Automatic Identification of Human Movement Variability

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1 Introduction

1.1 Aim

This report presents the progress of the PhD research project titled "Automatic Identification of Human Movement Variability" for the period between September 2015 and August 2016.

1.2 Background

As stated in the 9 Month Report that was submitted in August 2015, I am generally interested in using nonlinear dynamics methods that can provide insight into the variability of human activities. Particularly, I explored the use of the time-delay embedding and PCA methods applied to dance activities.

The research themes of the 9 Month Report can be summarised as follows:

- Revision of challenges in Human Activity Recognition using body-worn sensors.
- Revision of non-linear tools that measure variability.
- Revision of sensing technology to capture dance activities.
- Implementation of the Cao and mutual information algorithms in order to compute the Time-delay Embedding parameters m and τ.
- Implementation of an stochastic model to gain better understanding of the structure of human movement considering the repeativility and structure of the motion.
- Exceution of a preliminary experiment in which data from 13 participants of different levels of dance expertise were analysed with the time-delay Embedding and PCA methods. However, data collection for this experiment were corrupted due to the impression of sampling rate.

For further references refer to the 9 Month report **[ADD REF]**.

2 Progress

2.1 September 2015 to November 2015

I did research regarding the calculations of Euler angles from the low-cost (Razor 9DOF) IMU sensors as well as the sensor placement on the body. Additionally, I explore PCA and its use and analyse artificial signals with added noise.

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2.2 December 2015 to February 2016

The paper submission titled "Dancing in Time: applying time-series analysis to Human Activity" was rejected at the Human-Computer Interaction conference (CHI) 2016. From the reviewers' comments, I have learnt that the proposed methodology is too specific and it is not transferable for other applications. Additionally, the data set consisting of 1 expert, 1 intermeiate and 11 novice dancers, was too small to make statistically significant conclusions. However, reviewers pointed out that research in handwriting recognition presents metrics that might help us to recognise the dexterity of dance activities.

Addionally, a third pilot experiment was performed in which 7 participants danced six basic salsa steps with and without music. The experiment includes anthropomorphic data of the participants (gender, age, handedness, height, weight and ethnic group). However, I did not analyse the data becuase I found that the sampling rate of the low-cost (Razor 9DOF) IMU sensors were different to 50 Hz.

To gain a better understanding of the variability of human movement, I follow the work of Hammerla *et al.* [1] in order to implement a stochastic model that considers the repeativility and structure of the motion. Hammerla's model considers a constant period per repetition which leaves room to develop the model further. Therefore, I added a normalised random vector for frequency which basically varies the frequency (therefore the period) per repetition using gaussian random parameters (mean and standard deviation).

2.3 March 2016 to May 2016

I restated my research question which reads as follows:

- *Can I use the variability of simplistic movements not only to automatically identify an activity but also as an automatic index of users' performance over the course of practice?*

A fourth pilot experiment was performed due to the problems with sensor syncronisation, sample rate and drift. The experiment consists of six simplistic movements (static, horizontal, vertical, diagonal, circular and 8-shape) which were performed by six participants. For data collection low-cost (Razor 9DOF) IMU sensors were attached to the wrist of the participants.

I submitted the following body of work: (i) a Poster Abstract Submission to the University of Birmingham research poster conference.; (ii) an extended abstract (2 pages) and its poster submission to the The Fifth ACM International Symposium on Pervasive Displays; and (iii) an extended abstract (2 pages) submission to the 2nd International Symposium on Wearable Robotics. I also applied to the European computational motor control summer school, however I was not accepted due to the high number of applications.

A valiation test using the Razor 9DOF sensors and shimmer sensors was performed due to the fluctuation of the sample rate of the low-cost sensors. I also performed a benchmark for commertial IMUS (9DOF Razor, myAHRS+, EXLs3, WAX9, Xsens sensors MTw Awinda DK Lite, shimmer and Muse) which included: Price, Connectivity, Sensor range for accelerometer, gyroscope and magnetometer, sample rate, temperature, battery time and API.

