Towards the Analysis of Movement Variability in Human-Humanoid Imitation Activities

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ABSTRACT
In this paper, we present prelimary results for the analysis of movement variability in order to quantify face-to-face human-humanoid imitation activities. We applied the state space reconstruction's theorem to test our hyphothesis where participants, even performing the same arm movement, presented minor diferences in the way they moved. With this in mind, we asked eighteen participants to copy NAO's arm movements while we collected data from inertial sensors attached to the participants' wrist and compute the head pose estimation using the OpenFace framework. With the proposed metric, we found that two particpants were moving their arms asymetrically while the others move their arms, within a range of movement variability, symetrically. We also showed that two participants where moving their head even when NAO's head was static. Althought the work is in its early stage, the results are promising for applications in rehabilitation, sport science, enternatiment or education.

ACM Classification Keywords
I.2.9. Robotics: Sensors; G.3. PROBABILITY AND STATISTICS: Time series analysis

Author Keywords
Human-Robot Interaction; Human-Humanoid Imitation; Wearable Inertial Sensors; State Space Reconstruction; Nonlinear dynamics; Dynamics Invariants

INTRODUCTION
Movement variability is an inherent feature within a person and between persons [7]. Recently, Herzfeld et al. [5] conducted experiments to state that movement variability is not only noise but a source of movement exploration which at certaing point of the exploration such variability is a source of movement explotation. With this in mind, we have found that there is little research in the area of human-robot interaction that is focused on the quantification of movement variablity.

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METHOD

State Space Reconstruction's Theorem
The purpose of time-delay embedding, also known as State Space Reconstruction's Theorem, is to reconstruct the topological properties of an unknown $M-$dimensional state space $s(t)$ from a $1-$dimensional measurement $x(t)$ in order to reconstruct an $N-$dimensional embedding space (Figure 1). The

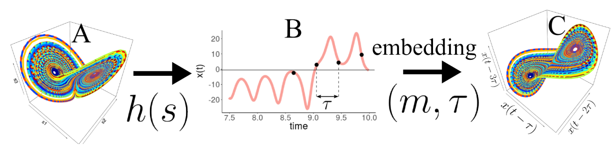

Figure 1. A. $M-$**dimensional state space** $s(t)$**; B.** $1-$**dimensional measurament time series** $x(t)$**; and C.** $N-$**dimensional reconstructed state space** $v(t)$ **where** $M \geq N$ **[9].**

time-delay embedding assumes that the time series is a sequence $x(t) = h(s(t))$, where $h : S \to \mathbb{R}^M$ is a measurement function on the unknown dynamical system, being $x(t)$ observable. Thus, the time delay reconstruction in m dimensions with a time delay τ is defined as: $\overline{x}(t) = (x(t), x(t-\tau), ..., x(t-(m-1)\tau))$. Then a further transformation is considered, e.g. PCA, in order to reduce the dimensionality of the $m-$dimensional reconstructed state space [11]. For this work, we assume that the signal, $x(t)$, is produced by some time-varying system in our case the time series are produced by the linear acceleration of the inertial sensors. The assumption that the signal exhibits systematic variability within and between persons leads to the assumption that this signal should, over some time period, exhibit a repeated pattern between and within persons. What we do not know is how realiable the quantification methods for movement variability are and how to establish levels of imitation with a given range of movement variability.

Determining the embedding parameters (m and τ)
Although State Space Reconstruction's Theorem has been used extensively in gait recognition and walking, running and cycling activities [4, 10], the computation of the minimal embedding parameters largely depend on the structure of the time series (amplitude, frequency, nonlinearity). For this work, we first compute the minimal embedding parameters using the Cao's algorithm [3] and the mutual information and then we manually increase the dimensionality of the reconstructed state space until the attractor is untangled.

EXPERIMENT DESIGN

Measuring Movement
To understand the movement variability of the participants, we use a very cheap Inertial Measurement Unit: SparkFun 9DOF RAZOR IMU SEN-10736 sensor board which transmit data via RN42 bluetooth module. For data collection, we set a sampling rate of 50 Hz from four RAZOR's sensors using ROS [8] (Figure 2A).

Time Series from the Accelerometer
The sequence $a(n)$ is the raw data collected from an triaxial accelerometer sensor ($a_{\{x,y,z\}}$). Then, for instance, the time-series $a_x(n)$ with a length of N samples is used to get the embedded stata space matrix, Ea_x, with m rows and $N-(m-1)\tau$ columns. Finally, PCA is applied to reduce de dimensionality of the data to get the first two componets of the rotated data in order to reconstruct the state space.

Head Pose Estimation
Estimating head pose in human-robot interactions is an active area of research where challenges like real-time tracking, the use of less invasive equipment or the preparation of calibration techniques remain to be solved. However, Lemaignan et al. [6] proposed a head pose estimator using a monococular RGB webcam which is able to track a head with rotations up to $\pm 40°$ horizontally and $\pm 30°$ vertically. Much recently, OpenFace, a fully open source real-time facial behavior analysis, non only provides head pose (orientation and motion) but also state-of-the-art performance in facial landmark motion, facial expressions, and eye gaze [1]. We therefore select the use of OpenFace because it can operate with a simple webcam in real-time (Figure 2B).

