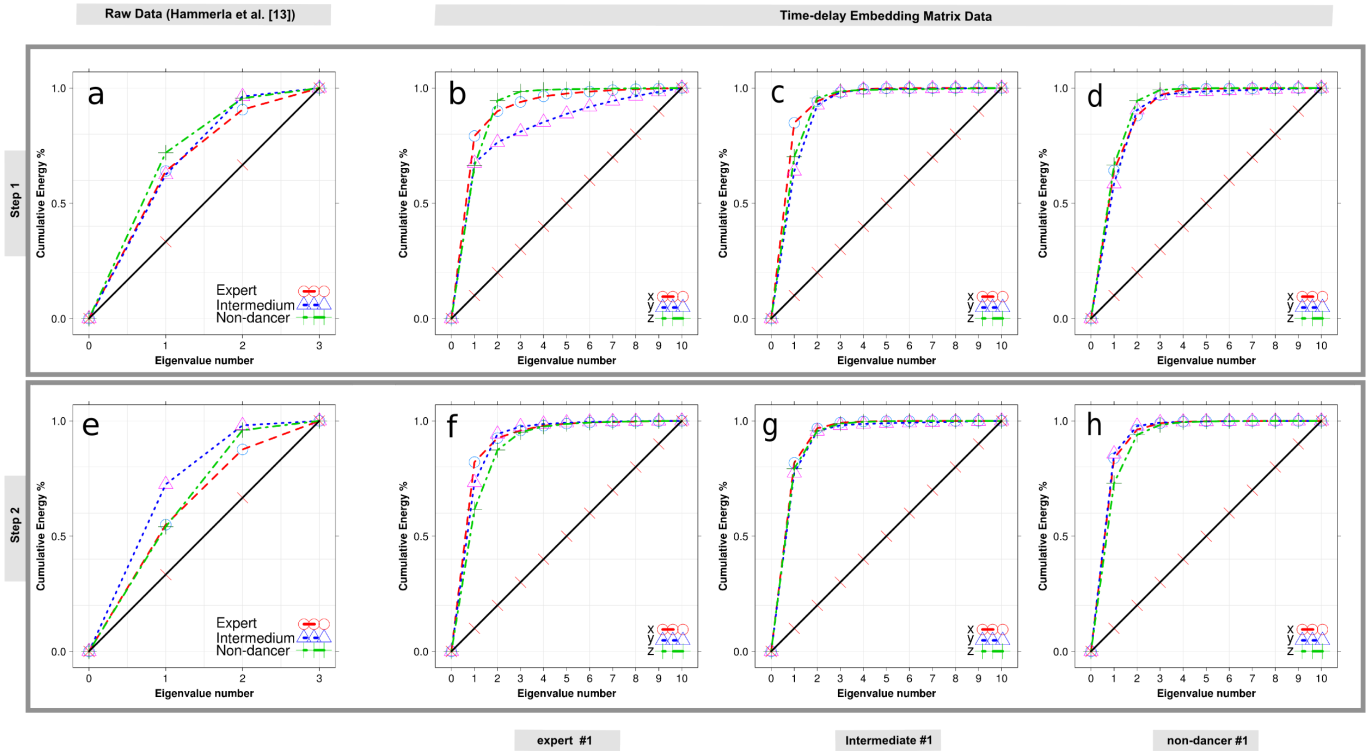

Figure 6. Cumulative energy percentage curves using the magnetometer sensor. (a,e) curves are based on the triaxial raw data. (b,d,c,f,g,h) curves are based on the time-delay embedded data for axis x, y and z. Curves are for expert, intermediate and non-dancer users for step 1 and step 2.

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 was 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.

DISCUSSION

Although time-delay embedding is subject to the embedded parameters, the phase space representation applies a model of consistency to the data for dexterity assessment. The control of variability then becomes desirable because expert dancers are better able to moderate their actions in response to contextual demands in a way that produces a state space reconstruction that appears consistent. The novice dancer, on the other hand, appears to been producing similar patterns of movement for both steps rather than attempting to fully engage with the requirements of step 2.

While the results provide some indication of difference between levels of dexterity, the interpretation of the state space reconstructions remains qualitative. While this is not unusual in the literature which applies time-delay embedding to the analysis of human activity, further work is required to develop reliable and robust quantitative techniques to analyse these reconstructions. A promising line of enquiry would be to investigate the geometry of the state space reconstructions which could be used to support comparison [22] and also could aid in the estimation of the minimal embedded parameters.

