...Movement Variability in Human-Humanoid Imitation

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ABSTRACT

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Author Keywords

Human-Humanoid Interaction; Human-Robot Interaction; Wearable Inertial Sensors; State Space Reconstruction

INTRODUCTION

Movement variability is an inherent feature within a person and between persons [11]. Recently, Herzfeld et al. [8] conducted experiments to argue that movement variability is not only noise but a source of movement exploration which at certaing point is becoming 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.

...I AM READING THESE PAPERS TO COMPLETE THE INTRODUCTION: Perception of Human Motion [3]. Pigeons and humans use action and pose information to categorize complex human behaviors [13]. The visual perception of velocity [5]. Implied Dynamics Biases the Visual Perception of Velocity [9]. Attention to body-parts varies with visual preference and verb–effector associations [4]. Comparing Biological Motion Perception in Two Distinct Human Societies [12]

METHOD

Reconstructed State Space

In this work we follow the notation employed in [15]. 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. 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 (Figure 1). Thus, the time delay

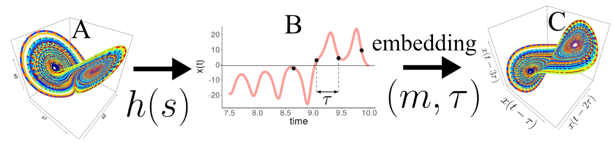

Figure 1. A. $M-$**dimensional complex system** $s(t)$; **B.** $1-$**dimensional measurement** $x(t)$; **and C.** $N-$**dimensional complex system** $v(t)$ **where** $M \geq N$

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 can be considered in order to reduce the $m-$dimensional time-delay embedding. For this work, we assume that the signal, $x(t)$, we are observing has been produced by some time-varying system (that is the human body movement). The assumption that the source of the signal exhibits systematic variation leads to the assumption that this signal should, over some time period, exhibit a repeated pattern. What we do not know is what this time period might be or what this repeated pattern might look like.

Determining the embedding parameters (m and τ)

Although Takens's Theorem has been used extensively in gait recognition and walking, running and cycling activities, some problems are still remaining to be solved. Sama et al. [14] estimated that the minimal embedded dimension (m_{min}) with False Nearest Neighbours (FNN) method. However, Cao [6] pointed out that FNN algorithm introduces new parameters (R_{tol} and A_{tol}) that lead to different results which cannot differentiate random series from deterministic series. Frank et al. [7] proposed a grid search method to find the minimal embedded parameters, but there are little details about their approach. Additionally, Sama et al. [14] states that the minimal embedding parameters largely depend on the application at hand. Thus, there is still research to be done to find the minimal dimension parameters (m_{min} and τ_{min}) to reconstruct the state space.

$E1(d)$ and $E2(d)$ values

Cao's method for computing the minimal embedding dimension is based on the mean values of $E1(d)$ and $E2(d)$ where d is the range of evaluation of the embedding dimension. Therefore, $E1(d)$ is used to obtain the minimal dimension m_{min} to which the values of $E1(d)$ stop changing when d comes from an attractor. $E2(d)$ values are used to distinguish deterministic signals from random signals in which case the $E2(d)$ values

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will be approximately equal to 1 for any d. Cao's method is a modified version of the FNN method, and $E1(d)$ and $E2(d)$ values are only dependant on m and τ [6].

EXPERIMENT DESIGN

Head Pose Estimation

Estimating head pose in human-robot interactions is an active area of research because of challenges like real-time tracking, the use of less invasive equipment or the preparation of calibration techniques. 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 [10]. Much recently, OpenFace, a fully open source real-time facial behavior analysis, provides state-of-the-art performance in facial landmark motion, head pose (orientation and motion), facial expressions, and eye gaze. Additionally, OpenFace can operate with a simple webcam in real-time [2].

EXPERIMENT

Hyphothesis

In our previous experiments of a face-to-face human-humanoid imitation activity [1] where we proposed metrics to quantify the level of imitation, we also observed (by eye) that efects like boredoom, fatigue or level of engagment might also be a factor that influence the way each person moves and therefore movement variability. 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 movement variability and therefore create realiable metrics to measure such variability.