EXPERIMENT

Hyphothesis
In our previous experiments of a face-to-face human-humanoid imitation activity [12], we applied the State Space Reconstruction's Theorem to quantify the level of imitation for horizonal and vertical upper arm movements. In such experiment, we observed in the recorded videos (only by naked eye) that the effects like boredoom, fatigue or level of engagment play an important role in the influence that each persons moves. With this in mind, we hyphothesised that not only the inertial sensors attached to the body can provide information about movement variability but also the face expressions and head pose estimation which, we believe, will lead us to get better understanding of the movement variability in human-to-humanoid activities and therefore create more realiable metrics to quantify such variability.

Participants and Procedure
To test our hyphothesis, we collected data from eigthteen healthy participants: eigth male participant (age 18 ± 3.43) and ten female (age 18 ± 0.43) in which inertial sensors were attached to the wrist of both the participant and the humanoid robot, and put the webcam in front of the participant for the head pose estimation (Figure 2A). In the experiment, participant were asked to imitate ten upper arm movements performed by NAO at a constant speed of 30 frames per seconds.

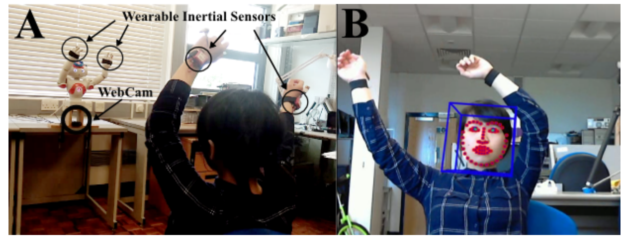

Figure 2. A. Experimental setup: face-to-face imitation with NAO humanoid robot; B. Head pose estimation with OpenFace [1]

RESULTS
In Figure 3A), we only presented time series for the participant 12 for the sensor 03 and sensor 04 to show the assimetry of the signals which is reflected in p12-s03 and p12-s04 in (Figure 3B) as well as in the error plot for s03 and s04 (Figure 3C). On the other hand, you can also notice that p17 in the error plot (Figure 3C) for the OpenFace presents a well distributed data in the interquartile range which means that the p17 were moving his head which is opposite to what the p14 did which head's movement was quite static.

CONCLUSION
Having proposed the use of the state space reconstruction and analysed the data from human-humanoid imitation activity, several questions remain to be investigated like the understanding of emotions and motions in one-to-one or one-to-many human-humanoid interactions. Considering the head pose estimation and the outcomes of the proposed metric, we observed that p04 and p17 particants moved their head as a tendency for the arm momvement given the fact that the robot's head was static in the activity. Such behavior requires further investigation in which, we believe that, the perception of movement is involved in this human-humanoid interactions. As pointed out by Blake et al. [2], the motor experience affects the visual sensitivity of human action.

In future experiments, there are four areas that we intend to investigate: (a) performance of experiments of with two-humans to one-humanoid and three-humans to one-humanoid interactions; (b) exploration of complex movements which can be performed by both persons and NAO; (c) data collection from a wider range of individuals (differing gender, age and state of health) and from additional inertial sensors attached to the body; and (d) application of deep learning techniques to automatically classify the movement variability.

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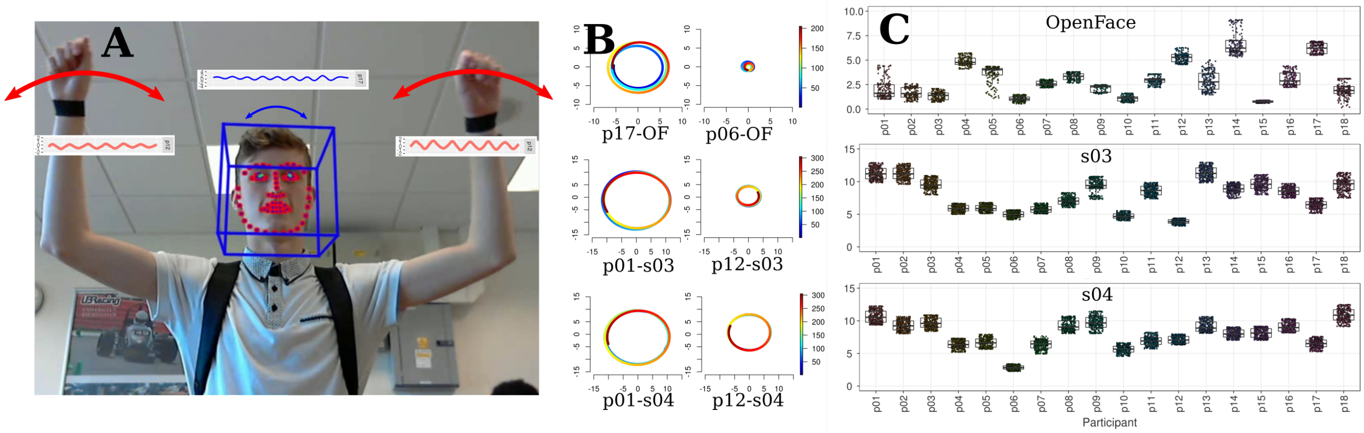

Figure 3. A. Time series for the inertial sensors $a_x(n)$ and the Head Pose Estimation in the T_x axis; B. State Space Reconstruction with $m = 100$ and $\tau = 4$ for participants 17 and 16 for the head pose estimation and participants 01 and 12 for sensor 03 and 04; C. Error bars for the head pose estimation, sensor 03 and sensor 04 for the eighteen participants.

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