Automatic Classification of Human Movement Variability in the context of Human-Robot Interaction. (DG-A)

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1 Introduction

This report presents the progress of the PhD research project titled "Automatic Classification of Human Movement Variability in the context of Human-Robot Interaction" for the period between September 2015 and August 2016.

1.1 Research Questions

As I have been exploring the area of Human Activity Recognition (HAR) using on-body sensors to measure the variability of human movement and with the need to automatically assses simple and repetitive actions for within and between subjects. I decided to replan the path of my PhD and restated my main research question which reads as follows:

- *Can I use the variability of simple movements not only to automatically classify an activity but also as an automatic index of users' performance using on-body sensors over the course of practice in the context of Human-Robot Interaction?*

The previous questions can be broken down into the following questions:

- *Which non-linear dynamics methods can provide insight in order to measure the variability of human activities?*
- *Which commertial inertial sensors can provide reliable data and which features the sensors should have to measure human movement?*
- *Which set of pre-processing, features and machine-learning algorithms can yield a good recognition rate to automatically measure the human movement variability?*
- *Can NAO, a humanoid robot, teach simple movements to user in order to automatically assess users's performance and give feedback to users in order to improve the quality of the movement?*

1.2 Summarise of the 9 Month Report

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. In particular, I explored the use of time-delay embedding and PCA methods applied to dance activities. Therefore, the research themes of the 9 Month Report can be summarised as follows:

- Review of challenges in Human Activity Recognition using body-worn sensors.
- Review of non-linear tools that measure variability.
- Review 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 a stochastic model to gain better understanding of the structure of human movement which is related to the repeatability and trajectory of the motion.
- Execution of the first pilot experiment in which data from 13 participants of different levels of dance expertise were analysed with the time-delay Embedding and PCA methods.

For further references refer to the 9 month report [1].

2 Progress

The following section presents summaries of the PhD advances for trimesters.

2.1 September 2015 to November 2015

To understand the data collected from the low-cost Razor 9DOF intertial sensor (from now on refered as razor), I conducted experiments with the firmware of the razor in which I set different sensitiviy values (2g,4g,8g,16g) to test the limits of the sensor and I test different baudrates with the ARF7044F bluetooth dongle fo the communication between the sensor and the machine. The outputs of the razor can be 3D raw or calibrated data from the accelerometer, gyroscope and magnetometer and Euler angles. On the other hand, as I have been understanding the euler angles, I found that both Lorenzi *et al.* and Arsenault and Whitehead pointed out that the use of quaternion representation is more benefical over other orientation representations such as Euler angles. This is because the 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 [2], [3], [4].

provide more evidence of I explore PCA and its use and analyse artificial signals with added noise.

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2.2 December 2015 to February 2016

In order to test my advances regarding the measure of dexterity using the taken's theorem and PCA methods with data collected from 13 participants, 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 to other applications. Additionally, the data set consisting of 1 expert, 1 intermeiate and 11 novice dancers, was too small to perform statistics. The reviewers pointed out that research in handwriting recognition presents metrics that might help us to recognise the dexterity of dance activities.

In order to improve my previous experiment, I conducted a second pilot experiment in which seven participants danced six basic salsa steps with and without music. For this experiment I included anthropomorphic data of the participants (gender, age, handedness, height, weight and ethnic group) in order to have a better experiment and with the idea to find any any extra relationship with the outcomes and the anthropomorphic data of the participants. However, I did not analyse the data because I found that the sampling rate of the low-cost (Razor 9DOF) IMU sensors was different to 50 Hz.

On the other hand, to gain a better understanding of the variability of human movement, I follow the work of Hammerla *et al.* [5] in order to implement a stochastic model that considers two random variables one to model the repeatability of the activity and the other to model the structure of the motion. Nonetheless, Hammerla's model considers a constant value for the periodicity of the movement which leaves room to develop the model further. I therefore added a random variable to vary the lenght in time of the repetition in order to explore a more realistic model. I belive that further experiments are requiered of which I can think of the creation of a nonlinear oscillator to vary the lenght in time of the repetition.

2.3 March 2016 to May 2016

Because of some issues such as the sensor syncronisation, sample rate and drift, a third pilot experiment was performed as a validation test. The experiment consists of six simple movements (static, horizontal, vertical, diagonal, circular and 8-shape) which were performed by six participants. For data collection, a low-cost Razor 9DOF and commercial shimmer sensors were attached to the wrist of the participants. Similarly, I created a list of commercial 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, syncronisation, orientation output, battery time and API.