2.4 June 2016 to August 2016

For data analysis, I proposed the use of the Georgia Tech Gesture Toolkit [2] which is based on the Hidden Markov Model Toolkit (HTK). I therefore installed HTK 3.5 on a machine with Ubuntu 14.01 x64.

I also proposed to use The Gesture Recognition Toolkit (GRT) as a machine learning library. GTR contains 15 machine-learning algorithms and 16 pre-processing, post-processing, and feature-extraction algorithms [3].

I presented a poster at the XIV Symposium of Mexican Students in the U.K. at the University of Edinburgh in which I received a prize for one of the two best posters presented.

I am testing the drift in the accelerometer and gyroscope sensors over long acquistion periods for two Razor 9DOF IMUS sensors. I am using Robot Operating System (ROS) to collect and process data from the sensors. For further experiments, I am also planning to create a Human-Robot Interaction with NAO Humanoid Robot in ROS.

3 Publication Plan

1) Journal Submission: Human Movement Science - Elsavier [Impact factor: 1.606] (December 2016). I plan to report the use of different nonlinear techniques (Empirical Mode Decomposition, Lyapunov exponent, fractal dimensionality, poincare maps) with the pre-processing and post-processing techniques on GRT using data from IMUs of simplistic human movements.
My aim is to gain a better understanding of the use of techniques and tools, in order to better measure the variability of simplistic activities
2) Journal Submission: IEEE Transactions on Pattern Analysis and Machine Intelligence. [Impact factor: 6.077] (April 2017). I plan to apply nonlinear techniques as a pre-processing technique to test different machine learning algorithms of the GTR in order to automatically clasify the variability of human movements.

4 Work Plan

The gantt chart 1 presents a monthly breakdown for the next six months.

5 Conclusion

Generally, I have been establishing and learning from the literature (refer to Appendix A), running and planning experiments (refer to Appendix B) and facing technical problems with the low-cost inertial sensors.

For the previous experiments, I noted that the embedded values (m and τ) were only computed from the expert dancer and the same values were also used for the intermediate and novice dancers, which means that further tests have to be done in order to validate the effect the embedded values have for different participants.

In terms of scientific publications two short abstracts were accepted in (i) the Fifth ACM International Symposium on Pervasive Displays, and (ii) the Second International Symposium on Wearable Robotics.

For future plans, a preliminary experiment is going to be performed (refer to Appendix B) and further experiment with an humanoid robot is going to be performed (refer to Appendix C).

Appendix A
Extensive, up to date literature survey

The aim of automatic activity recognition is to provide information about a user's activity generally by means of still images and video. However, this constrained environment using cameras has caused a shift toward the use of body-worn sensors [4]. Such sensors that are commonly used include accelerometer, gyroscope and magnetometer for applications such as detection falls, movement and analysis of body or a subject's postural orientation to mention but a few [5].

Although the advances in HAR has been providing good results in terms of recognition rates. There is little research investigating the automatic identification of variability in human activity recognition. Bulling *et al.*, for instance, stated that one of the common challenges in HAR using body-worn sensors is *intraclass variability* which occurs when an activity is performed differently either by a single person or several people [4] . Lim *et al.*, for example, performed an empirical study to test the motion variabilty presented between 20 gestures with 12 participants. Data was collected on hand orientation using a Microsoft Kinect sensor [6]. As expected, due to the intrinsic variability of human movement [7], there was statistical significant variability of the lenght of trace and speed of gesture movements. However, Lim *et al.* stated that "the gesture type did not show significant effect of the variation" [6].

On the other hand, another possible source of variability is the displacement of the body-worn sensors. For instance, Haratian *et al.* investigated the inadvertent changes in the position of on-body sensors due to rapid movements or displacement of sensors during different trials and seasons. They proposed the use of functional-PCA which separates determinist and sthocastic components of the movements in order to filter and interpret, what they called, "the true nature of movement data variabitliy" [8], [9], [10].

