Dancing in Time: applying time-series analysis to Human Activity

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ABSTRACT

There are many ways to classify, analyze and recognize human activity on the basis of data from sensors on the person or in the environment. However, these techniques are directed toward identifying discrete events or actions. In this paper, we are interested not simply in whether an action has been performed but in how well it has been performed, i.e., in identifying the dexterity of the person performing the activity. Dexterity can play an important role in monitoring behavior of patients undergoing rehabilitation, e.g., measuring their progress in relearning everyday skills, but could also be useful in evaluating people learning and developing new skills. Dexterity involves a trade-off between the stability and variability in performing activity, which means that these phenomena need to be considered over the entire performance of the activity. We show how time-series analysis allows us to measure dexterity and how this can distinguish levels of ability.

Author Keywords

Human Activity Recognition; Dexterity; Time-series analysis; Takens' Theorem.

ACM Classification Keywords

I.3.6 Methodology and techniques; H.1.2 User / Machine Systems; H.5.2. User Interfaces.

INTRODUCTION

There are three reasons why dexterity is relevant to the CHI community. First, as technology shifts into the 'smart home' or is worn on the person, there are increasing opportunities to gather data from sensors. Combinations of sensors which are active over long periods of time allow longitudinal study of activity. Second, collecting data over long periods, could involve a shift from the focus on specific events or actions to a focus on how activity might change over time. Central to this focus is an understanding of the way in which activity can exhibit variability or stability. In many techniques for the recognition of human activity, variability in signals is treated as noise and as something to filter prior to analysis. Shifting the focus to explore variability, therefore, requires different analysis techniques. Third, if the variability of activity is the focus of analysis, the one can interpret such activity in terms of how 'well' the action is performed.

Data from sensors on the person or in the environment are used to explain, interpret and make sense of the activities that people perform, with the aim of providing assistance (in the form of nudging, coaching or guidance). If we are developing technology that is intended to assist people, then it is important to know how 'well' people are performing the activity, i.e., are they improving (in the case of rehabilitation or in the case of training new skills)?, or are they deteriorating?, and which aspects of their activity seems to contribute most to these changes?

Human activity recognition

Bulling et al. [1] reviewed the state-of-the-art of Human Activity Recognition applied to data from body-worn inertial sensors. Figure 1 illustrates an activity recognition chain (ARC) related to such data. The first stage of the ARC is the collection of raw data from several sensors attached to the body. Sensor data over a given time, s_i, provide multiple values d^i, (e.g. d^1, d^2, d^3 for accelerometer x, y and z data):

$$s_i = (d^1, d^2,...d^t), \text{ for i = 1,... k} \quad (1)$$

where k denotes the number of sensors.

In the pre-processing stage of the ARC, raw multivariate data are transformed into a pre-processed data $D' = (d'1,...,d'_n)^T$, where d'_i is one dimension of the data and n is the number of total data dimensions.

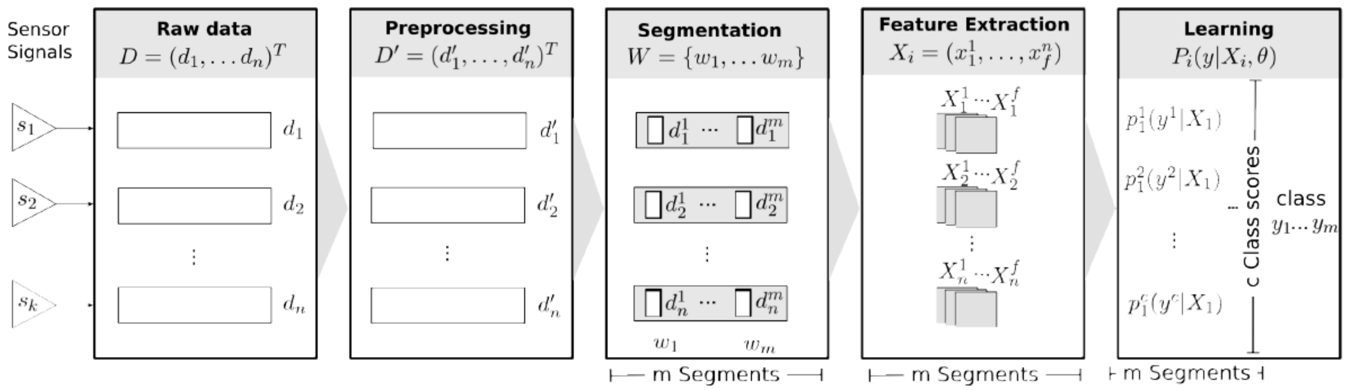

Figure 1. Activity Recognition Chain for processing sensor data (following [1])

Different methods for the pre-processing tasks may be applied to the raw data (e.g. synchronisation, calibration, unit conversion, normalisation, resampling, denoising, baseline drift removal etc.).

