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

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ABSTRACT

In this paper, we present preliminary results for the analysis of movement variability in human-humanoid imitation activities. We applied the state space reconstruction's theorem which help us to have better understanding of the movement variability than other techniques in time or frequency domains. In our experiments, we tested our hypothesis where participants, even performing the same arm movement, presented slight differences 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' wrists and estimated the head pose using the OpenFace framework. With the proposed metric, we found that sixteen out of eighteen participants imitate the robot well by moving their arms symmetrically and by keeping their heads static; two participants however moved their head in a synchronous way even when the robot's head was completely static and two different participants moved their arms asymetrically to the robot. Although the work is in its early stage, we believe that such preliminary results are promising for applications in rehabilitation, sport science, entertainment 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 movements [6]. Recently, Herzfeld et al. [4] conducted experiments to state that movement variability is not only noise but a source of movement exploration which at certain point of the exploration such variability is becoming a source of movement exploration. 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 variability.

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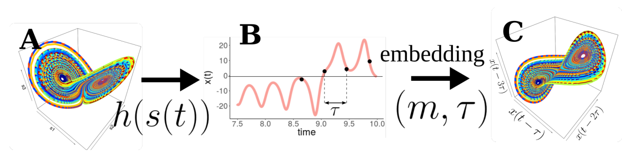

Figure 1. State Space Reconstruction. A. $M-$dimensional state space $s(t)$; B. $1-$dimensional measurement time-series $x(t)$; and C. $N-$dimensional reconstructed state space $v(t)$ where $M \geq N$ (adapted from [8]).

The paper is divided into an intuitive explanation of the state space reconstruction; the experiment section where reasons for measurement of arm and head pose movement are given, as well as the hypothesis and participant of the procedure are presented; we then show the state spaces plots and the error bars in the results section and finalised with our conclusions.

METHODS

State Space Reconstruction's Theorem

The purpose of the 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 time-delay embedding assumes that the time-series is a sequence $x(t) = h(s(t))$, where $h : S \rightarrow \mathbb{R}^M$ 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 to a $k-$dimensional space [10]. The advantage of the use of the state space reconstruction's theorem is its simplicity to reconstruct a state space that can help us to have better understanding of the movement variability regarding movement correlations and symmetry of movements where techniques in time and frequency domain tent to provide little insight about the movement variability the structure of the variability of the time-series.

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 [3, 9], the computation of the minimal embedding parameters largely depend on the structure of the time-series (amplitude, frequency, nonlinearity). To which, we however first compute the minimal embedding parameters using the Cao's algorithm [2] and the mutual information and then we manually increase the dimensionality of the reconstructed state space until the attractor is untangled. Refer to [2] for detailed explanation of the computation of the embedding parameters.

EXPERIMENT

Measuring Arm Movement with Wearable Inertial Sensors

To understand the movement variability of the participants, we use four Wearable Inertial Sensors (SEN-10736 SparkFun 9DOF RAZOR) which provide triple-axis accelerometer and triple-axis gyroscope (Figure 3A). The data were transmitted via a RN42 bluetooth module for which we set up a sampling rate of 50 Hz and collected data using ROS [7]. The sequences $(a_x(n), a_y(n), a_z(n))$ are the raw data collected from the triple-axis accelerometer sensor.

Head Pose Estimation with OpenFace

Due to the random head movements of participants while interacting with the robot, we believe that location of the head pose can provide useful information to have a better insight on the understanding of the movement variability. With this in mind, we found that 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 long-time preparation of calibration techniques of the motion capture systems remain to be solved. Recently, Lemaignan et al. [5] proposed a head pose estimator using a monocular RGB webcam which is able to track a head with rotations up to $\pm 40°$ horizontally and $\pm 30°$ vertically. However, OpenFace, a fully open source real-time facial behaviour analysis, not only provides head pose (orientation and motion) but also a state-of-the-art performance in facial landmark motion, facial expressions, and eye gaze [1]. For this work, we use the OpenFace because is easy to set up, is less invasive and can provide features for facial behaviour. It can also operate with a simple webcam in real-time (Figure 3B). OpenFace framework provide the location of the head with respect to camera in millimetre (poseTx, poseTy, poseTz).

Hypothesis

In our previous experiments of a face-to-face human-humanoid imitation activity [11], we applied the State Space Reconstruction's Theorem to quantify the level of imitation for horizontal and vertical upper arm movements. In such experiment, we observed in the recorded videos that effects like boredom, fatigue or level of engagement play an important role in the influence that each persons moves. To which, we hypothesised, in the context of human-agent interaction where more realistic scenarios and better models of interaction are needed, that not only the inertial sensors attached to the body can provide information about movement variability but also the facial expressions and head pose estimation. We believe that such combination of arm movement and head pose estimation will lead us to get better understanding of the movement variability in human-to-humanoid activities and therefore create more reliable metrics to quantify such movement variability.

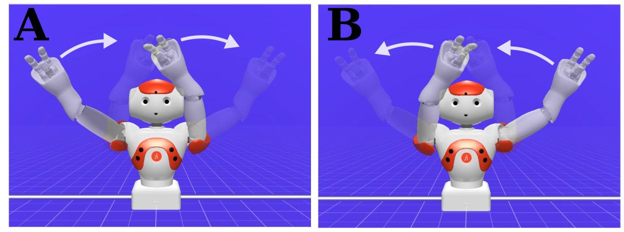

Figure 2. NAO's arm movements: A. from right to left and B. from left to right.