Regarding the sensor brands, Commotti *et al.* presented neMEMSi which is a microelectromechanical systems (MEMS) based inertial and magnetic system-on-bard with embedding processing and wireless communication. For validation purposed the neMEMSi was compared with respect to the state-of-the-art device Xsense MTi-30 in which the 3D static orientation acuracy is 0.057 degrees average on Roll, Pitch and Yaw and 3D dynamic orientation acuracy is 0.55 degrees average on Roll, Pitch and Yaw [11].

Furthermore, Galizzi *et al.* performed power consumption tests with the neMEMSi-TEG for Thermo-Electric-Generators in order to increase the lifetime of the batteries. They found that there is a trade off between accuracy, power consumtion and sampling rate. It can be said that the use of a gyroscope strongly affects the increase of power consumption and the static and dynamic error are within 1 degree and 10 degrees respectively when the sampling rate is higher than 50 Hz [12].

neMEMSi sensors has been used for Parkinson's Disease patients' rehabilitation in a Timed-Up-and-Go test, where data was gathered and analysed from 13 PD participants (mean age: 16.6±9) and 4 control subjects (mean age: 16.3±4) [13].

Similarly, neMEMSi-Smart has been used to assess the motor performance of elderly people in a six-minute walk test, using five adults with no pathologies (mean age: 31±6) and four elderly people with Type 2 Diabetes (mean age: 70.8±7) [14]. Further experiments were made by Lorenzi *et al.* in which the neMEMSi were attached to the head of 5 participants with Parkinson's Disease in order to automatically classify those human motion dissorders with an Artificial Neural Network [15]. However, the neck join added signals from many postural problems and irregular movements because of the Parkinson Disease. Therefore, in the most recent work of Lorenzi *et al.* two neMEMSi sensors were attached to the shins of 16 patients for fine detection of gait patterns which results in a "good" peformance in terms of sensitivity, precision and accuracy of the detection of freezing of gait (FOG) for elderly people with Parkinson's Disease [16].

Both Lorenzi *et al.* and Arsenault and Whitehead pointed out that the use of quaternion representation is more benefical over other rotational representations such as the Euler angles. For instance, quaternion representation does not suffer from the problem of gimbal lock and they are numerically stable since they do not require the calculations of many trigonometric functions [15], [17], [18].

Arsenault and Whitehead collected data from 10 individuals performing six gestures fifty times each, this lead to 3000 samples in total, with 500 samples per gesutre. For recognition purposes, they reported an improvement of the classification rates in terms of speed and accuracy using Markov Chain instead of Hidden Markov Models [17], [19]. They used a network of InvenSense MPU-6050 (3-axis accelerometer and 3-axis gyroscope) sensors with the PIC24 microcontroller.

APPENDIX B
DETAILED DESCRIPTION OF PRELIMINARY EXPERIMENT

B.1 Aim

Apply non-linear methods to time-series from intertial sensors of simplistic movements.

B.2 Materials and Methods

Data collection from 12 participants will be performed. Each participant is going to perform 7 simplistic movements (static standing, static in T position, horizontal, vertical, diagonal, circular and eight-shape) with their arms for three minutes per movement in six seasons. Three sensors will be attached to the wrist, forearm and upperarm of the participants.

Using the data set, it is planned to apply different nonlinear techniques (Empirical Mode Decomposition, Lyapunov exponent, fractal dimensionality, poincare maps). Also, the GRT is going to be used to apply techniques of pre-processing, post-processing and feature-extraction algorithms.

B.3 Results and Publication

By analysing the data using the nonlinear techniques, I expect to gain better insight to asses variablity of simplistic movements. I am therefore going to submit the outcomes of this experiment to the journal Human Movement Science by Elsavier (Impact factor: 1.606) on December 2016.

APPENDIX C
FURTHER EXPERIMENTING

In order to automatically access the variability of simplistic movements, I am going to implement a Human-Robot Interaction application with NAO humanoid robot [20] in which simplistic movements will be performed by NAO and participants are going to replicate the movements.

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