

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



Miguel P Xochicale  
@\_mxochicale



Chris Baber

Department of Electronic, Electrical and Systems Engineering  
University of Birmingham, UK

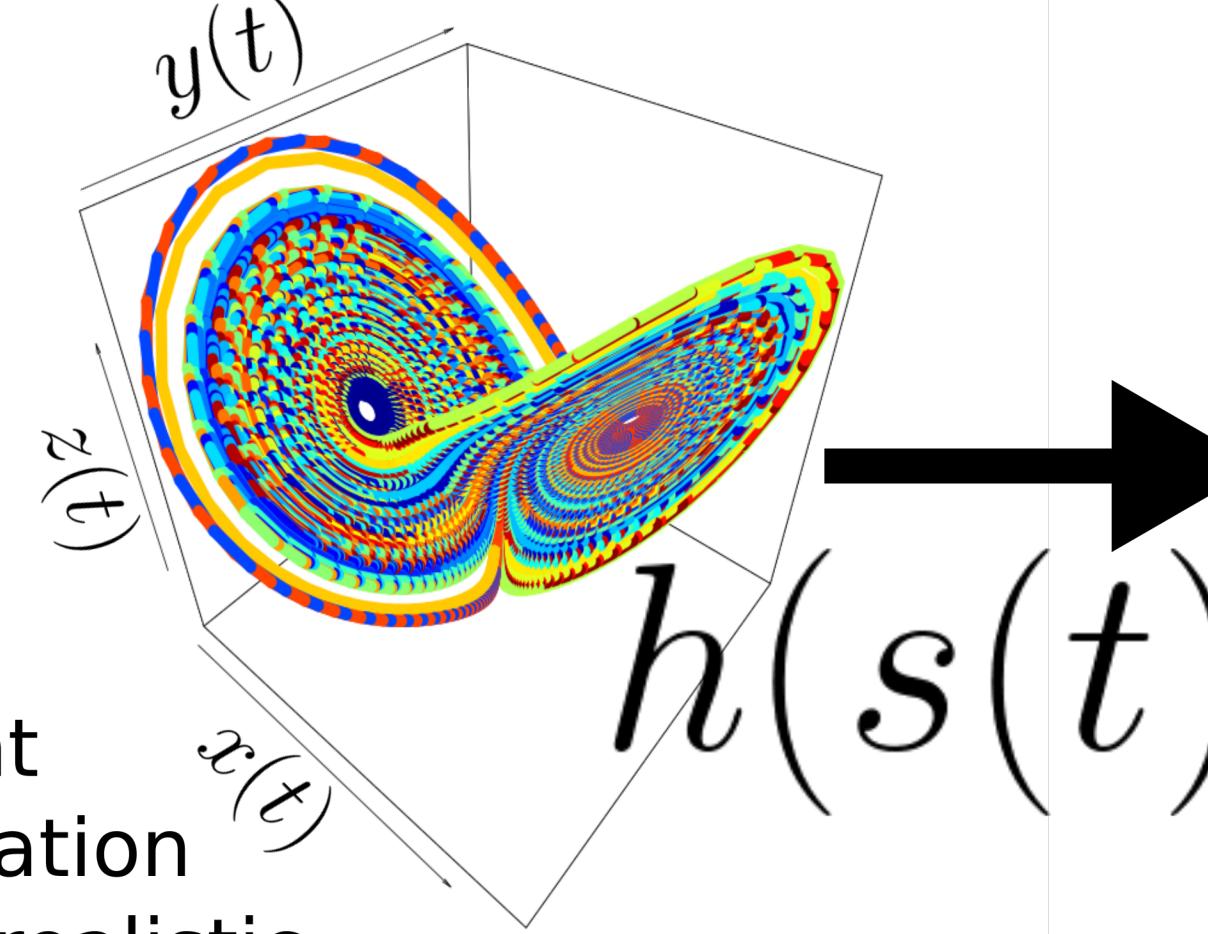


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## 1. Introduction

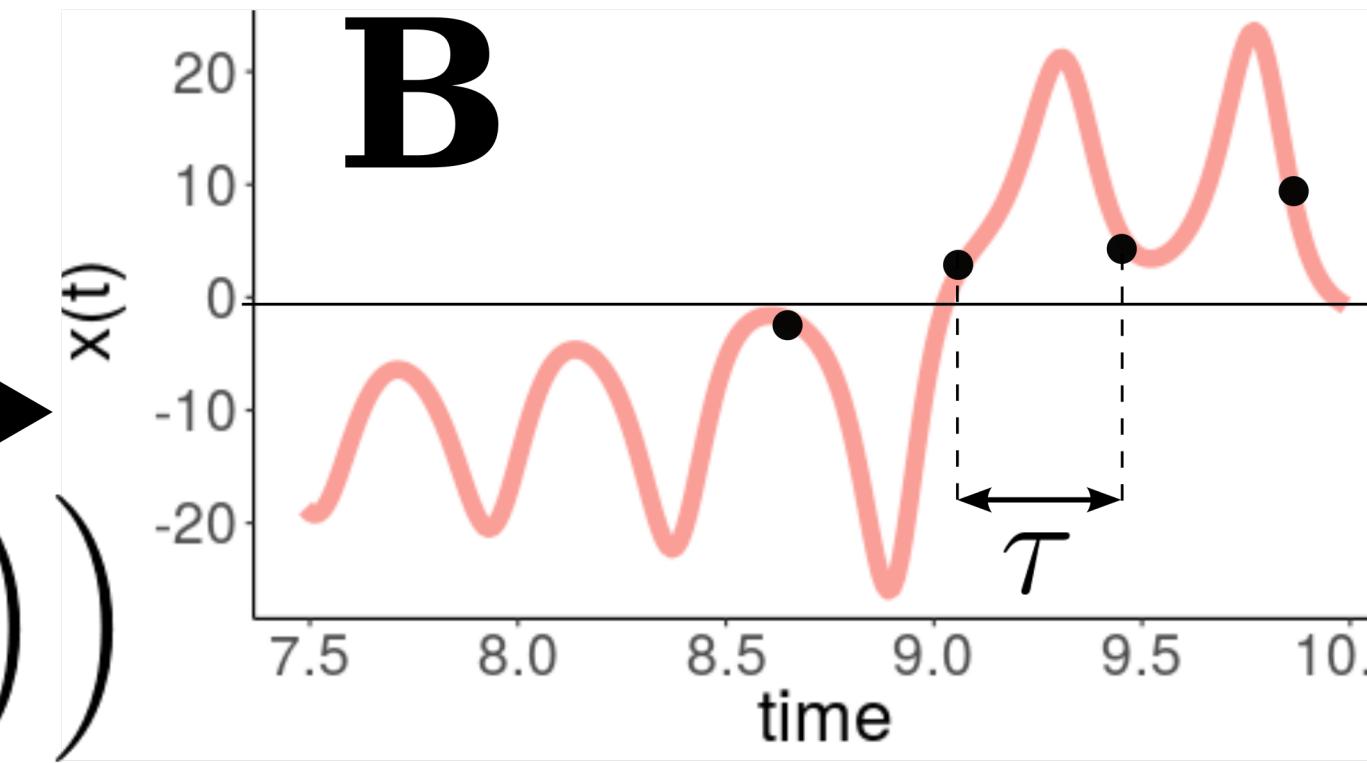
Movement variability is an inherent feature within a person and between persons movements [1]. Due to the complexity of the human motion activities and the multi-dimensional variables that are involved in such activities, the use of the non-linear dynamics invariants based on the state space reconstruction have been probed to be reliable techniques for a better insight of movement variability [2]. In this work, we have found that there is little research in the area of human-robot interaction where quantification of movement variability requires to be reliable for the creation of better models of interaction and for more realistic scenarios of interaction where the motion capture systems are usually expensive, invasive or take a long-time preparation for calibration.