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

$$W = \{w_1,..., w_m\} \quad (2)$$

where m correspond to the number of segments.

In Human Activity Recognition, segmentation of the data is problematic for several reasons, e.g., the difficulty of determining when an action begins or ends, separating multiple overlapping actions etc. In Automatic Speech Recognition, these problems can be addressed through the definition of basic units (e.g., phonemes) or assumptions about the manner in which these basic units can be combined. However, for Activity Recognition, we do not have clearly defined basic units nor agreement as to what would be an appropriate level at which to define these. The use of time-series analysis, as illustrated in this paper, allows us to define sequences of activity without the need to segment the data in specific actions. This provides a means of capturing the dexterity in performing a given activity which, as not previously, aligns with the notions of human activity as a dynamic system. Furthermore, the notion of functional dynamics (discussed in the section on 'dexterity in tool use') provides the foundations for a context-specific definition of the control, movement, regulatory and functional parameters which characterize a given activity. The goal would, thus, be to use this definition to specify the type of sensor data required to describe and analysis the activity. In order to explore these questions of variability, stability, and activity analysis we turn to the notion of dexterity.

DEFINING DEXTERITY

In common parlance, dexterity is synonymous with skill. However, this does not help in defining either term. We begin with the assumption that skill involves performing tasks to a specific standard and that dexterity is the psychomotor coordination that allows these tasks to be performed efficiently and effectively. In this case, 'skill' is the level of performance of the activity and 'dexterity' is the moment-to-moment coordination to achieve this level of performance. From this perspective, 'skill' relates to measures of performance, e.g., time and error, whereas 'dexterity' relates to measures of coordination (in order to achieve this performance).

In the robotics literature, 'dexterity' is the low level capability of robot manipulators to move, apply appropriate forces and torques, or manage velocities at individual joints [2]. In studies of human movement, dexterity relates to the ability to find an efficient solution to a motor problem in any situation [3]. Dexterity, in both of these domains, is the ability to adequately resolve the 'degrees of freedom' problem [4]. In any system with multiple joints and muscles, there are many ways in which a movement can be performed, resulting in many degrees of freedom. For Bernstein [4], the degrees of freedom problem can be simplified through the construction of a functional organization of structural elements (i.e., muscles, joints), which is known as a synergy (or coordinative structure) which reduces the control problem to managing this synergy.

Dexterity is not only concerned with the stability of movement (in finding an efficient and, by implication, consistent solution to a motor problem) but also its variability. Thus, dexterity is "…the capacity of goal-directed movement to adapt itself to changes in the external environment…" [5, p.342].

QUANTIFYING DEXTERITY IN HUMAN MOTOR PERFORMANCE

The challenge of determining whether a given activity has been performed at a given level of dexterity is not simply one of recognizing that the action has occurred but of interpreting the quality of that action. In this instance, 'quality' is defined in terms of the trade-off between variability and stability in the signal that describes the activity.

Dexterity in Human Motor Control

A central concern in the study of human motor control is the identification and analysis of "…the *functional strategies* adopted by an individual to achieve a goal, whether that goal is playing a piano…, holding a teacup or using a tool." [6] [italics added]. In this case, functional strategies refer to the manner in which the 'degrees of freedom' problem is solved through the coordination of muscle activation and joint motion. Thus, data could be collected from muscle activity, using electromyography (EMG), or joint motion, using vision-based motion capture, Inertial Measurement Units or gloves equipped with sensors. Analysis of these strategies is often in terms of 'Minimum *x*', where *x* could be jerk, energy, time, torque, velocity etc. [7]. From this perspective, one would expect dexterity to be characterized by optimal values of *x*. Often, the study of dexterity is conducted within the theoretical context of dynamic systems, with the aim of uncovering the system which was capable of producing the activity that exhibits optimal values of *x*.

Dexterity in Human Activity Recognition

Studying dexterity in terms of variability and stability implies the need to understand the profile of the activity over a period of time, rather than in terms of discrete events. As noted previously, many of the techniques used in activity recognition aim at identifying discrete events or sequences of discrete events. Alternatively, approaches to the study of dynamic systems, using time-series analysis, are concerned with the variation in the signal rather than in detecting specific features. From this, the analysis would show how repeated instances of actions could exhibit stability. Thus, time-series analysis techniques ought to provide us with insight into human dexterity.