The results in this paper are only from a single axis of single sensor (magnetometer). The $E2(d)$ values that the accelerometer data is more noisy since its variance is more spreaded accross the components of the PCA than that from the gyroscope and magnetometer. While this is most likely due to effects of gravity on the accelerometer (although the ADXL345 accelerometer used in the Razor offers simple gravity compensation), there interference with the signal can be further filtered and compensated. It would be interesting to determine how combinations of sensor data can be used to create similar state space reconstructions and this will be explored in the next phase of work.

Our work suggest that Hammerla's method may not be appropriable for dexterity assesment using raw data from the inertial sensors as well as the use of the time-delay embedded matrix data, because the cumulative energy percentage curves are hardly distinguished from both the level of expertise and the type of step.

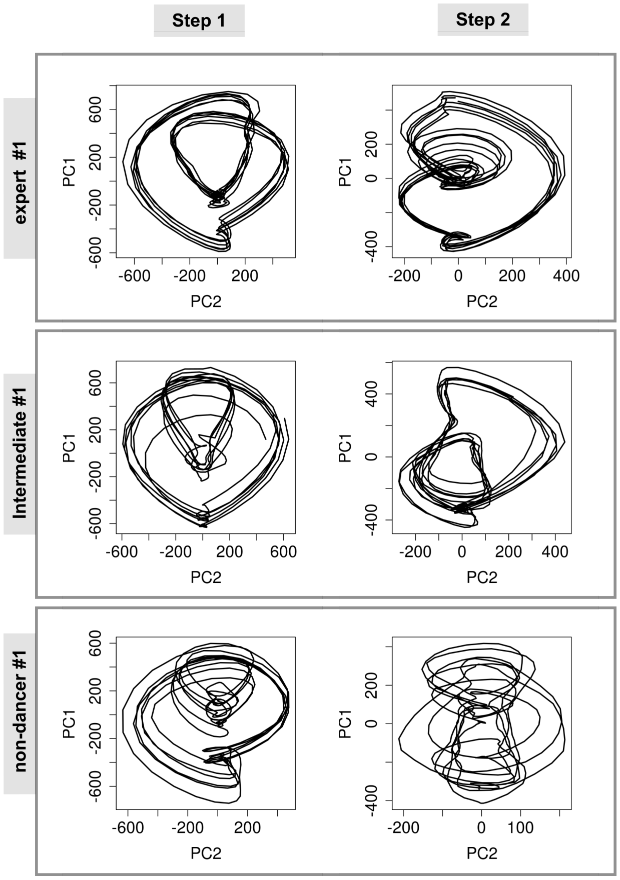

Figure 7. 2-D reconstructed state spaces for the expert, intermediate and non-dancer participants for step 1 (m_z data) and step 2 (m_y data). First two component of the PCA with embedding parameters ($m = 10$ and $\tau = 1$).

The aim of this work is to measure dexterity in dance from wearable IMUs. Signals from the IMUs are represented in a transformed time-delay embedded basis that reflects the non-linear dynamics of dance steps. This distinguishes expert, intermediate and beginner levels of dexterity for two dance steps. The approach can potentially be easily applied to other human activities.

ACKNOWLEDGMENTS

The work reported in this paper is partly supported by a studentship from National Council for Science and Technology, CONACyT, Mexico.

