Automatic Classification of Human Movement Variability in the context of Human-Robot Interaction.

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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 assess simple and repetitive actions within and across subjects in different seasons. I decided to re-plan the path of my PhD and therefore restated my main research question which reads as follows:

- *Can I use the variability of simple movements not only to automatically classify a human movement 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 question can be broken down into the following sub-questions:

- *Which non-linear dynamics techniques can provide insight in order to measure the variability of simple human movements?*
- *Which on-body sensors can provide reliable data and which features the sensors should have in order to reliably measure human movement?*
- *Which set of non-linear dynamics techniques as features, pre and post -processing, and machine-learning algorithms can yield a reliable recognition rate to measure the human movement variability ?*
- *Can NAO, a humanoid robot, teach simple movements to a user and automatically assess user's performance giving feedback to user in order to increase or decrease the variability of the movement?*

1.2 Summary of the 9 Month Report

As stated in the 9 Month Report that was submitted in August 2015, I am generally interested in using non-linear dynamics methods that can provide insight into the measurement of variability of human movements. In particular, I started to explore the use of time-delay embedding theorem and Principal Component Analysis (PCA) method applied to dance activities. 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 human movement variability.
- Review of sensing technology to capture human movement.
- 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 concerning the repeatability and trajectory of the human 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 theorem and PCA methods.

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

2 PROGRESS

The following section presents summaries of the progress in my PhD project.

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2.1 September 2015 to November 2015

To understand the data collected from the low-cost Razor 9DOF inertial sensor (from now on referred as razor), I conducted further experiments with the razor's firmware in which I set different sensitivity values (2g,4g,8g,16g) to test the limits of the sensor with regard to simple arm movements.

The outputs of the razor can be 3D raw or calibrated data from the accelerometer, gyroscope and magnetometer and Euler angles. However, as I have been studying the Euler angles, I found that both Lorenzi *et al.* and Arsenault and Whitehead pointed out that the use of quaternion representation is more beneficial over 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 arithmetic and trigonometric operations [2], [3], [4]. As a consequence of that I am planning to do further research regarding the use of the quaternion representation.

2.2 December 2015 to February 2016

I submitted a paper titled "Dancing in Time: applying time-series analysis to Human Activity" to the Human-Computer Interaction conference (CHI) 2016 in order to test my advances regarding the measure of dexterity of dance activities. For the CHI's submission I used the time-delay embedding theorem and PCA method with the data collected from 13 participants. However, the paper was rejected. The two main reasons for this are: firstly, the proposed methodology is too specific because it is only useful for specific axis of the sensor and with specific embedded values and it is non-transferable to other applications; secondly it was only tested with limited dance steps of a particular dance style. Additionally, the data set consisting of 1 expert, 1 intermediate and 11 novice dancers, was too small to perform statistics.

In order to improve my previous experiment, I conducted a second pilot experiment in which seven participants danced six basic salsa steps, both with and without music. For this experiment I included anthropomorphic data of the participants (gender, age, handedness, height, weight and ethnic group). However, I made the decision not to analyse the data because I found that the sampling rate of the low-cost (Razor 9DOF) IMU sensors was different to 50 Hz to which I tested different baudrates with the ARF7044F and BlueSMiRF bluetooth dongles to set a sample rate for data streaming of 50 Hz.

In addition, to gain a better understanding of the variability of human movement, I followed the work of Hammerla *et al.* [5] in order to implement a stochastic model that considers two normal random variables one to model the repeatability of the activity and the other one to model the structure of the motion. Despite that, Hammerla's model proposed a constant value for the periodicity of the movement which leaves room to develop the model further. I therefore added a third normal random variable in order to explore the variation of the length in time of the repetition. However, I believe that further experiments are required in order to vary the length of the repetition in a natural way.

2.3 March 2016 to May 2016

A third pilot experiment was performed as a validation test for the sensors because of some issues with regard to syncronisation, sample rate and drift. 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 right wrist of each participant. Similarly, I created a list of commercial IMUs [1] which included: Price, Connectivity, Sensor range for accelerometer, gyroscope and magnetometer, sample rate, temperature, syncronisation, orientation output, battery time and API.

In order to test the advances of my research I submitted the following body of work to this conferences:

(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 delivered my work in a friendly way to audiences 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 at University of Oulu, Finland with the title: "Understanding movement variability of simplistic gestures using an inertial sensor." For this work, I presented the outcome of the six participants performing six simple arm movements to which I applied the time-delay embedding theorem, PCA and percentage of cumulative energy to characterise variability of the movements. I also proposed that such method can be useful to determine different states of interactions with the display of user behavior (enthusiasm, boredom, tiredness or confusion) over the course of training, practice or rehabilitation. According to reviewers' feedback, further experiments are required to show exactly what PCA lacks in yielding insightful outcomes and to show more evidence of the variability within and across participants.

(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 analysed the data from thirteen participants who repeatedly dance two salsa steps (simple and complex) for 20 seconds. I then applied the time-delay embedding theorem and PCA method to obtain the reconstructed state space for visual assessment of the variability of dancers. However, reviewers of the paper mentioned that further explanation of the time-delay embedding theorem are required and that neither an analysis nor a quantification were presented except for the graphics that were linked with their level of skillfulness of the participants.

In addition, I applied to the European computational motor control summer school in order to gain better understanding about the biomechanics of the human body but I was not accepted because of the high number of applications.

1. 9DOF Razor, myAHRS+, EXLs3, WAX9, Xsens sensors MTw Awinda DK Lite, shimmer and neMEMSi

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.

