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

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ABSTRACT

In this paper, we present prelimary results to quantify one-to-one human-humanoid imitation activities using state space reconstruction's theorem. For which data was collected with inertial sensors attached to persons and the use of the Open-Face framework for head pose estimation. Troght the prosed metric, we found that were moving their arms asymetrically while the other move symetrically within a range of movement. Althought the work is in its early stage, the applications can be 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

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 movemennt variablity.

METHOD

State Space Reconstruction

In this work we follow the notation employed in [11]. The purpose of time-delay embedding, also known as Takens'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 time-delay embedding assumes that the time series is a sequence $x(t) = h(s(t))$, where

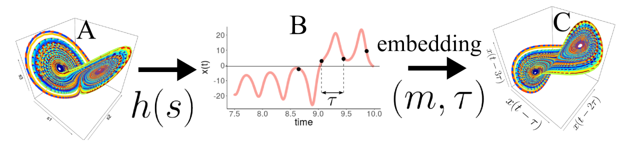

Figure 1. A. $M-$**dimensional state space** $s(t)$**; B.** $1-$**dimensional measurament time series** $x(t)$**; and C.** $N-$**dimensional reconstructed state space** $v(t)$ **where** $M \geq N$ **[9].**

$h : S \to \mathbb{R}^M$ 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: $\bar{x}(t) = (x(t), x(t-\tau), ..., x(t-(m-1)\tau))$. Then a further transformation is considered in order to reduce the dimensionality of the $m-$dimensional reconstructed state space. For this work, we assume that the signal, $x(t)$, is produced by some time-varying system in our case is the time series produced by the linear acceleration of the inertial sensors attached to both the person and the humanoid robot. 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 movement variability.

Determining the embedding parameters (m and τ)

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

EXPERIMENT DESIGN

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. 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 [6]. Much recently, OpenFace, a fully open source real-time facial behavior analysis, provides a state-of-the-art performance in facial landmark

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motion, head pose (orientation and motion), facial expressions, and eye gaze. Additionally, OpenFace can operate with a simple webcam in real-time [2] which is ideal for our experiments.

Measuring Movement

To understand the movement of the participants, we select a very cheap Inertial Measurement Unit: SparkFun 9DOF RAZOR IMU SEN-10736 sensor board which transmit data via RN42 bluetooth module. We set a sampling rate of 50 Hz to collecte data from four RAZOR IMUS connected throught ROS [8].

Time Series from the Accelerometer

In this work the sequence $x(t)$ is the raw data collected from an (IMU) for triaxial data for accelerometer ($a_{\{x,y,z\}}$), gyroscope ($g_{\{x,y,z\}}$) and magnetometer($m_{\{x,y,z\}}$) sensors. Then, for instance, the time-series a_x with a length of N samples is used to obtain the Time-delay embedded matrix, Ea_x, with m rows and $N-(m-1)\tau$ columns. Finally, the PCA algorithm is applied so as to obtain via eigenvalues ($\lambda_1,\ldots,\lambda_m$) and eigenvectors ($v_1,\ldots,v_m$) the principal components ($PC_1,\ldots,PC_m$) of the time-delay embedded phase space.

EXPERIMENT

Hyphothesis

In our previous experiments of a face-to-face human-humanoid imitation activity [1], we proposed a metric to quantify the level of imitation for horizonal and vertical upper arm movements. In such experiment, we also observed (only by naked eye) that the efects 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 inertial sensors attached to the body can provide information about movement variability but also the head pose estimation which, we believe, will lead us to get better understanding of the movement variability and therefore create more realiable metrics to quantify such variability.

Participants and Procedure

In this experiment, we collected data from eigthteen healthy participants: eigth male participant (age 18 ± 3.43) and ten female (age 18 ± 0.43). Besides the inertial sensors attached to the wrist of both the participant and the robot, we use the head pose estimation via webcam from OpenFace framwork in order to test our previous hyphothesis. For this, we designed an experiment where the participant imitates NAO robot' arm movements at a constant speed of 30 frames per seconds. Such NAO's arm movements were performed for ten times which were imitated in a face-to-face imitation activity (Figure 2A).