A



$h(s(t))$

B



embedding  
 $(m, \tau)$

C

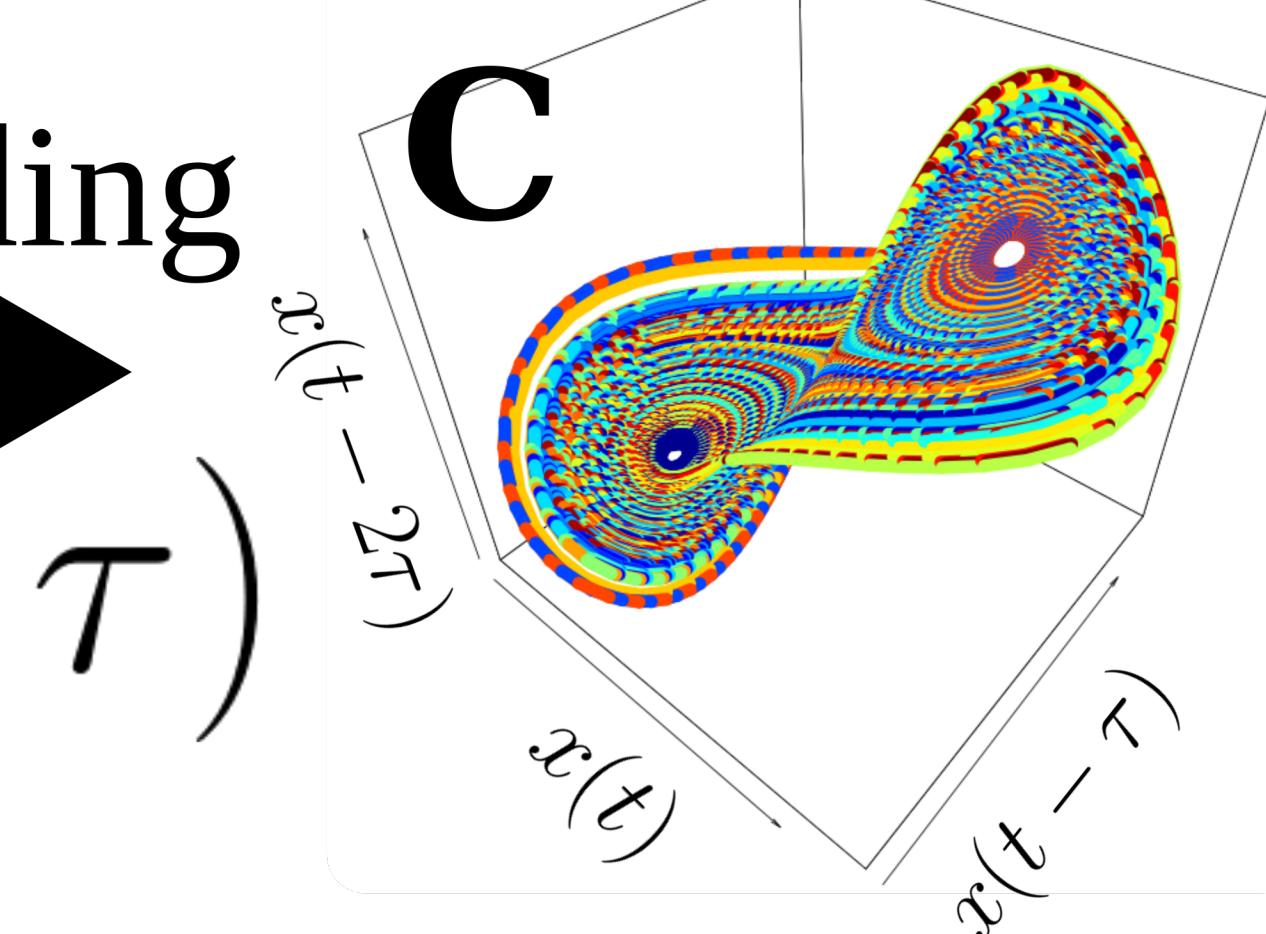


Figure 1. State Space Reconstruction's Theorem. A. unknown  $M$ -dimensional state space; B. 1-dimensional measured time-series  $x(t)$ ; and C.  $N$ -dimensional reconstructed state space  $X(t)$  where  $M \geq N$ .

## 2. Methods: State Space Reconstruction's Theorem

The purpose of the State Space Reconstruction's Theorem is to reconstruct an unknown  $M$ -dimensional state space from a 1-dimensional measurement function  $x(t) = h(s(t))$ . The theorem is based on  $m$  delayed copies of  $x(t)$  uniformly separated by  $\tau$ , the theorem is also known as the time-delay embedding and it is defined as a matrix  $X(t) = \{x(t), x(t - \tau), x(t - 2\tau), \dots, x(t - (m - 1)\tau)\}$  where  $(m, \tau)$  are the embedding parameters [3].

