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

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## ABSTRACT
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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 [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 certaing point of the movement performance 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 [9]. 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 $h : S \rightarrow \mathbb{R}^M$ 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 $\tau$ 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



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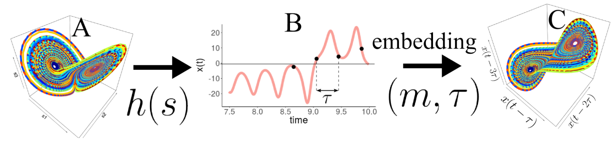


**Figure 1. A.** $M-$**dimensional state space** $s(t)$**; B.** $1-$**dimensional measurament time series** $x(t)$**; and C.** $N-$**dimensional reconstructed state space** $v(t)$ **where** $M \geq N$ **[7].**

some time-varying system which 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 source of 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 $\tau$)
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. [8] estimated that the minimal embedded dimension ($m_{min}$) with False Nearest Neighbours (FNN) method. However, Cao [3] pointed out that FNN algorithm introduces two parameters ($R_{tol}$ and $A_{tol}$) that lead to different results when distinguishing random series from deterministic series. Additionally, Sama et al. [8] states that the minimal embedding parameters largely depend on the structure (amplitude, frequency, nonlinearity) of the time series. Thus, there is still research to be done to find optimus values of the minimal dimension parameters ($m_{min}$ and $\tau_{min}$) to reconstruct the state space.

### $E1(d)$ and $E2(d)$ values
In this work, we follow the Cao's method [3] to compute the minimal embedding dimension. Cao's method is based on the mean values of $E1(d)$ and $E2(d)$ where $d$ is the range of evaluation for the embedding dimension. Therefore, $E1(d)$ is used to obtain the minimal dimension $m_{min}$ where 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 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 $\tau$ .

## 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 $\pm 40^{\circ}$ horizontally and $\pm 30^{\circ}$ vertically [5]. 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 for upper arm movements, we also observed (by eye) that efects like boredoom, fatigue or level of engagment might also be a factor that influence the way each vary beetween persons and within person. 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 more realiable metrics to measure such variability.

### Participants and Procedure

In this experiment, we only collected data for eigth male right-handed healthy participant (age 22+-1) and ten female (age 25 +-1). 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 designed an experiment where the user(s) imitate NAO robot' arm movements at a constant speed of 30 frames per seconds. Such experiment were performed for ten 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.

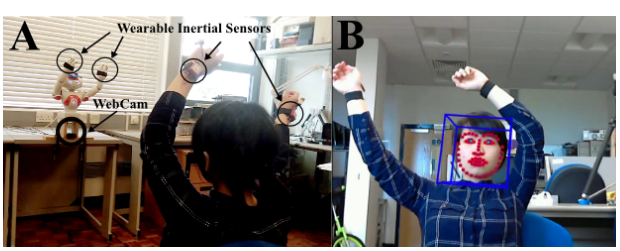


**Figure 2. A. Experimental setup: face-to-face imitation with NAO humanoid robot; B. Head pose estimation with OpenFace [2]**

### Head Pose Estimation

#### 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 ($\lambda_1,\ldots,\lambda_m$), eigenvectors ($v_1,\ldots,v_m$) and the principal components ($PC_1,\ldots,PC_m$) of the time-delay embedded phase space.

## 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.

* I am analising the data for the previos time-series as well as the data from the IMUS for the robot and the persons.

## CONCLUSION

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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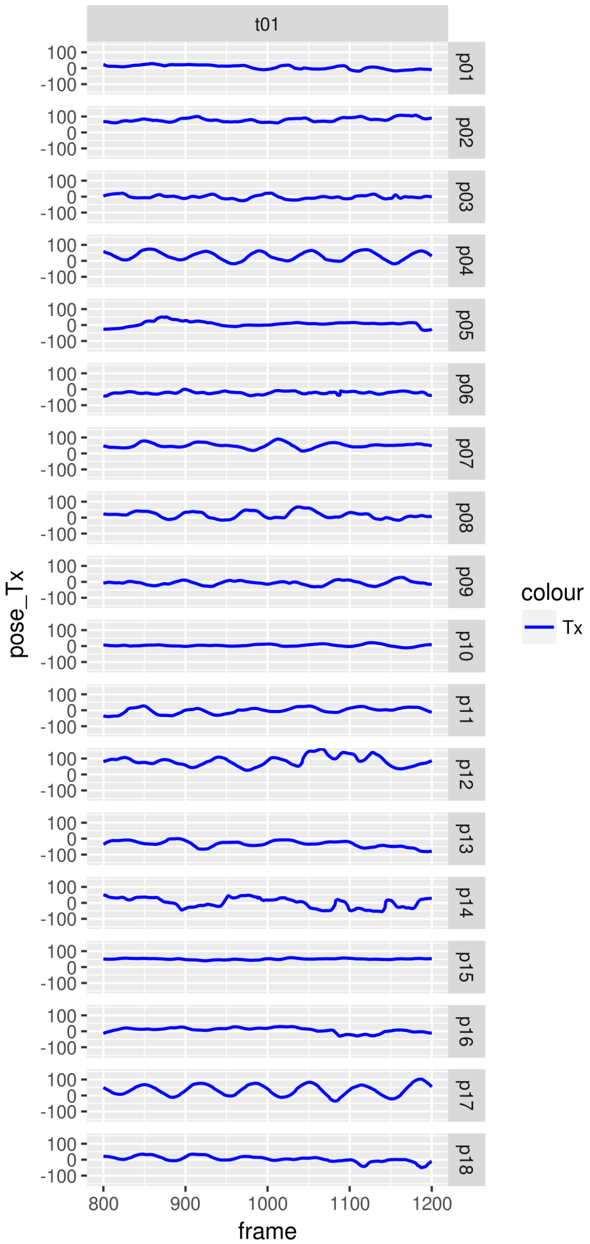


**Figure 3. Head Pose Estimation in the Tx axis for 18 participants**


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