REFERENCES

1. Ahmadi, A., Rowlands, D., and James, D. A. Towards a wearable device for skill assessment and skill acquisition of a tennis player during the first serve. *Sports Technology 2*, 3-4 (2010), 129–136.
2. Alexiadis, D. S., and Daras, P. Quaternionic signal processing techniques for automatic evaluation of dance performances from MoCap data. *IEEE Transactions on Multimedia 16*, 5 (2014), 1391–1406.
3. Aristidou, A., Stavrakis, E., and Chrysanthou, Y. Motion Analysis for Folk Dance Evaluation. *EUROGRAPHICS Workshop on Graphics and Culture Heritage* (2014), 20141304.
4. Bernstein, N. A. *The Coordination and Regulation of Movements*. Oxford, New York, Pergamon Press, 1967.
5. Bulling, A., Blanke, U., and Schiele, B. A tutorial on human activity recognition using body-worn inertial sensors. *ACM Computing Surveys (CSUR) 46*, 3 (2014), 1–33.
6. Cao, L. Practical method for determining the minimum embedding dimension of a scalar time series. *Physica D: Nonlinear Phenomena 110* (1997), 43–50.
7. Chu, N. N. Y., Yang, C. M., and Wu, C. C. Game interface using digital textile sensors, accelerometer and gyroscope. *IEEE Transactions on Consumer Electronics 58*, 2 (2012), 184–189.
8. Crotts, D., Thompson, B., Nahom, M., Ryan, S., and Newton, R. a. Balance abilities of professional dancers on select balance tests. *The Journal of orthopaedic and sports physical therapy 23*, 1 (1996), 12–17.
9. Davids, K., Glazier, P., Araujo, D., and Bartlett, R. Movement systems as dynamical systems: the functional roles of variability and its implications for sports medicine. *Sports Medicine 33*, 4 (2003), 245–260.
10. Frank, J., Mannor, S., and Precup, D. Activity and Gait Recognition with Time-Delay Embeddings Time-Delay Embeddings. *AAAI Conference on Artificial Intelligence* (2010), 407–408.
11. Griffith, N., and Fernström, M. LiteFoot: A floor space for recording dance and controlling media. *Proceedings of the 1998 International Computer Music Conference* (1998), 475–481.
12. Guastello, S. J., and Gregson, R. *Nonlinear Dynamical Systems Analyis for the Behavioral Sciences using Real Data.* CRC Press., 2011.
13. Hammerla, N., Ploetz, T., Andras, P., and Olivier, P. Assessing Motor Performance with PCA. *Proc. Int. Workshop on Frontiers in Activity Recognition using Pervasive Sensing (in conjunction with Pervasive 2011)* (2011), 18–23.
14. Kelso, J. S. *Human motor behavior: An introduction.* Psychology Press., 2014.
15. Kugler, P., Kelso, J., and Turvey, M. *The development of movement control and coordination.* Chichester: John Wiley., 1982.
16. Lynch, A., Majeed, B., O'Flynn, B., Barton, J., Murphy, F., Delaney, K., and O'Mathuna, S. C. A wireless inertial measurement system (WIMS) for an interactive dance environment. *Journal of Physics: Conference Series 15* (2005), 95–100.
17. Miura, A., Fujii, S., Yamamoto, Y., and Kudo, K. Motor Control of Rhythmic Dance from a Dynamical Systems Perspective. *Journal of Dance Medicine and Science 19* (2015), 11–21.

18. Miura, A., Kudo, K., Ohtsuki, T., Kanehisa, H., and Nakazawa, K. Relationship between muscle cocontraction and proficiency in whole-body sensorimotor synchronization: a comparison study of street dancers and nondancers. *Motor control 17*, 1 (2013), 18–33.
19. Paradiso, J., and Hu, E. Expressive footwear for computer-augmented dance performance. *Digest of Papers. First International Symposium on Wearable Computers*, October (1997), 20–21.
20. Park, C., Chou, P. H., and Sun, Y. A wearable wireless sensor platform for interactive dance performances. *Proceedings - Fourth Annual IEEE International Conference on Pervasive Computing and Communications, PerCom 2006* (2006), 52–57.
21. Ramsay, J. R., and Riddoch, M. J. Position-matching in the upper limb: professional ballet dancers perform with outstanding accuracy. *Clinical rehabilitation 15*, 3 (2001), 324–330.
22. Samà, A., Ruiz, F. J., Agell, N., Pérez-López, C., Català, A., and Cabestany, J. Gait identification by means of box approximation geometry of reconstructed attractors in latent space. *Neurocomputing 121* (2013), 79–88.
23. Uzal, L. C., Grinblat, G. L., and Verdes, P. F. Optimal reconstruction of dynamical systems: A noise amplification approach. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics 84*, 1 (2011).
24. Wei, Y., Yan, H., Bie, R., Wang, S., and Sun, L. Performance monitoring and evaluation in dance teaching with mobile sensing technology. *Personal and Ubiquitous Computing 18*, 8 (2014), 1929–1939.
25. x, x, and x. xxx. *xx 00* (0000), 00–00.
26. Yamamoto, Y., and Gohara, K. Continuous hitting movements modeled from the perspective of dynamical systems with temporal input. *Human Movement Science 19*, 3 (Aug. 2000), 341–371.