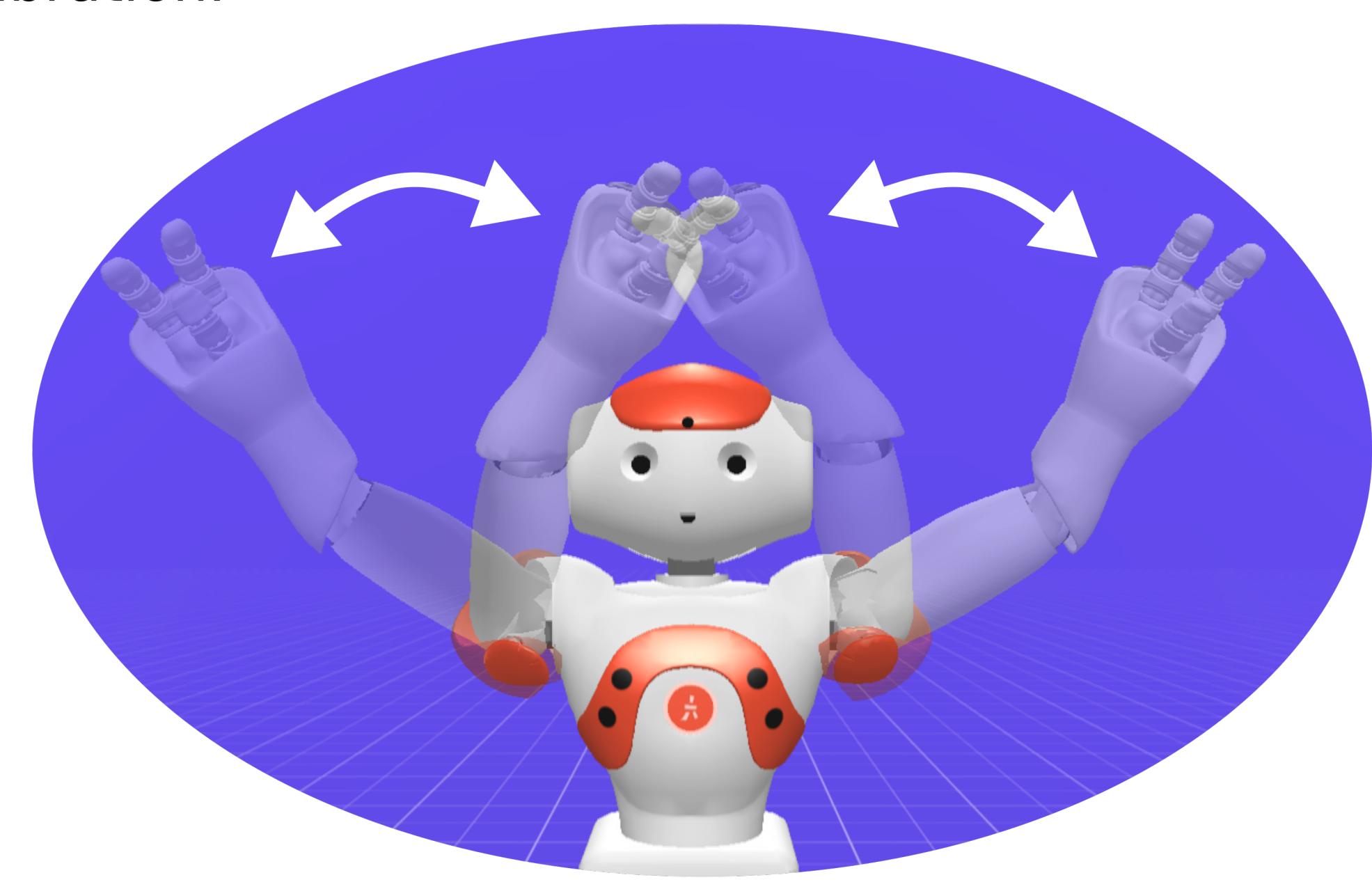


Figure 2. NAO's arm movement

