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 interested in the question of how the time-delay embedding and PCA methods can provide insight into the variability of human activities particularly for 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 algorithms to compute the Time-delay Embedding parameters m and τ.
- Implementation of an stochastic model to understand the possible sources of variablity.
- Exceution of a preliminary experiment in which 13 participants of different level of expertise were invited in order to apply the time-delay Embedding and PCA methods.

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" were rejected at the CHI 2016 conference. From the reviewers comments, I have hence learnt that the proposed methodology was very weak compare to the current literature in HAR. To which reviewers pointed out that handwriting recognition presents metrics that might help us to recognise dexterity.

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

Similarly, to gain a better understanding of the varialibility of human movement, the model for variability proposed by Hammerla was replicated using a normalised random vector for frequency.

2.3 March 2016 to May 2016

My restated research question 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?*

I performed a fourth pilot experiment with simplistic movements, since data syncronisation of 4 IMUS and the complexity of movements in dance is different challenge. Therefore, six simplistic movements (static, horizontal, vertical, diagonal, circular and 8-shape) 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 non reliablitity of the low-cost sensors it was performed a valiation test using the 9dof sensors and shimmer sensors. I perform a benchmark for commertial IMUS including: 6 IWAX9 Inertial Sensors from University of Newcastle, Xsens sensors, shimmer and itt.

2.4 June 2016 to August 2016

In order to identify the simplistic gestures. I proposed to use the Georgia Tech Gesture Toolkit which is based on HTK. I therefore installed HTK 3.5 on a linux machine with Ubuntu 14.01 x64.

I also propose to use The Gesture Recognition Toolkit (GRT) which is a machine learning library. GTR contains a large number of machine-learning algorithms, pre-processing, post-processing, and feature-extraction algorithms.

I presented the XIV Symposium of Mexican Students and Studies at the University of Edinburgh to which I received a price for the two of the best posters.

I expanded the benchmark for the inertial sensors with i) neMEMSi, ii) Axivity and iii)HM-AHRS. Additionally, I am testing the drift in ACC and GYR over long acquisition periods of two Razor 9DOF IMUS sensors.

3 Publication Plan

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

4 Work Plan

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

5 Conclusion

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

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

I noted that the embedded values were only computed fro the expert dancers and those values were also used for the intermediate and novice dancers. which means that further test has been done to validate the effect of m and tau values for different particpant.

Appendix A
Extensive, up to date literature survey

Variability is an inherent characteristic of human movement [1]. To date, research investigating the automatic identification of variability in human activity recognition is minimal. For instance, Bulling *et al.* [2] 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. Furthermore, Lim *et al.* performed a empirical study to test the motion variabilty presented between 20 gestures and 12 participants in which each gesture was perfomed three times using the orientation hand from a Microsoft Kinect sensor referemce coordinates. As it is expected due to the intrinsic varialibility of human movement, they presented a statistical significant effect of variability in the lenght of trace and speed of gesture movements however "the gesture type did not show significant effect of the variation" [3].

There are also another sources for variability. For instance, Haratian *et al.* investigated that innadvert changes in the position of on-body sensors due to rapid movements or placement of sensors during different trials and seasons which can contribute to the movement variability. Therefore, Haratian *et al.* propose the use of f-PCA for filtering and interpretation of what they called "the true nature of movement data variabitliy" [4], [5], [6].

With regard to the sensor validation, I found that Commotti *et al.* performed a validation test against xsense MTi-30 module.

In static conditions the accuracy is pretty good, within 0.8 degrees if the magnetometer is well calibrated. During movements of course depends on the dynamics, but can range between 2 and 5 degrees. [7], [8]

platform has taken over the neMEMSi one in our research projects related to rehabilitation of patients suffering from neurological diseases.

[9], [10], [11], [12], [13]

Window size [14].

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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