Using NAO Robot to improve the quality of life in the elderly

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Index Terms

Engineering; Robotics; Health Sciences

1 Abstract

The use of Robots to improve the quality of life of person has many examples. For instance, NAO has been used to teach diabetic children about various aspects their condition. NAO is used for arm rehabilidation therapy for children in which children find the Robot interaction more engaging and the increase of children's motivation to perform adecuate rehabilitation therapy.

The predictions for 2050 of elderly people will hist almost one million people in Japan, similarly the projection for elderly people in 2050 will be around 19 million.

For this proposal, I am aiming to show prelimirary outcomes of the use of NAO as a instructors for users to copy movements in scensarios for enternaitnmanet or rehabilitation.

Present literature review of robots for elderly care, areas of care, etc.

For this work, the results of 12 participants performing 6 different movements in six seassons. I will present the advances and disavantages of using on-body inertial sensors, methodologies for data processing and the measure of the quality of activities accrosss particiapants.

Industrial Application

1.1 Background

Insufficient physical activity is the 4th leading global risk for mortality in the world [1]. It is estimated to be responsible for 6% of deaths globally, after high blood pressure (13%), tobacco use (9%), high blood glucose (6%) and right before overweight and obesity (5%).

World Health Organization. Global health risks: mortality and burden of diseases attributable to selected major risks. WHO, Geneva (2009)

Application of a wireless BSN for gait and balance assessment in the elderly [1]. Mobile Devices For The Real Time Detection Of Specific Human Motion Disorders [2].

Wearable Sensors for Human Activity Monitoring: A Review

1.2 Materials and Methods

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:

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- 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 Results

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).

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 [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 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 Conclusion

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 Applications

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

Variability is an inherent characteristic of human movement [4]. To date, research investigating the automatic identification of variability in human activity recognition is minimal. For instance, Bulling *et al.* [5] 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 with 12 participants in which each gesture was perfomed three times. The data collection was based on the orientation hand given by a Microsoft Kinect sensor as reference coordinates. As it is expected due to the intrinsic varialibility of human movement, participants presented a statistical significant effect of variability in the lenght of trace and speed of gesture movements. However, it is worthwhile to note that "the gesture type did not show significant effect of the variation" [6].

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. Haratian *et al.* 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" [7], [8], [9].

Commotti *et al.* performed a evaluation with regard to the orientation resolution in which its neMEMSi was compared with respect to the state-of-the-art device Xsense MTi-30. They present noise standard deviation lower than 0.1 degrees for all the Euler angles components in static conditions after single rotations around each axis 3D dynamic orientation acuracy is 0.55 degrees average on Roll, Pitch and Yaw. 3D static orientation acuracy is 0.057 degrees average on Roll, Pitch and Yaw [10].

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 power consumption. and when the sampling rate is higher than 50 Hz the static and dynamic error are witing 1 degree and 10 degrees resctively [11].

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 sensors is used 13 PD participants [12]. Similarly, neMEMSi-Smart has been used to assess motor performance for elderly people Six-minutes walk test. 5 adults with no pathologies of mean age 31+-6 4 elderly people with diabethes type 2 of mean age of 70.8+-7 [1].

Lorenzi *et al.* used the neMEMSi attached to the head of participants where the mass center of the sensors oscillates in the y direction to automatically clasify human motion dissorders in Parkinson's Disease. Steep lenght with a small population of 5 healthy young persons to the spread of SL between participatns to train an Artificial Neural Network with three test: the stop state, the step shortening and the trunk fluctuations [13]. Continuing with the research interest in analysing human motion dissorder such as freezing of gait (FOG) for elderly people with Parkinson's Disease, Since the previous approached the sensor is attached to the head it means that the neck join added signals from many postural problems and irregular movements due to the Parkinson Disease. Therefore, Lorenzi *et al.* added two neMEMSi sensors which were attached to the shins for fine detection of gait patterns. using quaternions With 16 patients for 110 minutes of monitoring time the systems with two sensors present a good peformance in terms of sensitivity, precision and accuracy of the detection of FOG [2]

In the same fashion as Lorenzi *et al.* [2], Arsenault and Whitehead pointed out that using quaternion representation present more benefits over other rotational. For instace, is that they do not suffer from the problem of gimbal lock or generative points during computation, also they are numerically stable since they do not require the calculations of many trigonometric functions. Also for classification purposes, Arsenault and Whitehead reported an improvement of the classification using Markov Chain than Hidden Markov Models. 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 [14], [15]

Window size [16].

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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