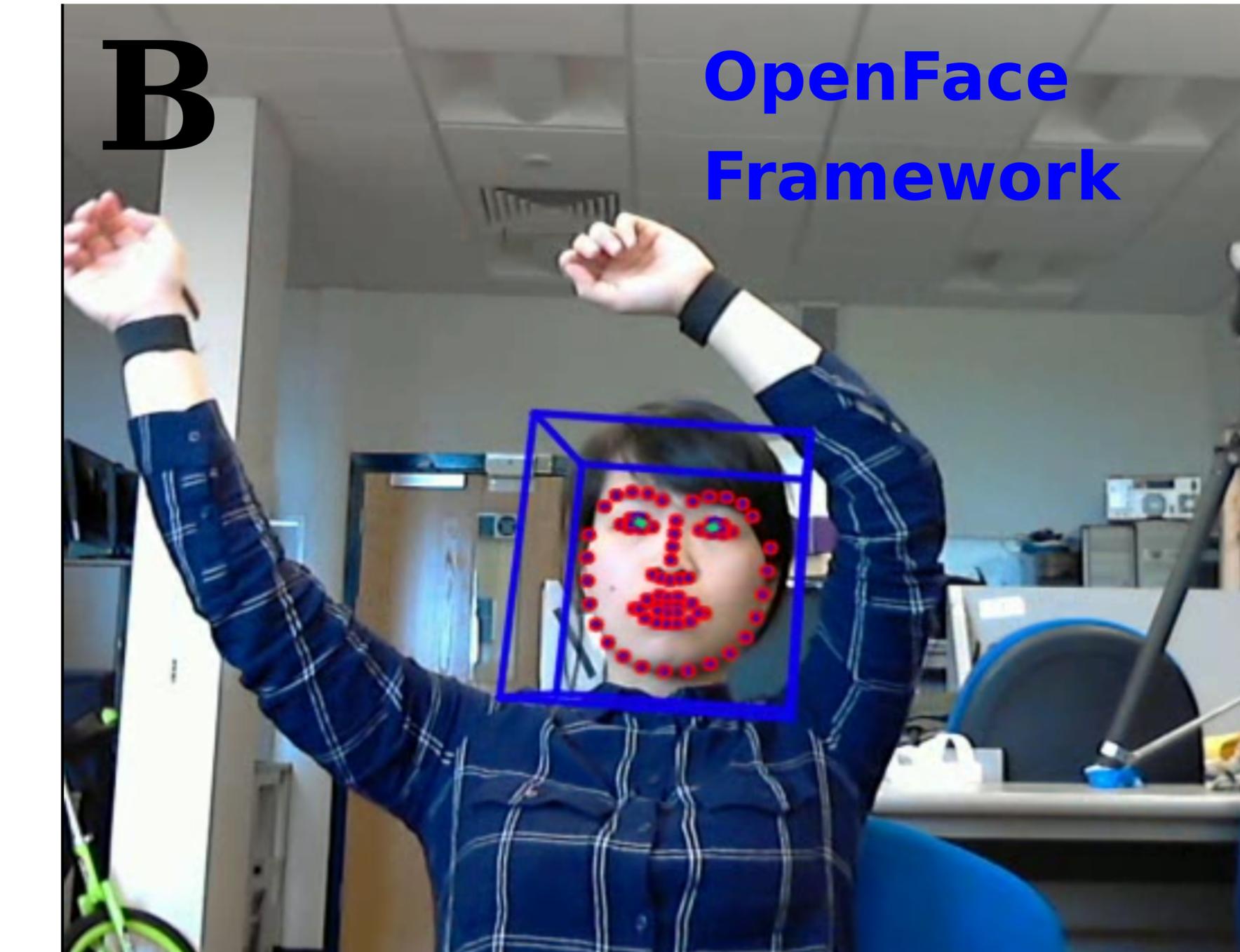
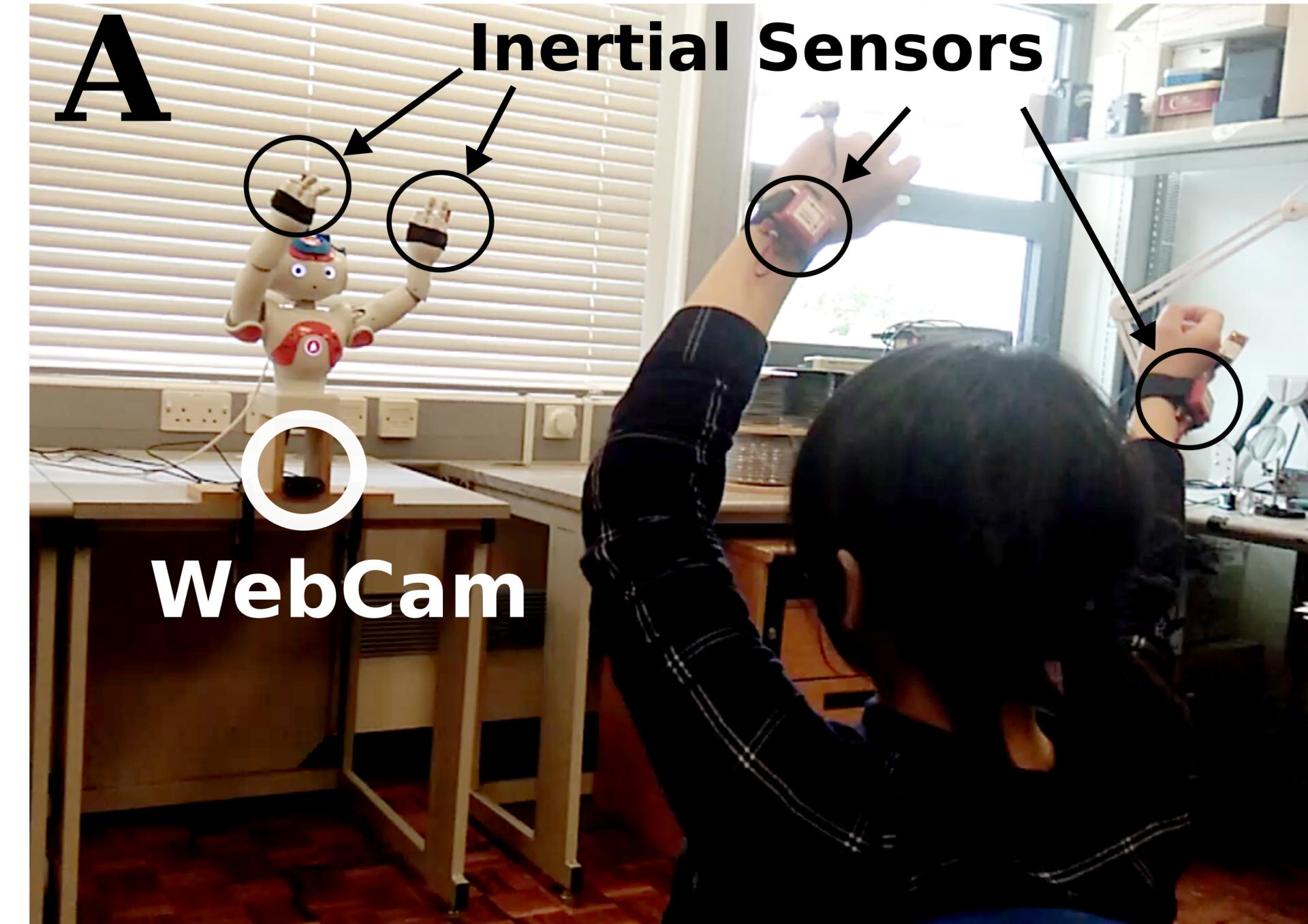


