Towards the Quantification of Human-Robot Imitation Using Wearable Inertial Sensors

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ABSTRACT

In this study, we propose a metric in order to quantify how close a healthy participant imitates a robot for which we use inertial sensors attached both to a person and to a humanoid-robot. For the experiment, twelve healthy participants were invited to perform simple arm movements in order to apply the state space reconstruction which is based on the method of time-delay embedding and PCA. Although the performed arm movements with healthy participants were very simple, the study reveals that participants show different ranges of the proposed metric that can be linked to level of imitation. Such a metric can be improved in order to determine a detailed scoring of human-robot imitation during training or rehabilitation activities.

CCS Concepts

•**Computer systems organization** → **External interfaces for robotics;**

Keywords

Human-Robot Imitation, Movement Variability, Wearable Inertial sensors, Non-linear Dynamics, State Space Reconstruction

1. INTRODUCTION

Recently, NAO, a humanoid robot, has successfully been used either as a fitness coach for elderly or as an instructor of rehabilitation for children. For instance, Görer *et al.* used NAO as an exercise tutor and Asus Xtion RGB-D camera to extract joint angles of a human demonstrator and participants [3]. Absolute differences of joint angles between the human demonstrator and participatns are used to create a corrective feedback for the movement of the elderly with respect to (i) speed adjustment, (ii) amplitude adjustment, (iii) mirroring detection, and (iv) motion. However, on one hand, when participants are seated the RGB-D camera cannot provide correct skeleton information of the participant, and, on the other hand, there is room for implementation of a detailed scoring of human-robot imitation since the score is only based on how well the participant follows the verbal commands of the robot. Similarly, Guneysu *et al.* used NAO and wearable inertial sensors to monitor motions of arm rehabilitation of children [4]. The challenge for Guneysu *et al.* is to keep the children's motivation in order to imitate movements for arm rehabilitation therapy. For this, NAO successfully captures the attention of children, while the use of inertial sensors is ideal to avoid any obstructions between the children, the therapist, and the robot. However, as part of their study, it turns out that four physiotherapists have their own way to move while performing arm motions which is reflected in the differences of frequency and amplitude of the movements as well as in the initial positions of the hands.

For this study, we are therefore proposing a framework based on the state space reconstruction in order to explore a metric that can help us to determine how close the participants mimic the original movement of the robot. We also use inertial sensors to avoid any obstructions during the interaction and NAO to control simple movements that participants have to imitate.

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2. METHODS

2.1 Research Questions

How to analyse data collected from wearable inertial sensors attached both to a person and to a humanoid-robot in order to quantify how close a participant imitates a robot?

2.2 Participants

Twelve right-handed healthy participants (two females and ten males) mean age 19.5±0.79 (from now on abbreviated as p01 to p12) were invited to participate in this study. All participants provided informed consent forms prior to participation. The design of the experiment was approved by University of Birmingham ethics approval process.

2.3 Procedure

Participants were asked to imitate horizontal and vertical arm movements performed by NAO. Such simple movements were repeated ten times for both the participant and the robot in a front to front imitation activity to which wearable inertial sensors were attached the right hand of the participant and to the left hand of the robot (Figure 1-A). Data were then collected at a sampling rate of 50Hz with two NeMEMSi inertial sensors which provide tri-axial data of accelerometer, gyroscope and magnetometer sensors and quaternions [1].

It is important to note that due to the reduced space, we are only presented results for the horizontal movement and we focus our analysis on the z axis from the gyroscope sensor (g_z) which is mostly affected by the nature of the horizontal movement (Figure 1-A).

3. STATE SPACE RECONSTRUCTION

The State Space Reconstruction (SSR) is based on the methods of time-delay embedding and PCA [2]. Our motivation to use the method of time-delay embedding is due to the non-linear structure of the time-series which is presented as different periods and amplitudes of the time-series between repetitions of movements and across movements of participants (Figure 1-B,C). The method of time-delay embedding is an array of delayed copies of the available time series $x(n)$ and is defined as $\overline{x}(n) = \{x(n), x(n-\tau), x(n-2\tau), \ldots, x(n-(m-1)\tau)\}$ where m is the embedding dimension and τ is the delay embedding. PCA is used as a method for dimensionality reduction due to its non-parametric feature. PCA is therefore applied to $\overline{x}(n)$ in order to get $PC_1, PC_2, \ldots, PC_m$ to which we use PC_1 and PC_2 to create a state space reconstruction (Figure 1-D,E and F). Finally, we computed euclidean distances in the state space from (0,0) point to each $(PC_1(i), PC_2(i))$ point where $1 \leq i \leq m$ in order to obtain the box-and-whisker plots for each participant (Figure 1-G).

4. PRELIMINARY RESULTS

On one hand, it is expect that the robot performed very similar repetitions of movements which are visualised in the orange time-series (Figure 1-B,C) and therefore produced a tight circular shape in the reconstructed state space (Figure 1-D). On the other hand, different amplitude and period of the time-series for participant 05 (Figure 1-C) are related to a disjointed circular shape of the reconstructed state space (Figure 1-F). Such shapes in the reconstructed state space are linked either to a maximum interquartile range in the box-and-whisker plot or to a little interquartile range of the respective box-and-whisker plot (Figure 1-G).

5. CONCLUSIONS AND FUTURE WORK

We proposed a metric to quantify how close a participant can imitate a robot for simple arm movements to which it can be noted that the proposed metric reveals that participants show different ranges of imitation which can be linked to a scoring of human-robot imitation. However, our main concerns when quantifying human-robot imitation is the lack of metrics to say who can be considered a bad, intermediate or good imitator.

For future work, there are four areas that we are going to investigate: (i) data collection from a wider range of individuals (gender, age and healthy and unhealthy) and from additional inertial sensors attached to the body, (ii) explore complex movements which can be performed by both persons and NAO, (iii) undertake a wider review of non-linear techniques that can be used for the assessment of human-robot imitation, and, (iv) explore the use of convolutional neural networks for automatic classification of the levels of human-robot imitation.

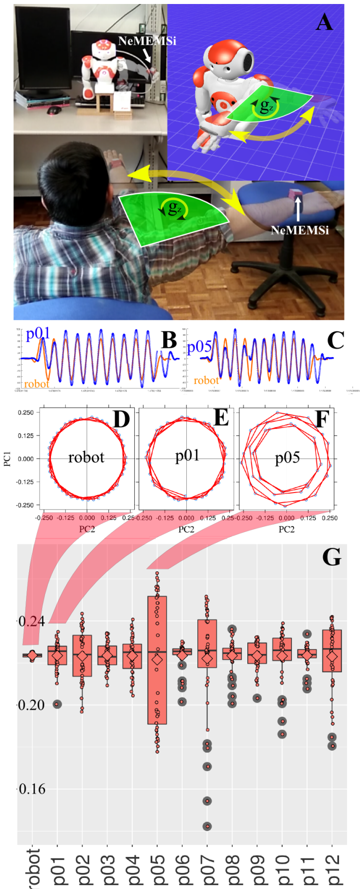

Figure 1: Horizontal movement performed by both NAO and participant 05 (A). Smoothed angular acceleration g_z for participant 01 and robot (B) and for participant 05 and robot (C). Reconstructed state spaces ($m = 40$, $\tau = 10$) for robot (D), participant 01 (E), and participant 05 (F). Euclidean distances from the reconstructed state space for the robot and twelve participants (G).

6. REFERENCES

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