Hammerla et al. [8] used Principal Components Analysis (PCA) to analyze the energy spectra from the output of an accelerometer (attached to a kitchen whisk when users whisked cream for 5 minutes). The advantage of this task for analysis is that it lends itself to a highly repetitive structure. Indeed, much of the exploration into dynamic systems is based on repetitive tasks because these provide a signal in which one can assume stability. While this has proven to be a promising approach, the application of PCA to the accelerometer data could skew the analysis as a result of the variation in the data itself. Furthermore, the simplicity of the task makes in difficult to consider 'skill' or dexterity in the performance of whisking. In this paper we consider alternative techniques which can be applied to the study of dynamic systems in terms of a set of simple, repetitive tasks.

ANALYTIC TECHNIQUES

In our work, dynamic systems are analyzed using $1/f$ scaling and time-delay embedding. Dynamic systems exhibit variability which appears to follow $1/f$ scaling which representation of pink noise (if it originates in a stable system) or white noise (if it originates from a random source). This has been used to characterize human movement [9]. Time-delay embedding is a popular technique in the analysis of human gait and has also been applied to activities such as running and cycling [10]. The analysis assumes that the signal to be analyzed originates from a dynamical system which has a characteristic time series.

Calculating 1/*f* scaling

The underlying assumption of $1/f$ scaling is that the magnitude of activity scales across the frequency spectrum of the signal captured from that activity in a power law with exponent β, where $0 < \beta \leq 1$, i.e., $1/f^{\beta}$, or exponent α when $\alpha = 1$, i.e., $1/f^{\alpha}$. The $1/f$ scaling is typically expressed in the frequency domain, involving Fourier transform of the signal. In this scaling, frequency and power are inversely related (hence, $1/f$). Generally, this results in a plot of log f against log power.

Calculating Time-delay embedding parameters

In order to calculate dimensions for time-delay embedding, we follow the notation employed in [11]. The purpose of time-delay embedding, is to reconstruct a D-dimensional manifold M s(t)of an unknown dynamical system from time series x(t) of that system. This assumes 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 then leads to the further assumption that this signal should, over some time period, exhibit a repeated pattern or a meta-stability. What we do not know is what this time period might be or what this pattern might look like. Thus, time-delay embedding looks for the values of embedding dimensions which can describe these patterns.

The analysis assumes that the time series is a sequence $x(\mathrm{t}) = \mathrm{h}(s(\mathrm{t}))$, where $\mathrm{h} : M \rightarrow \mathbf{R}^D$ is a measurement function on the unknown dynamical system which is x(t) observable. The time delay reconstruction in m dimensions with time delay τ is defined as: $x(\mathrm{t}) = (x(\mathrm{t}), x(\mathrm{t} - \tau),..., x(\mathrm{t} - (m - 1)\ \tau))$ which defines a map $\Phi: M \rightarrow \mathbf{R}^m$ such that $\mathrm{x(t)} = \Phi\ \mathrm{(s)}$. 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 $\mathrm{N} - (m - 1)\ \tau$ columns.

Finally, Principal Component Analysis (PCA) is applied so as to obtain eigenvalues ($\lambda 1, \ldots \lambda m$), eigenvectors ($v_1, \ldots v_m$) and principal components ($PC_1, \ldots PC_m$). While this description outlines the general approach, a challenge remains as to how define the embedding dimensions. We follow the approach proposed by Cao [12].

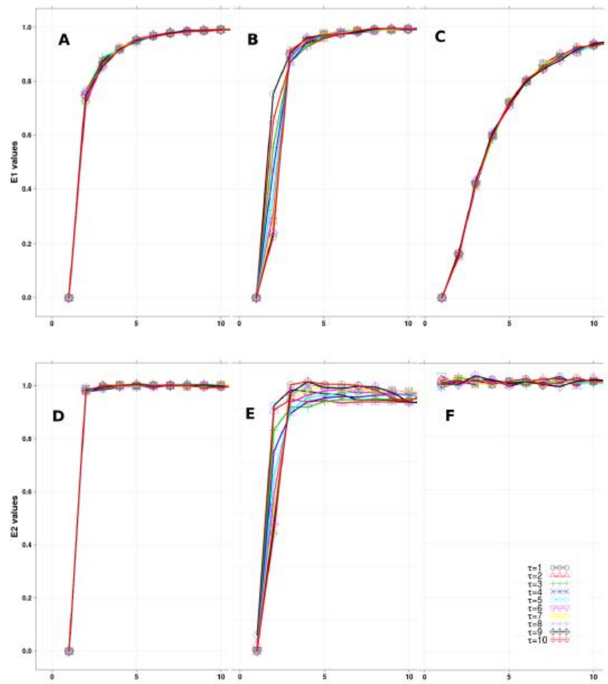

Figure 2. The values of E1(d) and E2(d) with different time delay embedding parameters from periodic (A,D), chaotic (B,E) and random (C,F) time series.