Figure 3.A. Front to front Human-Humanoid Imitation Activity with upper arm movements where the participant(s) and NAO worn inertial sensors. B. OpenFace framework [4] for head pose estimation.

## 4. Results and Discussion

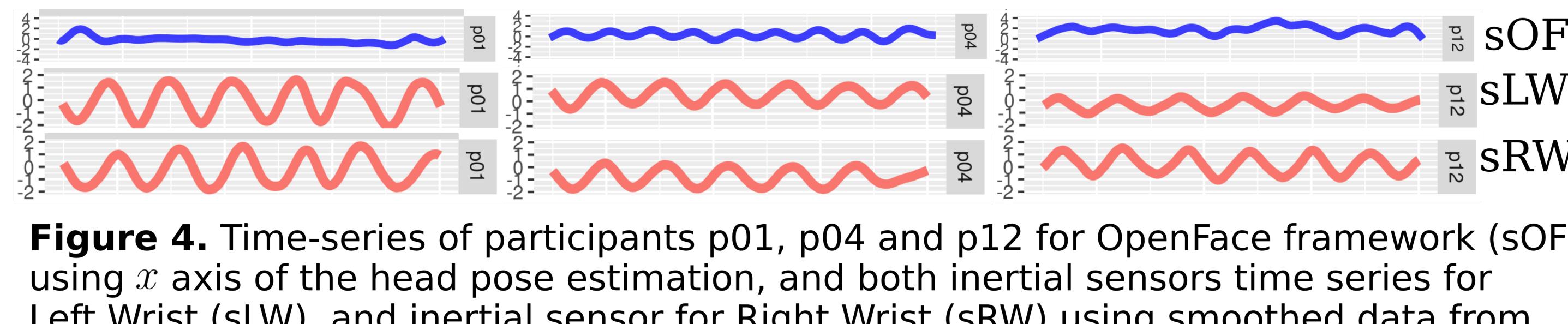


Figure 4. Time-series of participants p01, p04 and p12 for OpenFace framework (sOF) using  $x$  axis of the head pose estimation, and both inertial sensors time series for Left Wrist (sLW), and inertial sensor for Right Wrist (sRW) using smoothed data from accelerometer in  $x$  axis.

