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, 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 the movement (trajectory of the motion) and additive noise (repeativility).
- Sumarize the number of experimens and failures with data collection: Exceution of a preliminary experiment in which 13 participants of different levels of expertise were invited in order to apply the time-delay Embedding and PCA methods. Data collection for this experiment were corrupted due to the impression of sampling rate and the drift presented when collecting data from two sensors.

2 Progress

2.1 September 2015 to November 2015

2.2 December 2015 to February 2016

The paper titled submission "Dancing in Time: applying time-series analysis to Human Activity" was rejected at the CHI 2016 conference. From the reviewers comments, I have learnt that the proposed methodology is too specific and it is not transferable for extra applications. Additionally, the data set is too small to make statistical [READ BOOK SCANNED PHOTOS FROM OPPO]. Data were collected from 13 participants of which one was expert, one was intermediate and 11 novice dancers. [FIND THE REVIEWS FROM CHI] To which reviewers pointed out that handwriting recognition presents metrics that might help us to recognise dexterity.

Addionally, a third pilot experiment were performed in which 7 participants danced six basic salsa steps with and without music. The experiment includes anthropomorphic data of the participants (genre, age, handedness, height, weight and ethnic group). However, the sampling rate of the low-cost (Razor 9DOF) IMU sensors were different to 50 Hz since less than 50 samples were obtained for one second.

To gain a better understanding of the varialibility of human movement, I follow the work of Hammerla in order to implement a stochastic model that considers the structure of the movement (trajectory of the motion) and additive noise (repeativility). Hammerla's model considers a constance period per repetition which make the model irreal. Therefore, I added a normalised random vector for frequency which basically varies the frequency (therefore the period) per repetition according using gaussian random parameters (mean and standard deviation).

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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 and activity but also as a automatic index of users' performance over the course of practice?*

Due to the problems with sensor syncronisation, drift and sample reate a fourth pilot experiment was performed. The experiment consists of six simplistic movements (static, horizontal, vertical, diagonal, circular and 8-shape) which were performed by six participants. Data was recorded using an inertial IMUs attached to the wrist of the participants. The the sample rate of the low-cost (Razor 9DOF) IMU sensors was fixed to 50 Hz.

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

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

2.4 June 2016 to August 2016

For the data analysis, I proposed the use of the Georgia Tech Gesture Toolkit which is based on 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 [1].

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 price for two of the best posters.

I am testing the drift in ACC and GYR over long acquisition periods of two Razor 9DOF IMUS sensors. I am using Robot Operating System (ROS) to collect and process data from the sensors. I am also planning to connect NAO Humanoid Robot to ROS in order to create a human-robot application for my experiment.

3 PUBLICATION PLAN

1) Journal Submission: Human Movement Science - Elsavier [Impact factor: 1.606] (December 2016).
   In this publication I plan to report the use of different nonlinear techniques (Empirical Mode Decomposition, Lyapunov exponent, fractal dimensionality, poincare maps) couple with the pre-processing and post-processing techniques using GRT to the data collection from IMUs of simplistic human movements. My aim is to gain better understanding in the use of techniques and tools to have better insight to 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 use use nonlinear techniques as a pre-processing techniques 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 X?X presents a monthly breakdown for the next six months.

5 CONCLUSION

Little advances have been made since the 9th month report. I have been basically establishing and learning from the literature, running prelimirary experiments and facing technical problems with the low-cost inertial sensors.

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

For the embedded values (m and τ) I noted that the values 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 for different particpant.

APPENDIX A
EXTENSIVE, UP TO DATE LITERATURE SURVEY

The aim of automatic activity recognition is to provide information about user's activity generally by means of still images and video. However, the contrained enviroments where it is used still images or video shifted caused to shift toward the use of body-worn sensors [2]. Such sensors are commonly accelerometer and gyroscope and magnetometer and the are of application is vary such as detection fall, movement and analysis of body or a subject's postural orientation to mention but a few [3]. Although the advances in HAR has been providing good results in terms of recognition rates, energy consumption of the sensors. To date there is little research investigating the automatic identification of variability in human activity recognition. For instance, Bulling *et al.* 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 [2] .

Lim *et al.*, for example, performed an empirical study to test the motion variabilty presented between 20 gestures with 12 participants. The data collection was based on the orientation hand given by a Microsoft Kinect sensor [4]. As it is expected participants presented a statistical significant effect of variability in the lenght of trace and speed of gesture movements due to the intrinsic varialibility of human movement [5]. However, it is worthwhile to point out that Lim *et al.* stated that "the gesture type did not show significant effect of the variation" [4].

Another possible source of variability when using body-worn sensors is the displacements of the sensors. For instance, Haratian *et al.* investigated the inadvertent changes in the position of on-body sensors due to rapid movements or displacements of sensors during different trials and seasons. They proposed the use of functional-PCA which separate determinist and sthocastic components of the movements in order to filter and interpreting, what they called, "the true nature of movement data variabitliy" [6], [7], [8].

Commotti *et al.* presented neMEMSi which is a 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 [9].

Furthermore, Galizzi *et al.* performed power consumption test with the neMEMSi-TEG for Thermo-Electric-Generators in order to increase the lifetime of the batteries. They found that the there is a trade off between accuracy, power consumtion and sampling rate. It can be said that the use of a gyroscope strongly affect the increase of power consumption and the static and dynamic error are withing 1 degree and 10 degrees resctively when the sampling rate is higher than 50 Hz [10]. neMEMSi has been used for Parkinson's Disease patients rehabilitation in a Timed-Up-and-Go test in which a Body Sensor Network with 5 neMEMSi sensors is used with 13 PD participants (mean age: 16.6$\pm$9) and 4 control (mean age: 16.3$\pm$4) [11]. Similarly, neMEMSi-Smart has been used to assess motor performance for elderly people in a Six-minutes walk test with 5 adults with no pathologies of (mean age: 31$\pm$6) and 4 elderly people with diabethes type 2 (mean age: 70.8$\pm$7) [12].

Lorenzi *et al.* attached the neMEMSi to the head ,where the mass center of the sensors oscillates in the y direction, of 5 participants to automatically clasify human motion dissorders in Parkinson's Disease using an Artificial Neural Network [13]. However, the neck join added signals from many postural problems and irregular movements due to 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 presenting 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 [14]. In the same fashion as Lorenzi *et al.* [14], Arsenault and Whitehead pointed out that the use of quaternion representation is more benefical over other rotational representations such as the Euler angles. For instace, quaternion representation do not suffer from the problem of gimbal lock and they are numerically stable since they do not require the calculations of many trigonometric functions [13], [15], [16].

For their experiment, they collect data of six gestures from 10 individuals and each gesture was performed 50 times leading to 500 samples per gesture and 3000 samples in total. For recognition purposes, they reported an improvement of the classification rates in terms of speed and accuracy using Markov Chain than Hidden Markov Models [15], [17] They use a network of InvenSense MPU-6050 (3-axis accelerometer and 3-axis gyroscope.) with the PIC24 microcontroller.

Another important point when you are recognising gestures is the segmentation or windowing, Recently, Banos *et al.* demonstrated that large window size does not lead good recogntion perfomance. Therefore using a data set of 17 participants peforming 33 fitness activities reported that short windows (0.25-0.5 s) lead to better recognition performances [18].

Appendix B
Detailed Description of Preliminary Experiment

B.1 Aim

B.2 Materials and Methods

B.3 Feature Analysis

B.4 Results

B.5 Publication

Appendix C
Further Experimenting

C.1 NAO

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