A Nonlinear Dynamics Approach to Human Activity Recognition Using Inertial Sensors

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ABSTRACT
The aim of the PhD is to gain understanding of concepts from nonlinear dynamics that can be used to extract features to identify complex activities such as dance, juggling, cycling, rowing to mention but a few. Additionally, the nonliner dynamics methodology is meant to be complimentary to other Human Activity Recognition approaches. The research will contribute to the novel analysis and interpretation of data from inertial sensors and provide open source software and hardware to recognize activities in more realistic conditions.

Author Keywords
Human Activity Recognition; Body Sensor Networks;
Machine Learning Algorithms; Nonliner Dynamics.

INTRODUCTION
Human Activity Recognition (HAR) has been a challenging task [1], since human body activity is complex and highly diverse [31]. One of the challenges is that, unlike speech, we do not have a single model of how the signal is produced. This either means that we have to create unique generation models for all types of activity, or we have to ignore generation models in favour of finding patterns in the data. While both approaches are commonly used, they do tend to limit how well the field of HAR can advance. A further point is that HAR tends to focus on defining events and sequences of events. The approach of the research, using nonlinear dynamics, takes a different perspective with a high level view of sets of events over time and with the focus on temporal dynamics rather than event transition or event definition.

HAR has given several frameworks in recognizing primitive activities such as walking, jogging, cycling, jumping; nonetheless, little work has been been done in identifying complex activities that for instance involve dance. Dance activities reflects the dancer's profile i.e., rhythmic sense, home country [29], personality, biological features (i.e., genre and age), dancing skills (i.e., fluency of the motion, adding erractical or additional movements, coordination and turbulence in dance, steadynees of the rhythm, predictability of the motion) [24]. Recently, researchers in human body activity and gait recognition have proposed the use of concepts from nonlinear dynamics (*e.g.* time-delay embedding theorem [22, 46] and attractors in the state space [3, 4]) that have been proven to be an efficient approach for classification purposes as well as for indentification activities in real time in low-powered devices.

Henceforth, the current PhD work is aimed to gain understanding of concepts from nonlinear dynamics that can be used to extract features and to address the multiattribute classification problem that is involved in dance activities.

Research Questions
HAR deals with many issues which are a) the different types of activities to recongnise, b) the selection of motion capture system which should be unobtrusive and inexpensive, c) the selection of algorithms for feature extraction and classification, d) and the response time (offline or online) [33]. Yet, the chosen approach varies almost as greatly as the types of activities that have been recognized and types of sensor data that have been used [31]. Additionally, HAR has many challenges that motivate our work to find new techniques in order to recognize activities in more realistic conditions. Therefore, finding appropriate methods for HAR is not only motivated by the fact that the motion capture system should be nonintrusive and easy-to-wear but also that theoretical approach should be well suited for real-time applications.

To fullfil the previous-stated seatbacks, the following research questions will be addressed:

1. Which concepts from nonlinear dynamics could be use to obtain another features for human body analysis?
2. How can motion of the body parts (wrist, ankle, hips, shoulders, etc) be quantified so as to set features for the better characterization and identification of the human body activities?
3. How do common machine learning algorithms relate to the data collected from dancing, and how does the output of these algorithms compare and contrast with the results from nonlinear dynamics?

PREVIOUS WORK
Reviews of motion capture systems, machine learning approaches in HAR and human body analysis using nonlinear dynamics are presented in the following sections.

Motion Capture Systems
Motion capture systems can be chategorised into three approaches: vision-based [21]; floor-sensor based [39, 49, 2, 58, 61, 36, 44, 48, 42, 55, 41] ; and inertial-sensor based [43, 6, 9, 59, 27]. Although vision-based and floor-sensor based are rooted in non-intrusive motion capture systems, these are still required to be used into the space where users are constrained to move around. On the other hand, wearable systems have been proven to be the least instrusive and easy-to-use sensors.

However, the choosen approach for the motion capture system varies as greately as the types of activities that have been recognized and many other factors such as type of sensors, data connection protocol, obstrusiveness, recognition performance, energy consumption, flexibility, computational processing, features, learning, and accuracy are considered for the performance of the motion capture system [33].

Machine Learning Aproaches in HAR

Much attention has also been given in recent years to use machine learning algorithms in HAR since the identification of activities entail a large number of attribute values and different transition points between activities; to this end several approaches have been used i.e. Suppor Vector Machines [22, 46, 47], template matching [37, 34], Hidden Markov Model [32, 38, 18, 10, 20, 17], Dynamic Time Warping [8, 12, 16], Neural Networks [45, 30, 35, 11], and most recently Dynamic Bayesian Networks [19, 57], Emerging Patterns [25, 31], Conditional Random Field [56] and Skip Change Conditional Random Field [31]. However, much research remains to be done to find suitable machine learning algorithms to identify complex activities that are presented in dance activities.