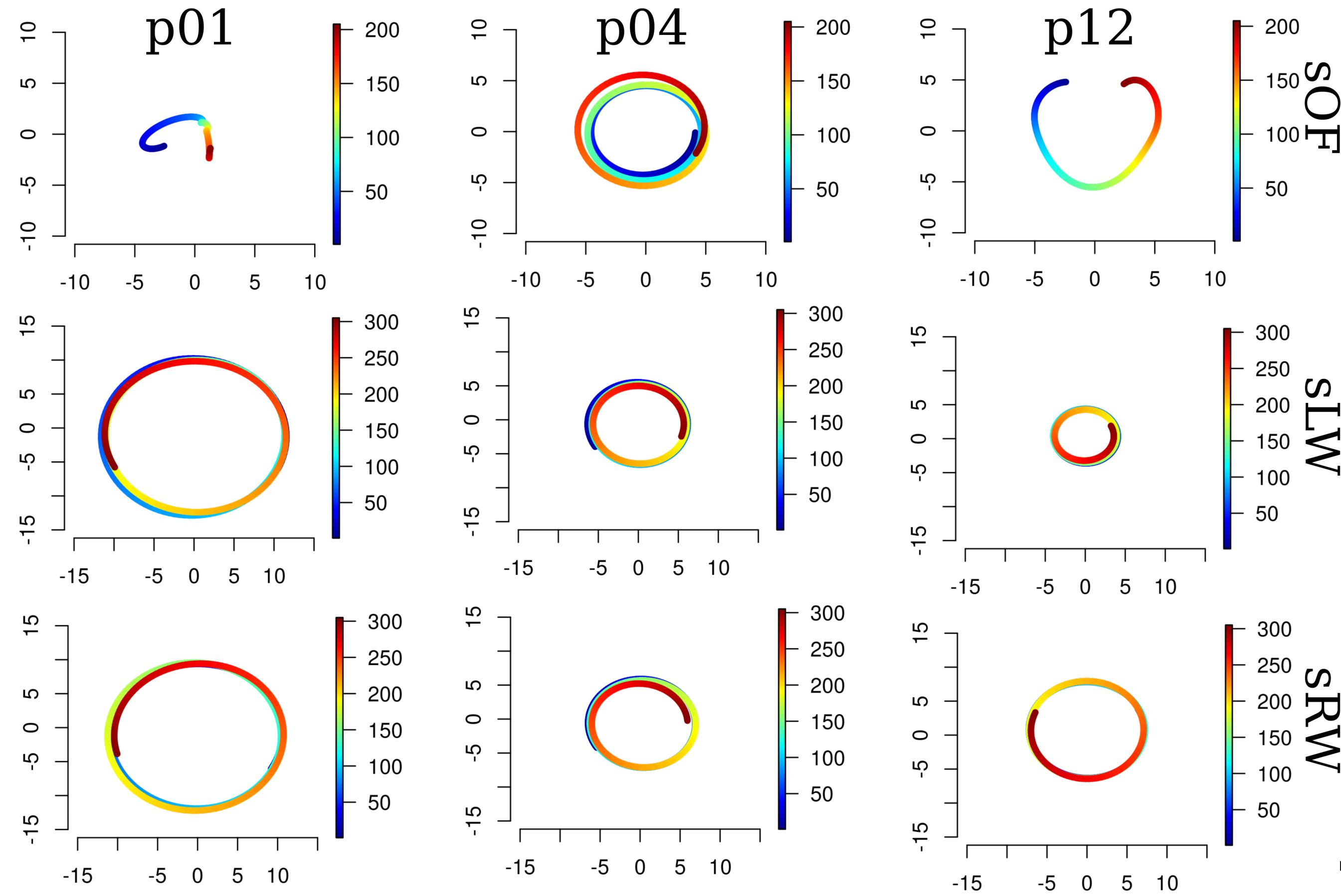


Figure 5. 2-D state space reconstruction with  $m = 100$  and  $\tau = 4$  for p01, p04 and p12 using the time-series of sOF, sLW and sRW.