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. $E1(d)$ is used to obtain the minimal dimension m_{min}. We compute $E1(d)$ values for $1 < \tau < 10$ to exemplify the dependency of τ given periodic, chaotic or random time series (Figure 2). The value of $E1(d)$ can be taken as the point at which the curve asymptotes. 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*. Similarly, we computed $E2(d)$ values for periodic, chaotic and random time series, to exemplify the no significant dependency on τ , where $1 < \tau < 10$.

The method of choosing the minimum time-delay embedding, τ_{min}, was proposed by Fraser et al. [13] 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 is $\tau_{min} = 18$. On the other hand, for random time series the mutual information plot have no local minimum and values are monotonically decreasing which means that $\tau_{min} = 1$. However, further research has to be done when data comes from a periodic time series since its minimum in the mutual information plot appears to be at $\tau_{min} = 3$.

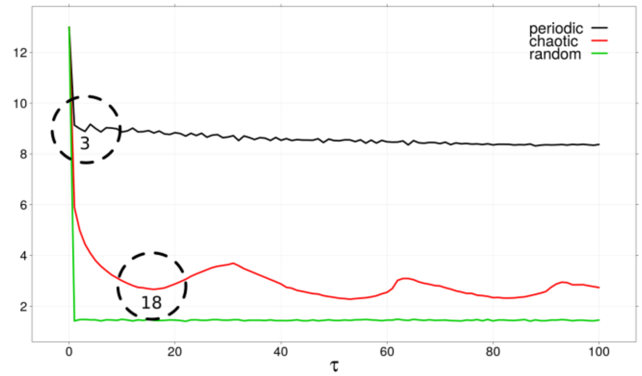

Figure 3. Defining minimum time-delay embedding for periodic, chaotic or random time series.

DEXTERITY IN SIMPLE, REPETITIVE TASKS

For the initial analysis, we consider simple, repetitive tasks, such as drumming or using a handsaw. The aim is to demonstrate how the analysis methods can be applied to data from sensors and from motion capture, and how the results of these analyses allow us to distinguish between different levels of dexterity. For this discussion, we focus on the use of a handsaw.

Dexterity in Tool Use

Given the assertion that dexterity relates to the functional strategies that people apply in order to adapt their activity to context; we begin with the question of what functional strategies apply to tool use? In a series of papers studying the kinematics of skilled and novice flint-knappers[1], Blandine Bril and her colleagues [14, 15, 16] develop the concept of functional dynamics. The approach follows Bernstein's notion of synergy discussed above. For Bril, synergy relates to the different parameters that can be controlled in tool use. She defines the Functional parameter in terms of the intended outcome of the action but which is outside the direct control of the person. For flint-knapping, this is the kinetic energy with which one stone hits another which results in the impact force on the flint. This is affected by the Control parameters, which are properties of the stones being used as hammers. The human responds to the control parameters through movement (e.g., angle of

[1] Flint-knapping is the art of fashioning tools from stone. Typically, a piece of flint is shaped using a hammer stone to fashion a blade or arrow head. Experienced flint-knappers work as experimental archaeologists to study how ancient stone tools could have been made.

blow or distance the hammer stone is moved) and regulatory parameters (e.g., potential energy) in order to produce an appropriate functional parameter. We have applied this concept to sawing by jewellery students. A Principal Components Analysis was applied to 13 measures from sensors on the handles of jewellers' saws, and this produced a five component solution: sawing action, grasp of handle, task completion time, lateral deviation of sawing strokes, and subjective rating of the lines that were cut [17]. Higher ability related to grasp of the handle and sawing action and these correspond to the regulatory and functional parameters for this task.

In addition to studying jewellery saws, we have looked at sawing wood. This involved the use of motion capture (figure 4). Initial analysis was applied 1/*f* scaling to the velocity data collected from participants sawing into wood.

Figure 4. Participant with retroreflective markers on hand, elbow, shoulders and tip of saw.