In order to present my little advances, the following body of work were submitted: **(i)** a Poster Abstract Submission to the University of Birmingham research poster conference with the title "Measuring the Variability of Human Movement," in which I learnt to do public engagement. I deliver my work in a friendly way to audences of different background and ages. **(ii)** an extended abstract (2 pages) and its poster submission to the The Fifth ACM International Symposium on Pervasive Displays with the title: "Understanding movement variability of simplistic gestures using an inertial sensor" In collaboration with Dr Mourad Oussalah from University of Oulu. For this work, I present the outcome of the six participants, wearing inertial measurement units on their wrist, performed six actions using the time-delay embedding theorem, PCA and percentage of cumulative energy to characterise variability of the movements. We also propose that such method can be useful to determine different states of interactions with the display of users behavior (enthusiasm, boredom, tiredness or confusion) over the course of training, practice or rehabilitation. **(iii)** an extended abstract (2 pages) submission to the 2nd International Symposium on Wearable Robotics with the title: "Analysis of the Movement Variability in Dance Activities using Wearable Sensors." For this abstract, I analyse the data from thirteen participants who repeatedly dance two salsa steps (simple and complex) for 20 seconds. I then applied the time-delay embedding and PCA to obtain the reconstructed state space for visual assessment of the variability of dancers. Such reconstructed state space is graphically linked with their level of skillfulness of the participants.

On the other hand, to understand more about the biomechanicas of the human body, I applied to the European computational motor control summer school, but I was not accepted because of the high number of applications.

2.4 June 2016 to August 2016

Following my plans to do public engagement, 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.

In order to explore classification algorithms for human activities, I am using The Gesture Recognition Toolkit (GRT), a machine learning library, which contains 15 machine-learning algorithms and 16 pre-processing, post-processing, and feature-extraction algorithms [6]. Similarly, I proposed the use of the Georgia Tech Gesture Toolkit [7] which is based on the Hidden Markov Model Toolkit (HTK 3.5), I have been however learning how to make sense of the data that feed the HTK toolkit.

On the other hand, I am doing experiments with the drift in the accelerometer and gyroscope sensors over long acquistion periods for two Razor 9DOF IMUS sensors using Robot Operating System (ROS).

3 Publication Plan

Two journals for publication were selected based on the relation with my research questions:

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

4 WORK PLAN

To tackle the research questions, tasks(T) for the following seven months are planned as follow:

- T1 [September]: Buy 7 neMEMSi (quoted for 1122.40 € in June 2016). Set the sensors and the experiment for data collection.
- T2 [October]: Collect data of simple movements from 12 participants in six seasons.
- T4 [November]: Analyse the data using non-linear dynamics to gain understanding of the variability of both within participants and across participants
- T5 [December]: Write up and submit a journal to Human Movement Science – Elsevier.
- T6 [January/February 16]: Use the data collected on October 2015 with the Gesture Recognition Toolkit to test different machine-learning, pre-processing, post-processing, and feature-extraction algorithms.
- T6 [March 16]: Write up and submit a journal to IEEE Transactions on Pattern Analysis and Machine Intelligence.

5 CONCLUSION

In conclusion, I have been establishing and learning from the literature (refer to Appendix A). I run the second and third experiments. For the data of the first experiment, 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 at (i) the Fifth ACM International Symposium on Pervasive Displays, and (ii) the Second International Symposium on Wearable Robotics. However, I found some technical problems when using two or more low-cost inertial sensors such as the syncronisation, the drift over short and long period of acquisition. To avoid this problem, I create a list of commercial sensors in order to compare their performance and select one sensor with good 3D resolution, to which I select the neMEMSi sensor becuase the 3D resolution is quite similar to the MT20i from Xsens.

For future plans, a four experiment is going to be performed (refer to Appendix B) and a further experiments with a humanoid robot are 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 [8]. Such sensors that are commonly used include accelerometer, gyroscope and magnetometer for applications such as detection of falls, movement and analysis of body or a subject's postural orientation to mention but a few [9].

Although the advances in Human-Activity Recognition (HAR) have 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 [8] . 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 [10]. As expected, due to the intrinsic variability of human movement [11], there was statistical significant variability of the length of trace and speed of gesture movements. However, Lim *et al.* stated that "the gesture type did not show significant effect of the variation" [10].

On the other hand, another possible source of variability is the displacement of 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 deterministic and stochastic components of movements in order to filter and interpret, what they called, "the true nature of movement data variability" [12], [13], [14].

Regarding the sensor brands, Commotti *et al.* presented neMEMSi which is a microelectromechanical system (MEMS) based on inertial and magnetic system-on-bard with embedding processing and wireless communication. For validation purposed the neMEMSi was compared with the state-of-the-art device Xsens 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 [15].

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 [16].

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$\pm$9) and 4 control subjects (mean age: 16.3$\pm$4) [17].

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$\pm$6) and four elderly people with Type 2 Diabetes (mean age: 70.8$\pm$7) [18]. Further experiments were conducted by Lorenzi *et al.* in which the neMEMSi was 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 [2]. 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 [19].

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 [3], [20]. 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 dynamics methods to time-series from intertial sensors of simple movements.

B.2 Materials and Methods

Data collection from 12 participants was performed. Each participant is going to perform 7 simple 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 were 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 assess variability of simple movements. I am therefore going to submit the outcomes of this experiment to the journal Human Movement Science by Elsavier (Impact factor: 1.606) in December 2016.

APPENDIX C
FURTHER EXPERIMENTING

In order to automatically assess the variability of simple movements, I am going to implement a Human-Robot Interaction application with NAO humanoid robot [21] in which simple movements will be performed by NAO and participants are going to replicate the movements.

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