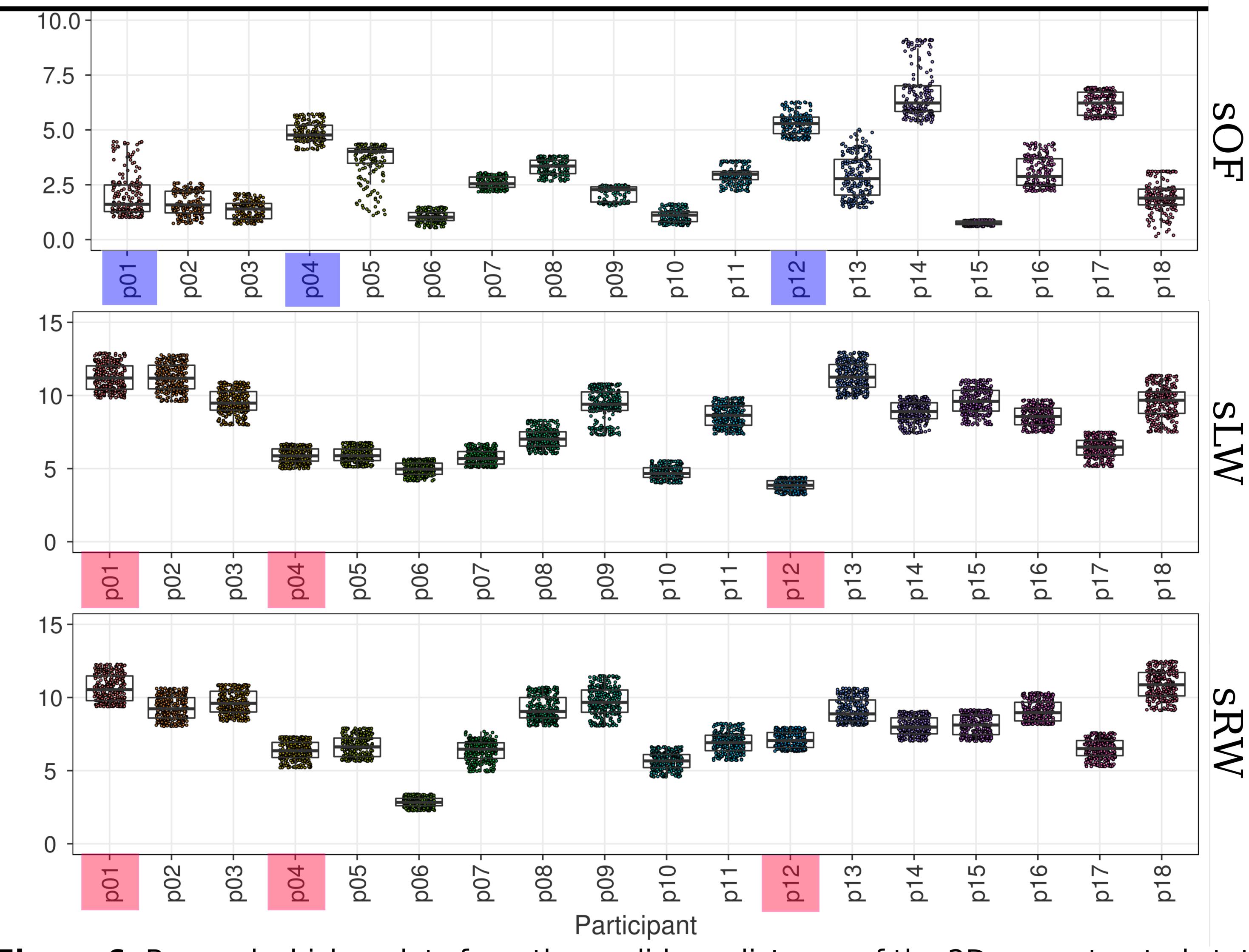


Figure 6. Box and whisker plots from the euclidean distance of the 2D reconstructed state space for Head Pose estimation (sOF), left wrist sensor (sLW) and right wrist sensor (sRW).

## 5. Conclusion and Future work

We not only presented visual differences of movement variability for arms and head pose between eighteen participants, but also we quantified such movement

variability using the state space reconstruction's theorem. Considering that the participants were young healthy subjects, we quantified that participants p06 and p12 did not imitate NAO well because their arms moved assymetrically and p04 and p17 moved their head while NAO's head was static. With this in mind, we believe that such results are promising for applications in rehabilitation, sport science, entertainment or education.

In future experiments, we intend to investigate: (i) the variability of motions and emotions in a one-to-one and one-to-many human-humanoid interactions; (ii) the exploration of more complex movements; (iii) the collection of data from a wider range of individuals; &, (iv) the application of deep learning techniques for the automatic classification of the movement variability.

## 6. References

- [1] K. M. Newell and D. M. Corcos. 1993. *Variability and Motor Control*. Human Kinetics Publishers
- [2] Juan-Carlos Quintana-Duque. 2012. *Non-linear Dynamic Invariants Based on Embedding Reconstruction of Systems for Pedaling Motion*. In 9. Symposium der dvs-Sektion Sportinformatik, Univ. Konstanz.
- [3] L. C. Uzal, G. L. Grinblat and P. F. Verdes. 2011. *Optimal Reconstruction of dynamical systems: A noise amplification approach*. Physical Review E - Statistical Nonlinear and Soft Matter Physics 84, 1 (2011).
- [4] Tadas Baltrušaitis, Peter Robinson, and Louis-Philippe Morency. 2016. OpenFace: an open source facial behavior analysis toolkit. In IEEE Winter Conference on Applications of Computer Vision.



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