Details of the data collection and analysis can be found in [18], but basically we asked people to saw across the wood (horizontally) in a manner that was assumed to be familiar and up the wood (vertically) in a manner that was consistent with the use of jewellers' saws but unfamiliar to our participants. Figure 5 shows the power spectral density plots of a sample of these data. The graphs plot log of frequency to log of power in the signal. The steeper the slope, the more likely the signal arises from a regular source, i.e., the slope indicates pink noise. As the slope becomes less steep, so the source can be assumed to exhibit greater randomness. This could be interpreted as the level of stability in the control of the saw for this task, with lower dexterity arising from less stable control and resulting in a shallower slope in the graph.

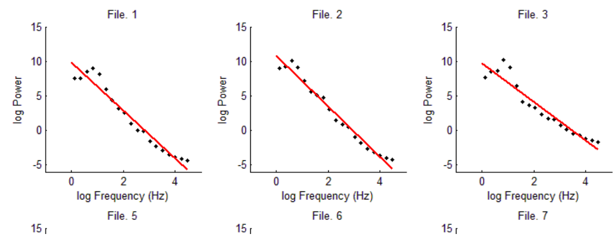

Figure 5. 1/*f* scaling plots of 3 participants showing steep slopes (file 1 and file 2) and shallower slope (file3).

Applying time-delay embedding to the data allows us to identify stability in the signal. Figure 6 shows the analysis of two participants performing this task: the top one shows much greater stability than the bottom one, with the resulting signal being densely packed and regular in shape.

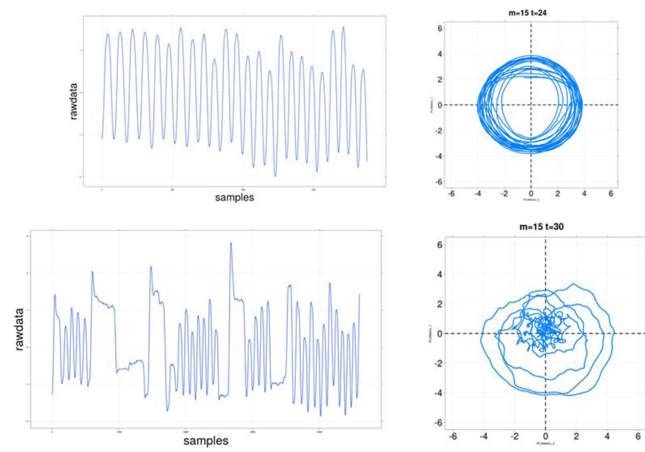

Figure 6. Raw velocity profile (left) and reconstructed time-series analysis (right) for 2 participants performing the horizontal sawing task.

A similar analysis was performed on data for the same two participants on the vertical task (figure 7). It is interesting to note the visual differences in the horizontal (which we define in the easiest) and the vertical task. In the vertical task, even for the more dexterous saw-user (the top graphs in the two figures), there is a more open and less regular pattern in the signal.

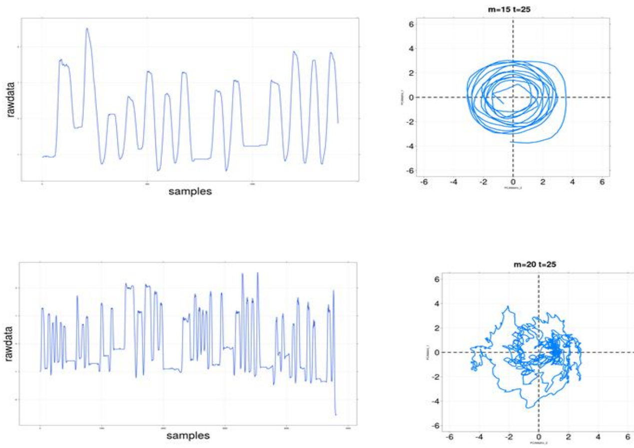

Figure 7. Raw velocity profile (left) and reconstructed time-series analysis (right) for 2 participants performing the vertical sawing task.

Conclusions

Even though the analysis is of simple, repetitive actions using saws, it is apparent that there is variation in the signals being analyzed. The stability in the signal (figures 6 and 7) and the slope of the $1/f$ plots (figure 5) can be interpreted in terms of the level of dexterity in performing the action.

The analysis also highlights the manner in which dexterity relates to the ability of people to recognize and manage key parameters that influence their activity. A possible consequence of this is that it might be more beneficial to focus on defining the parameters that people *seem* to be controlling than on recognizing the action they are performing *per se.* One could, for example, use the sensor data from the handles in this study to recognize that grip force is higher than average which, in turn, might reduce flexibility about the wrist which, in turn, might reduce adaptability in the movement. The chain of interpretation could then lead not only to the identification of a potential problem, i.e., reduce adaptability, but also a possible cause, i.e., tight grip. From this, it is possible to provide guidance which is not simply prescriptive ("don't grip too tight") but also grounded in a contextual explanation relating to wrist flexibility and adaptation. On the other hand, changes in grip force could be indicative of a deterioration in ability of the person performing the task, e.g., due to fatigue. The point that we are making is that focusing on dexterity as a composite measure of performance, rather than the discrete output of different sensors or the discrete definition of specific tasks can have positive benefits for designing technology for assisting people.