Human Body Analysis Using Nonlinear Dynamics

Recently, the use of intertial-based motion capture system in human body activity and gait recognition has been proposed the use of concepts from nonlinear dynamics that implements methods to obtain; for instance, the state space reconstruction, determinism test, Lyapunov exponents and Poincaré maps. These concepts have been proven to be efficient approaches to meet the computitional requirements for processing information in real time [22, 46, 23, 40, 3, 4].

Similarly, video-based approaches have been proven to present good results to recognize more complex human body activities such as the dextery of tennis players using attractors and fractal properties [60, 50] , identification of dancing ballet, jumping, running, sitting and walking activities using the attractors of the reconstructed state space, multivariate phase space reconstruction and Maximal Lyapunov Exponent [5, 7, 53], and the recongnition of two-dimensional single-stroke patterns of 26 letters through modeling the attractor behaviors [28].

On the other hand, concepts from nonlinear dynamics also have been used to understand the behavior of human body activities for clinical applications, for instance Vieten *et al.* [54] quantify differences between gait patterns under constraints by approximating the time series data that underlying limit cycle attractors. Harbourne *et al.* [26] presented evidence to make diferentiation between health and nonhealth subjects and to identify difference between young and old people by analysing the changes in the attractor in the state space. Zhang *et al.* [62] demonstrated that the points of the Poincaré section are highly susceptible to noise; however, the use of power spectrum density analysis of the correlation coefficient demonstrate a relationship between $1/f$ noise and healthy subjects is very strong. Buzzi *et al.* [13] demonstrated satisfactorily that elderly subjects increased the inability to compensate the natural stride-to-stride variations by using the Lyapnov Exponent (LyE) and surrogate LyE (s-LyE). Terrier *et al.* [51] analysed and characterized the synchronization of steps with an auditory stimulus to evaluate gait stability and fall risk by using the maximum LyE. It is important to mention that researchers in this area have been made a greater emphasis on the need for embedded software to make accessible tools for physical therapist.

HOW WILL THE PHD ADVANCE RESEARCH?

This PhD will extend the field of HAR in three signigicant ways. First, by analysing the time-series of the inertial sensors as a nonlinear systems, the research will create novel analysis of these data. Second, by builing a Body Sensor Network, the research will create a non-intrusive motion capture system as well as open source software which will be suitable for online activity recognition in a more realistic condition. Third, by applying different machine learning algorithms to classify the complex activitites involved in dance, the research will contribute to interpretation of the data so as to evaluate the accuracy in different classifiers.

RESEARCH METHODS

Takens's Theorem

In this work we follow the notation employed in [15, 52]. The purpose of the Takens's Theorem also knowns as time-delay embedding 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. The time series is a sequence $x(t) = h(s(t))$, where $h : M \rightarrow \mathbb{R}^D$ is a measurement function on the unknown dynamical system, being $x(t)$ observable. 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 $\Phi : M \rightarrow \mathbb{R}^m$ such that $\overline{x}(t) = \Phi(s)$. $\Psi : \mathbb{R}^m \rightarrow \mathbb{R}^n$ is a further transformation that is considered as a more general transformation in which for the current work we are applying the Principal Component Analyis PCA algorithm (Figure 1).

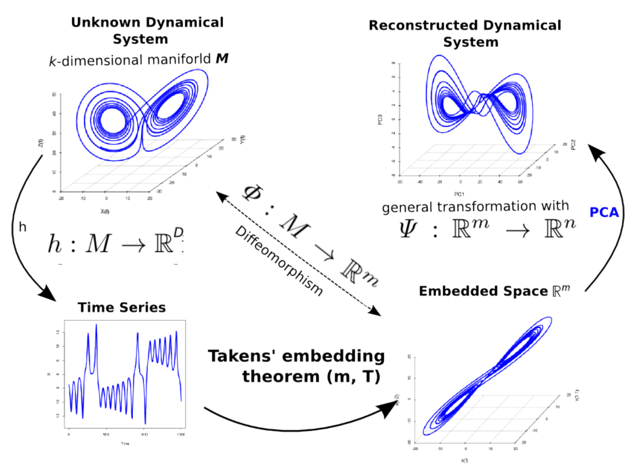

Figure 1. The reconstruction problem

Although the Takens's Theorem is well studied, there is still research to be done to find the optimal embedded parameters

(m and τ) that largely depends on the application at hand [22, 46].

CURRENT PROGRESS

Body Sensor Network

A body sensor network has been built using four Razor 9DOF Inertial Measurement Units using Bluetooth (Adeunis ARF7044). The data is collected at a sampling rate of 50 Hz by using a C++ class. Both hardware and software are under development and these work on GNU\Linux (Ubuntu 12.04 32 bits distribution).

