Nonlinear Dymanics to Human Activity Recognition Using Inertial Sensors

Three Month Report

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Introduction

Human Activity Recognition (HAR) has been a challenging task [2], since human body activity is complex and highly diverse [30]. HAR has many potential applications; for instance, these can be seen in personal assistants, surveillance, patient monitoring, sports analysis, dance activities, human-robot interaction and biometrics to mention but a few [1]. HAR has been provided several frameworks in recognizing primitive activities such as walking, jogging, cycling, jumping; nonetheless, few work has been been done in identifying complex activities that for example involve dance.

Dance activities reflects the dancer's profile i.e., rhythmic sense, home country [28], 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) [23]. Henceforth, for the current PhD work we are focusing on the multiattribute classification of dancing activities since these are complex and highly dinamical activities to identify.

On the other hand, 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 responding time (offline or online) [32]. 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 [30]. Additionally, HAR has got many challenges that motive our work to find new techniques in order to recognize activities in a more realistic conditions. Therefore, finding appropriate methods for HAR is not only motivated by the fact that the motion capture system should be non-intrusive and easy-to-worn but also that theoretical approach should be well suited for real-time applications.

Thus, the aim of the PhD is focused on a fully understanding of the concepts from non-linear dynamics that can be used as a feature extraction for machine learning algorithms so as to provide a robust HAR approach for real-time applications using inertial sensors.

This three month report is organised as follows: First, the state-of-the-art in motion capture systems, machine learning approaches in HAR and human body analysis using nonlinear dynamics are reviewed in Section 2. Sencond, the propose framework and the workplan is shown is presented in section 3.

2

Previous Work

The central goal of the research proposal is focused on a fully understanding of concepts from nonlinear dynamics that can be used for human activity recognition so as to provide a robust approach for real-time identification using inertial sensors. Thus, reviews of motion capture systems are presented. Additionally, different approaches for HAR that use concepts from nonlinear dynamics are reviewed.

2.1 Motion Capture Systems

Motion capture systems can be chategorised into three approaches: vision-based [20]; floor-sensor based [3, 35, 38, 40, 41, 43, 47, 48, 53, 56, 59] ; and inertial-sensor based [7, 10, 26, 42, 57]. Although vision-based and floor-sensor based are rooted in non-intrusive motion capture systems, these are still subjected 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 human activity recognition 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 accuraty are considered for the performance of the motion capture system [32].

2.2 Machine Learning Aproaches in HAR

It has also given much attention in recent years the use of machine learning algorithms in HAR since the activities to identify entail a large number of attribute values and there are different transition points between activities; to this end several approaches have been used i.e. Suppor Vector Machines [21, 45, 46], template matching [33, 36], Hidden Markov Model [11, 16, 17, 19, 31, 37], Dynamic Time Warping [9, 13, 15], Neural Networks [12, 29, 34, 44], and most recently Dynamic Bayesian Networks [18, 55], Emerging Patterns [24, 30], Conditional Random Field [54] and Skip Change Conditional Random Field [30]. However, many research remains to be done for using a suitable approach in identifying activities in a more realistic condition.

2.3 Human Body Analysis Using Nonlinear Dynamics

Recently, the use of intertial-based motion capture system in human body activity and gait recognition have 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 that have been proven to be a efficient approaches to meet the computitional requirements for processing information in real time [4, 5, 21, 22, 39, 45].

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 [49, 58] , 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 [6, 8, 51], and the recongnition of two-dimensional single-stroke patterns of 26 letters through modeling the attractor behaviors [27].

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.at.* [52] quantify differences between gait patterns under constraints by approximated the time series data that underlying limit cycle attractors. Harbourne *et. at.* [25] showed evidence to make diferentiation between health and nonhealth subjects and identify difference between young and old people by analysing the changes in the attractor in the state space. Zhang *et al.* [60] proved 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.* [14] 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.* [50] 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, researcher in this area have been made a greater emphasis on the need for embedded software to make accessible tools for physical therapist.

3

Proposed Framework and Timeline

The proposed framework is divided into five modules (Figure 3.1): 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 dacing, cycling.