DEXTERITY IN COMPLEX ACTIVITY

Much of the research into dexterity in human performance has focused on simple, repetitive tasks. A more interesting challenge arises from the study of dexterity in complex activity. In this section, we apply the techniques to Salsa dancing.

Understanding dance

As Miura et al. [19] point out, "…how the human motor system produces dance movements is still poorly understood." A key issue concerns the manner in which experienced dancers solve the 'degrees of freedom' problem as they encounter changing contextual demands. Such contextual demands could include the rhythm and tempo of the music, or the transition from current posture to a desired posture (in terms of the dance 'step' to be performed), or dancing with a partner. Experienced dancers show much better precision in synchronizing movements to beat than non-dancers [20], exhibit superior postural stability [21], and show superior ability in position matching of upper limbs [22]. This suggests that there will be measurable differences in terms of the movement and regulatory parameters that dancers control in order to satisfy the functional parameter of, say, keeping in time with the music or in maintaining a particular body line.

Dexterity in Dancing Salsa

In this study, we collected data from an Inertial Measurement Units (IMUs) mounted on people as they performed Salsa dance steps. The aim was to contrast expert with novice performance, and to use any differences as a way of exploring dexterity in dance.

Participants

Thirteen participants participated in this study. An expert salsa dancer (male, with 14 years of experience) defined the steps for the participants to follow and also provided the baseline (expert) data set. An intermediate dancer (male, 4 years of experience) followed the steps. A group of eleven non-dancers, who were students of engineering (mean age 22 years; 4 female and 7 male) also followed the dance steps. For this paper, we focus on the data from 3 individual dancers: the expert, the intermediate and one of the non-dancers who found the task difficult.

Experimental Conditions

The design of the experiment was approved by the University of XXX ethics approval process. 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.

Figure 8. Stills from instructional videos illustrating the steps used in the study.

A series of video clips demonstrating Salsa steps, ranging from simple mambo steps to more complex side crossover steps, were recorded by the expert dancer (figure 8). Each video clip showed one step repeated about 5 times for 20 seconds.

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). An example of the foot patterns for the mambo step is shown in figure 9.

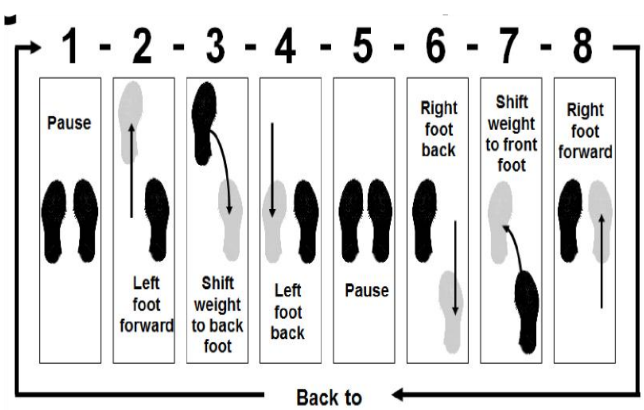

Figure 9. Step patterns for mambo step.

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 for two Salsa step patterns: step 1 = mambo and step 2 = side crossover.

Estimation of the Minimal Time-Delay Embedding Parameters for the Salsa Dance Steps

Data from the IMU 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 obtain four curves that correspond to each delay embedding parameters (τ = 1; 2; 3; 4) for dimension that are in the range $0 < d < 40$. From $E1(d)$ values (Figure 10) one can notice that the minimal value for the embedded dimension is approximately equal to $m_{min} < 10$. 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 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 embedding dimension (m = 10) in $E1(d)$ values (Figures 10). We therefore computed time-delay embedded matrix with m = 10 and τ = 1 for each axis of the IMU. 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 axes ($Ea_{\{x,y,z\}}$, $Eg_{\{x,y,z\}}$,$Em_{\{x,y,z\}}$) for step 1 and step 2 from expert, intermediate and non-dancer participants. Table 1 also helps 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.