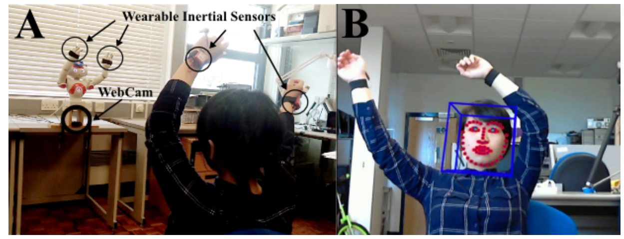

Figure 2. A. Experimental setup: face-to-face imitation with NAO humanoid robot; B. Head pose estimation with OpenFace [2]

RESULTS

In Figure 3, we can observe that particpant 04, 08 and 17 present an oscillation in the head which is an unpected behaviour since NAO was static.

CONCLUSION

Althought the robot's head was static, we observed that p04 and p17 particants moved their head as a tendency for the arm momvement to which we believe that such behavior requires further investigation where the perception of movement is involved. As posed by Blake et at. [3], motor experience of affect the visual sensitivity to human action.

Having proposed and analysed the data from human-humanoid imitation activity, several questions remain to be investigated to understand emotions and motions in one-to-one or one-to-many human-humanoid interactions.

In future experiments, there are three areas that we intend to investigate: (a) provide further understanding of human movement variablity (b) perform experiments of interaction with two-humans to one-humanoid and three-humans to one-humanoid interactions. (c) exploration of complex movements which can be performed by both persons and NAO; (d) data collection from a wider range of individuals (differing gender, age and state of health) and from additional inertial sensors attached to the body.

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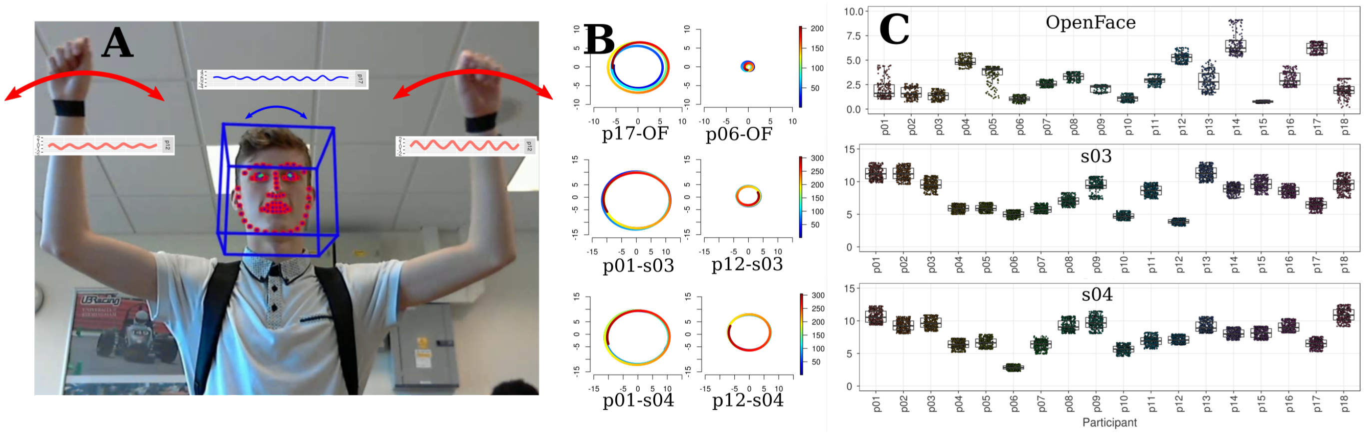

Figure 3. Head Pose Estimation in the Tx axis for 18 participants

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