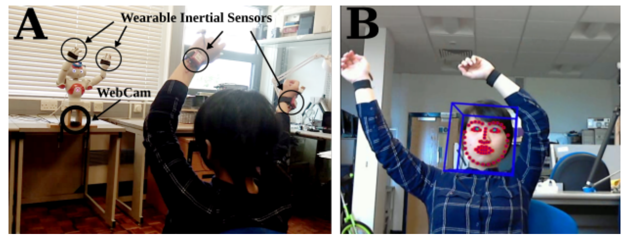

Figure 3. A. Experimental set-up of Human-Humanoid Imitation Activities; B. Head pose estimation with OpenFace [1].

Participants and Procedure

To test our hypothesis, we collected data from eighteen healthy participants: eight 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 3A). In the experiment, participant were asked to imitate NAO's upper arm movements with ten repetitions (Figure 2).

RESULTS

In Figure 4, we show the time-series for the participants p01, p04 and p12 for the x axis of the head pose estimation with respect to the camera (sOF) and the the smoothed data from the acceleremoters in x axis $a_x(n)$ for sensors attached to the Left Wrist (sLW) the Right Wrist (sRW). We particularly observed slight similarities for the sLW and sRW time-series for which it can be pointed out that participant p04 moved their arms symmetrically as shown in the 2D reconstructed state space (p04-sLW and P04-sRW) and the error bars. We also showed that participants p06 and p12 moved their arms asymmetrically as shown in the state space reconstruction (p12-sLW and P12-sRW) and in the error bars.

With regard to the time-series from the head pose estimation sOF, we observed that pretty much all the participants moved their heads while moving their arms. Nonetheless, participants p04 and p17 were moving their heads in a synchronous way with their arm movements. Such head movement of participants p04 and p17 can be observed in the time-series p04-sOP of Figure 4A. However, the state space reconstruction p04-sOF of Figure 4B showed a clearly representation of such synchronicity between arm and head movements. It can also

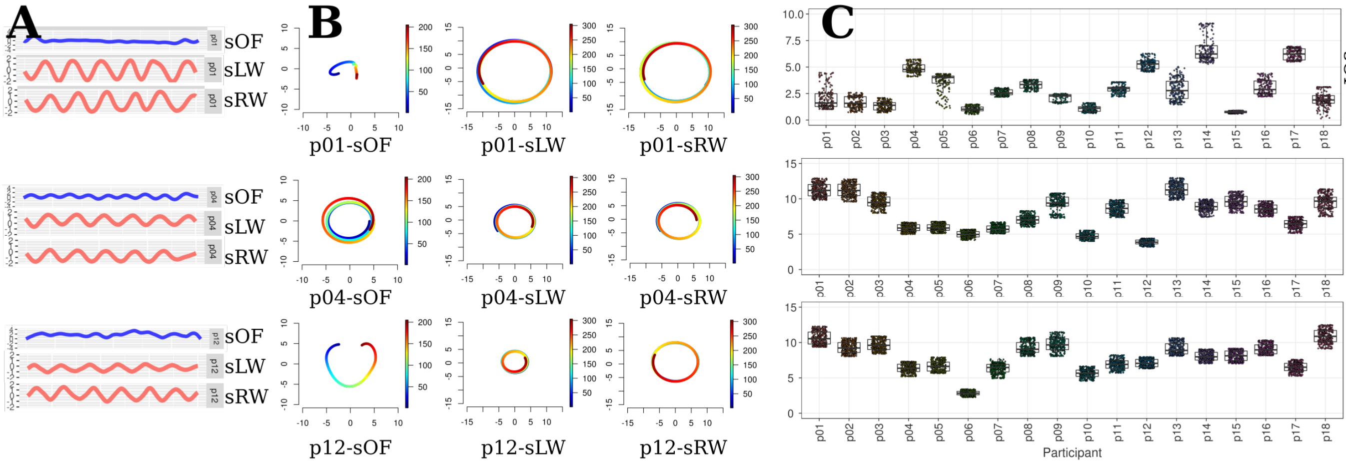

Figure 4. A. Time-series for participants p01, p04 and p12 for sensor OpenFace (sOF) using the x axis of the head pose estimation with respect to the camera, sensor Left Wrist (sLW) and sensor Right Wrist (sRW) using the smoothed data from the acceleremoters in x axis $a_x(n)$. B. 2-D state space reconstruction with $m = 100$ and $\tau = 4$ for participants p01, p04 and p12 using sOF, sLW and sRW. C. Error bars for the eighteen participants for sOF, sLW and sRW.

be noticed the well distributed data in the interquartile range for participants p04 and p17 (Figure 4C).

CONCLUSION

We propose the use of the state space reconstruction's theorem to analyse movement variability in a human-humanoid imitation activity. To which, we not only presented visual differences of movement variability of arms and head between eighteen participants, but we also quantified such movement variability. For instance, sixteen out of eighteen participants imitate the robot well by moving their arms symmetrically and by keeping their heads static, but participants p04 and p17 moved their head in a synchronous way even when the robot's head was completely static. We also quantify that participants p06 and p12 did not imitate the robot well to which their arms moved asymetrically to the robot. With this in mind, we believe that such results are promising for applications in rehabilitation, sport science, entertainment or education.

In future experiments, there are four areas that we intend to investigate: (a) such as the understanding of variability of emotions and motions in one-to-one or one-to-many human-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 (different 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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