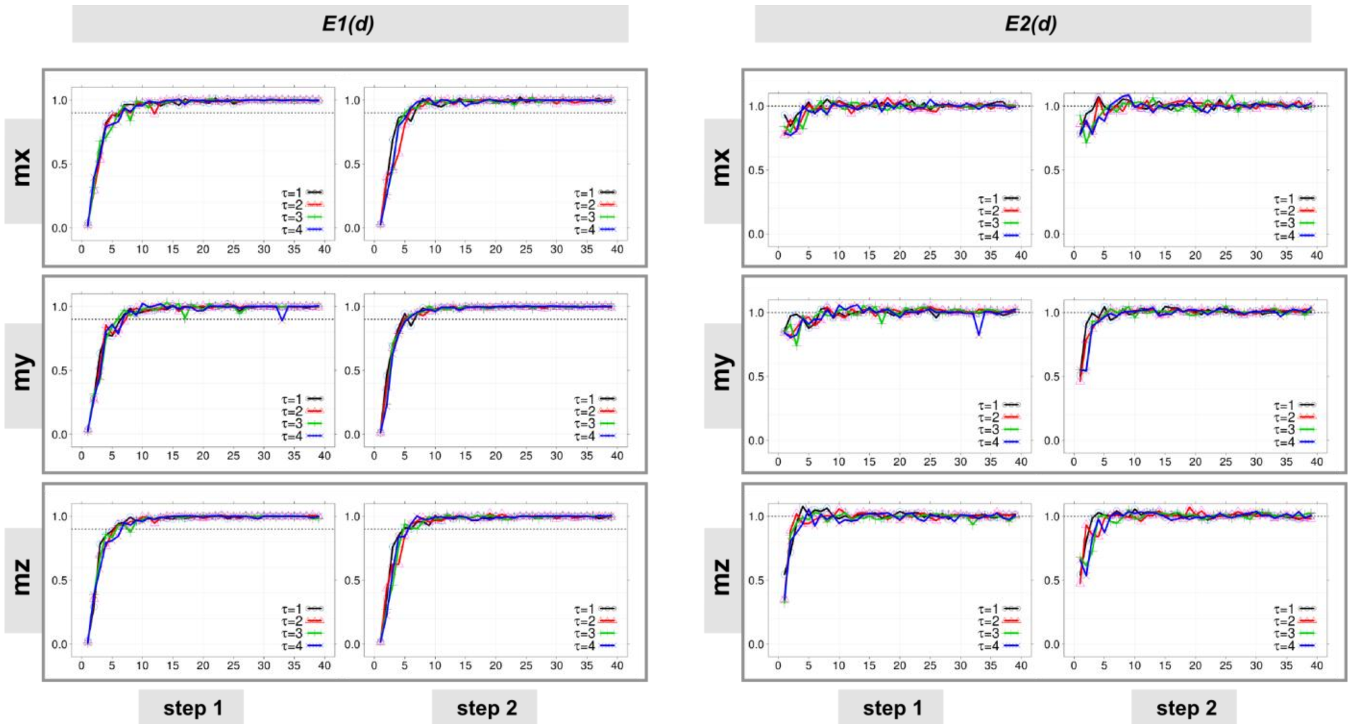

Figure 9. $E1(d)$ and $E2(d)$ values for τ = 1; 2; 3; 4 with 0 < d < 40 from magnetometer sensor ($Em_{\{x,y,z\}}$) of the expert dancer for two steps. The dashed straight line for $E1(d)$ and $E2(d)$ corresponds to the value 0.9 and 1, respectively.

Table 1. Percentage contribution to variance of the first two PCA components (C1 and C2) to the embedded dimension, *m*, in x,y,z for the magnetometer data

	Step 1			Step 2		
	C1	C2	C1+C2	C1	C2	C1+C2
EXPERT						
Emx	79	11	90	82	10	93
Emy	67	9	77	73	21	87
Emz	66	28	95	56	26	87
INTERMEDIATE						
Emx	85	41	94	82	15	97
Emy	64	29	93	77	18	96
Emz	70	25	96	79	17	96
NOVICE						
Emx	64	24	88	84	12	96
Emy	59	32	91	86	12	98
Emz	67	28	95	73	21	94

Using the data from the magnetometer data and the derived embedding dimensions, we analyse performance of the expert, intermediate and novice dancers performing the two steps of interest. The results of this analysis are shown in figure 11.

Conclusions

The aim of this study was to measure dexterity in dance from wearable IMUs. Signals from the IMUs are represented in a canonical basis that reflects the nonlinear dynamics of dance steps.