Preliminary Experiments

By establishing a basic latin dance foot pattern as the human activity to characterize, the user has been asked to perform this activity in repetitive times. The inertial sensor was worn in the right ankle. We then collected the time series for the roll euler angle (Figure 2 (a)). The embedding parameters for the the time-delay embedding reconstruction are $m = 30$, $\tau = 3$. Finally, we transform the reconstructed state space by using the PCA algorithm and plot the first three components (Figure 2 (b)). We empirically used different values for

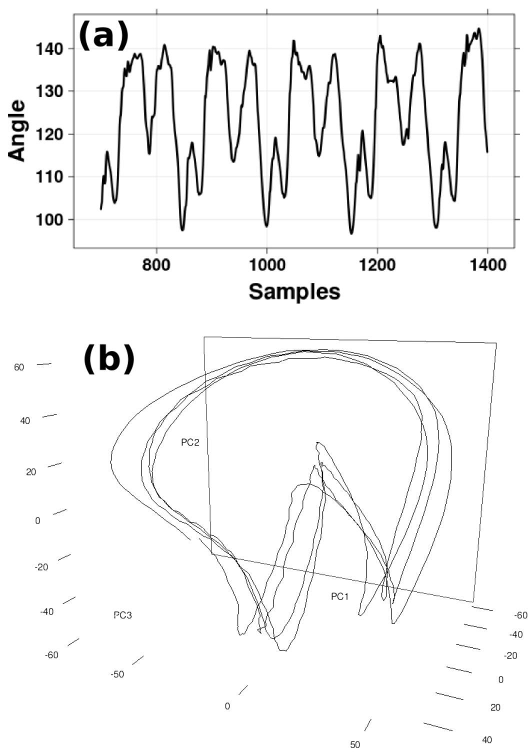

Figure 2. (a) Time series for the roll euler angle, (b) First three components of PCA of the reconstructed state space with $m = 30$, $\tau = 3$.

the embedding parameters that resulted in well reconstructed state space. However, we are analysing the time series of different sensor position as well as the use of different components so as to obtain optimal embedded parameters for the reconstructed state space by using Cao's method [14].

SIX MONTH PLAN

The proposed framework is divided into five modules (Figure 3): 1) Data acquistion using a Bluetooth body sensor network with Inertial Measurement Units, 2) Reconstruction of the state space with a C++ class, 3) nonlinear measuraments and feature extractions by means of Principal Component Analysis, 4) classification using state-of-the-art multiatribute machine learning algorithms, and 5) application(s) such as dancing. Based on the proposed framework, tasks for the following 6 months are planned as follows:

- T1 [February]: Review of state-of-the-art machine learning methods for human activity recognition using wearable sensors.
- T2 [March]: Define the human activity experiment and recruit subjects to collect data so as to test the proposed PhD framework by means of a suitable machine learning algorithm.
- T4 [April]: Write and submit a paper in the 19th annual International Symposium on Wearable Computers (Full/Note Paper Due: 10 April)
- T5 [May-June]: Update the hardware of the body sensor network by using Bluetooth low energy devices.
- T6 [May-June]: Update the open source sofware library for the body sensor network.
- T6 [July]: Write the 9th month report and create a publication plan for the next year.

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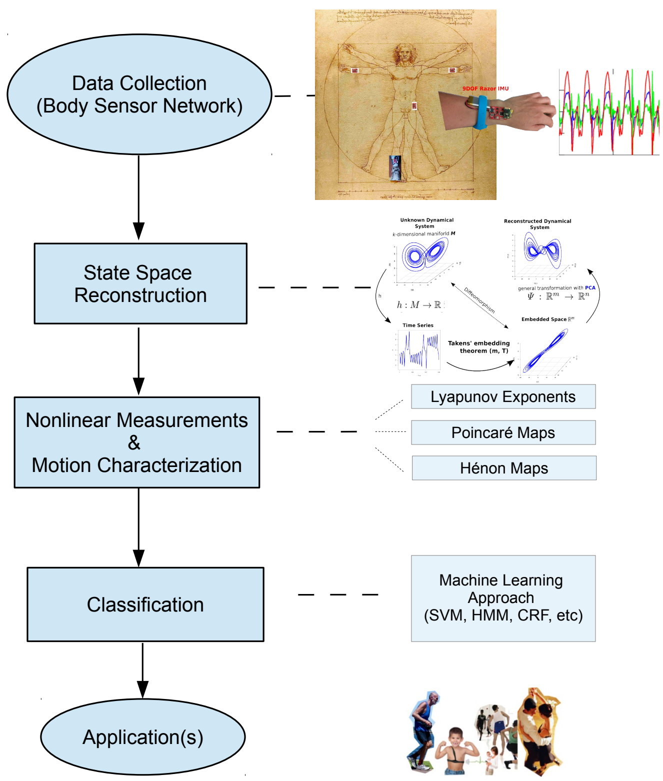

Figure 3. PhD Framework

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