In order to explore classification algorithms for human activities, I am exploring the use of 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 doing little advances since I need to make sense of the data that is fed to the HTK toolkit.

Additionally, I was doing experiments with the drift in the accelerometer and gyroscope sensors over short and long acquisition 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 pros and cons of different nonlinear dynamics techniques (Time-delay embedding, Empirical Mode Decomposition, Lyapunov exponent, fractal dimensionality and Poincaré maps) using data from IMUS of simple upper body movements. My aim with this publication is to contribute to field of human movement with a better understanding of the use of non-linear dynamics techniques in order to measure the variability of simple movements. For further details about the experiment refer to Appendix B.
2) Journal Submission: IEEE Transactions on Pattern Analysis and Machine Intelligence. [Impact factor: 6.077] (March 2017).
   I plan to apply non-linear 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, six tasks(T) for the following seven months are planned as follow:

- T1 [September]: Buy 7 neMEMSi (quoted for 1070 € in August 2016) [8]. Set the sensors and the experiment for data collection.
- T2 [October]: Collect data of simple movements from 12 participants in six seasons.
- T3 [November]: Analyse the data using non-linear dynamics techniques to gain understanding of the variability for within and across participants.
- T4 [December]: Write up and submit a journal to Human Movement Science – Elsevier.
- T5 [January/February 17]: Use the data collected on October 2015 with the Gesture Recognition Toolkit to test different pre-processing, post-processing, feature-extraction and machine-learning algorithms.
- T6 [March 17]: Write up and submit a journal to IEEE Transactions on Pattern Analysis and Machine Intelligence.
- T7 [End of March 17]: Evaluate the outcomes of the previous months and create a plan for the following six months.

5 Conclusion

In conclusion, I have been establishing and learning from the literature (refer to Appendix A). I run the second and the third experiment because of the following reasons: (i) the data was too small to perform statistics; (ii) the sample rate were not fixed to 50 Hz; (iii) there were problems sensors with regard to the synchronisation and drift; and (iv) simple movements were chosen instead of complex movements. From 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 over different participants.

In terms of scientific publications, two short abstracts were accepted one at the Fifth ACM International Symposium on Pervasive Displays, and the other at the Second International Symposium on Wearable Robotics. From this submissions, I have learnt that further work is required such as the presentation of the pros and cons of using the time-delay embedding theorem and PCA and quantification of the variability.

From the technical side, I found some problems when using two or more low-cost inertial sensors such as the synchronisation, the drift over short and long period of acquisition. I therefore created a list of commercial sensors in order to compare their performance. From this, I selected the neMEMSi sensor because of the body of scientific work that covers MEM design, validation tests and applications in the rehabilitation area (refer to Appendix A).

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

Appendix A
Extensive, up to date literature survey

A.1 Measurement of Human Movement Variability

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 [9]. 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 [10].

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 classification 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 [9] . Similarly, Lim *et al.*, for example, performed an empirical study to test the motion variability presented between 20 gestures with 12 participants. Data were collected on hand orientation using a Microsoft Kinect sensor [11]. Lim *et al.* applied General extreme value model, Dagum model and Birnbaum-Saunders model to approximate the data to normal distributions for the trace length, the speed motion and range of trace length, respectively. However, the models didn't fit well with the data to which a nonparametric Friedman test was conducted to verify individual differences of the length of trace and speed of gesture movements. Also, the cumulative distribution functions for the range of speed and motion were computed in order "to infer how much range covers how many population stochastically the percent of user population who could use " [11]. I believe that further research is required to show the weakness and usefulness of Lim *et al.* methodology in terms of the approximation of the data to normal distributions.

Additionally, 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 (f-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]. Similarly, further research is required to make better conclusions about the use of f-PCA.

A.2 Validated Sensor: neMEMSi

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 my PhD project, it is required to collect validated data to which the neMEMSi was compared with the state-of-the-art device Xsens MTi-30 in which the 3D static orientation accuracy is 0.057 degrees average on Roll, Pitch and Yaw and 3D dynamic orientation accuracy is 0.55 degrees average on Roll, Pitch and Yaw [15]. Additionally, 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 consumption 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].

Concerning scientific research applications of the neMEMSi, research has been done with rehabilitation of patients suffering from neurological diseases for the past two years [2], [17], [18], [19]. For instance, 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 disorders 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 resulted in a "good" performance in terms of sensitivity, precision and accuracy of the detection of freezing of gait (FOG) for elderly people with Parkinson's Disease [19].

A.3 Machine Learning with on-body sensors

In terms of segmentation or windowing of the data, Banos *et al.* demonstrated that large window size does not lead good recognition performance. Therefore, Banos *et al.* reported that short windows (0.25-0.5 s) lead to better recognition performances for a data set of 17 participants performing 33 fitness activities [20].

For recognition purposes, Arsenault and Whitehead reported an improvement of the classification rates in terms of speed and accuracy using Markov Chain instead of Hidden Markov Models [3], [21]. They collected data from 10 individuals performing six gestures fifty times each, this lead to 3000 samples in total, with 500 samples per gesture with 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 inertial sensors of simple movements.

B.2 Materials and Methods

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

Using the data set, it is planned to apply different non-linear techniques (Empirical Mode Decomposition, Lyapunov Exponent, Fractal Dimensionality, Poincaré 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 non-linear 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 Elsevier (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 [22] in which simple movements will be performed by NAO and participants are going to replicate the movements.

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