From visual inspection of the data from the dancers (figure 11), one can see that the 'expert' performance of the two steps shows some stability across the two steps (in that the traces are visual similar), but also a change in pattern indicating variability. The intermediate and novice dancers, show a pattern which looks similar to the expert for step 1 but have much greater variation in step 2. We propose that this indicates individual difference in performance which might also reflect differences in ability. As step 1 was quite simple, the stability of the three traces (in terms of the dense packing of the lines) and consistency across participants reflects a common approach to the performance. 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 skill levels. This suggests that the expert is producing more repeatable, more consistent actions than the other skill levels.

For step 2, on the other hand, (which was a more complicated sequence of movements), one can see a marked contrast across skill 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

In terms of human activity, dexterity is the ability to perform an action with sufficient stability to be consistent across repetitions, but with sufficient variability to allow adaptation to changing contextual demands.

Although Takens' Theorem is still subject to the embedded parameters, the phase space representation applies a model of consistency to the data for skill 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 unable to maintain consistent patterns of movement for both steps and struggles to fully engage with the requirements of step 2.

One way of considering this contrast between variability and stability is to view human activity as a dynamic system and then to consider the time-series data that such a system produces. This paper reports two applications of time-series analysis to signals from motion capture and sensors mounted on a tool-handle or the person. The results indicate that differences in the analysis can be related to the level of ability of the participants from whom the data were generated. Consequently, dexterity is indicative of level of ability and the analysis shows clearly how higher ability corresponds to greater stability.

Techniques from time-series analysis not only extend the repertoire of methods used by human activity recognition but also allow us to relate these methods to theories of how human activity is performed and coordinated. Taking the dynamic systems approach to describing human activity provides closer alignment to the turn to embodied cognition. In particular, our work is motivated by the developing area of Radical Embodied Cognitive Science [23], which elucidates the relationship between human activity and the environment in which it is performed. This combines Gibsonian ecological psychology [24] with concepts and models from system dynamics [25]. From this perspective, the challenge is to capture human activity not simply as a sequence of 'events' but as the managed performance of a dynamic system.

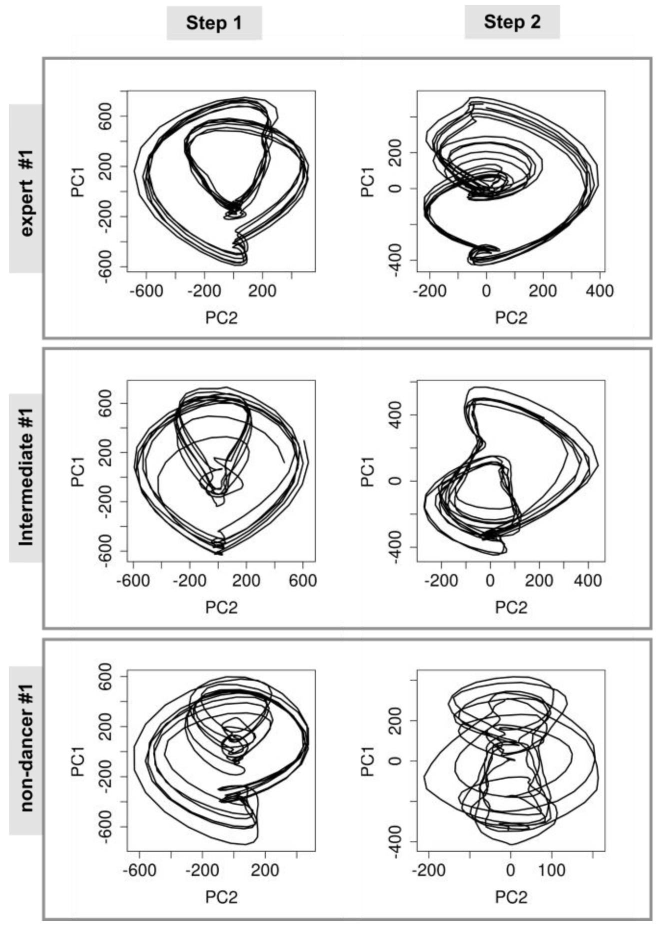

Figure 11. Comparison of expert, intermediate and novice dancers performing two Salsa dance steps.

In terms of the CHI community, we began this paper with the suggestion that dexterity is of interest in recognizing human activity using new forms of technology. We suggest that recognizing dexterity is part of the ongoing trend towards extending human activity recognition, from a focus on actions as discrete events to higher-level characterization of activity. Such characterization could include dexterity but could also include the prediction of intent in performing an action. As we continue to wear computers and as the internet of things spreads across our environment, it becomes important to understand not only what a person is doing but also how well and why they are doing it.

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