Participants and Procedure

For our pilot experiment, we only collected data for one male right-handed healthy participant (age 35, height 177cm, weight 85kg). Besides the inertial sensors attached to both the participant and the robot, we use the head pose estimation via webcam in order to test our previous hyphothesis. For this, we design a pilot experiment where the user(s) imitate NAO robot' arm movements at three speeds: (a) 15 frames per seconds; (b) 30 frames per seconds; (c) and 45 frames per seconds. Such experiment were performed six times by the same participant in order to test the factor of fatigue or boredoom (Figure 2A).

We use OpenFace [2] to measure the head pose which let us hyphothesis that the participant is engagaed when he/she stared the robots within certain range of movements.

RESULTS

I AM WORKING IN THIS SECTION WHERE I WILL PRESENT THE RESULTS OF ONE PARTICIPANT PERFORMING THE ARM MOVEMENTS FOR SIX TRIALS AT SPEEDS OF 15, 30 and 45 USING THE DATA FROM THE IMUS AND THE HEAD POSE ESTIMATOR (Figures 3 and 4).

CONCLUSION

In future experiments, there are three areas that we intend to investigate: (a) provide further understanding of human movement variablity (b) two-humans to one-humanoid and (c) three-humans to one-humanoid interactions.

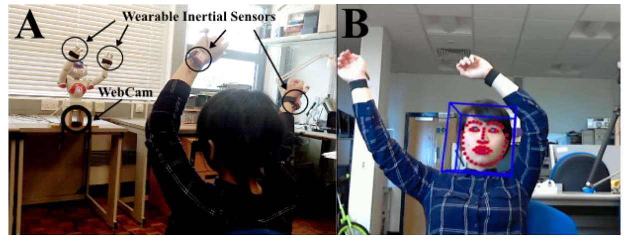

Figure 2. A. Experimental setup: face-to-face imitation with NAO humanoid robot; B. Head pose estimation with OpenFace [2]

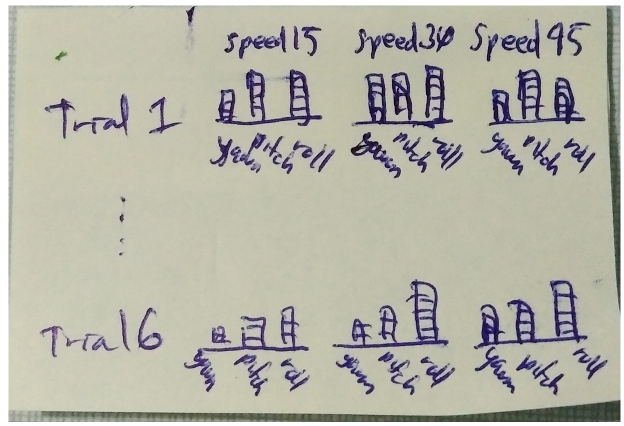

Figure 3. Head Pose Estimation of six trials at three speeds 15, 30 and 45

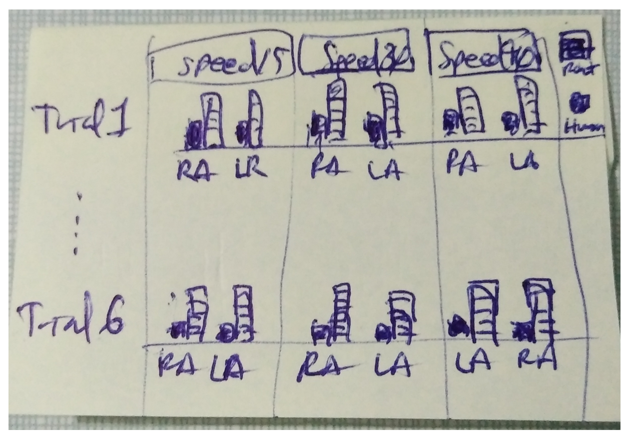

Figure 4. Right Arm (RA) and Left Arm (LA) from Human and robot arm movememtns of six trials at three speeds 15, 30 and 45

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