Based on the proposed framework, tasks for the following 6 months are planned as follow:

- T1 [February]: Review of state-of-the-art of 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 conferece paper in The 19th International Symposium on Wearable Computers
- T5 [May-June]: Update the hardware of the body sensor network by using Bluetooth low energy devices and inductive wireless chargers.
- 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.
- T9: Comparison of the proposed approach with recent methods.
- T10 Writing, review and PhD thesis defence.

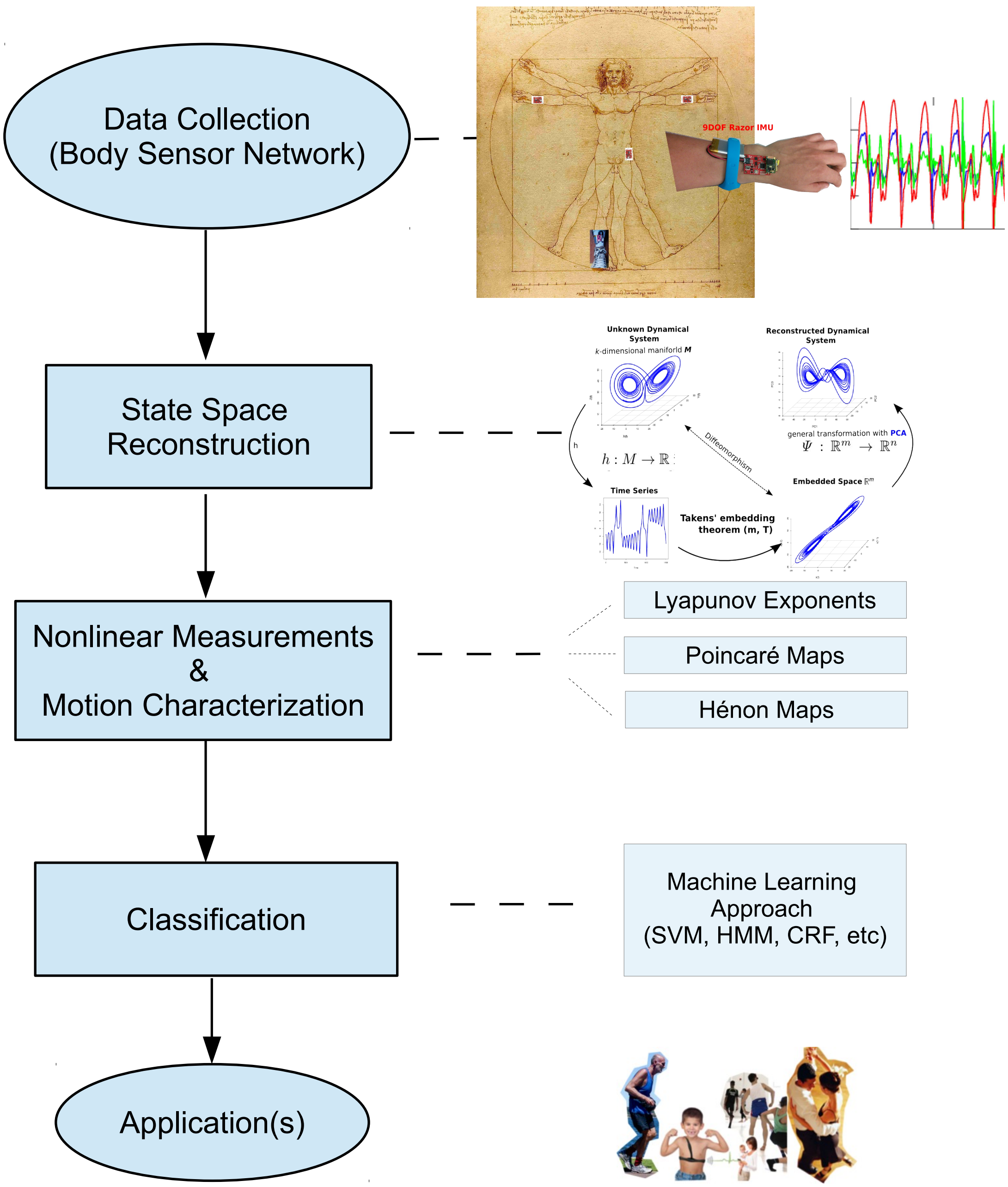

Fig. 3.1 PhD Framework

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