...Movement Variability in Human-Humanoid Imitation

Leave Author Anonymous[*]
Institute for Clarity in Documentation
City, Country
e-mailaddress

Leave Author Anonymous
Institute for Clarity in Documentation
City, Country
e-mailaddress

Leave Author Anonymous
The Thørväld Group
City, Country
e-mailaddress

ABSTRACT

This paper provides a sample of a LaTeX document which conforms, somewhat loosely, to the formatting guidelines for ACM SIG Proceedings.[1]

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability;

KEYWORDS

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

ACM Reference format:
Leave Author Anonymous, Leave Author Anonymous, and Leave Author Anonymous. 2018. ...Movement Variability in Human-Humanoid Imitation. In *Proceedings of HRI conference, Chicago, USA, March 2018 (HRI'18),* 3 pages.
https://doi.org/10.475/123_4

1 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]

[*]Dr. Trovato insisted his name be first.
[1]This is an abstract footnote

2 METHOD

2.1 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 $h : S \to \mathbb{R}^M$ is a measurement function on the unknown dynamical system, being $x(t)$ observable (Figure 1).

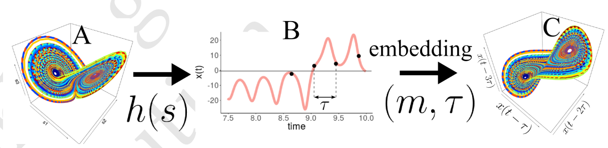

Figure 1: A. $M-$dimensional complex system $s(t)$; B. $1-$dimensional measurement $x(t)$; and C. $N-$dimensional complex system $v(t)$ where $M \geq N$

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 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.

2.2 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.

2.3 $E1(d)$ 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 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].

3 EXPERIMENT DESIGN

3.1 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 ±40° horizontally and ±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].

4 EXPERIMENT

4.1 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.

4.2 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 designed 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 for 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.

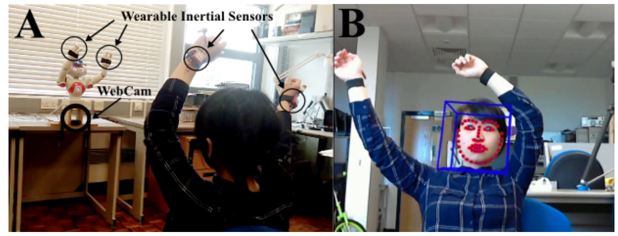

Figure 2: A. Experimental setup: face-to-face imitation with NAO humanoid robot; B. Head pose estimation with OpenFace [2]

5 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).

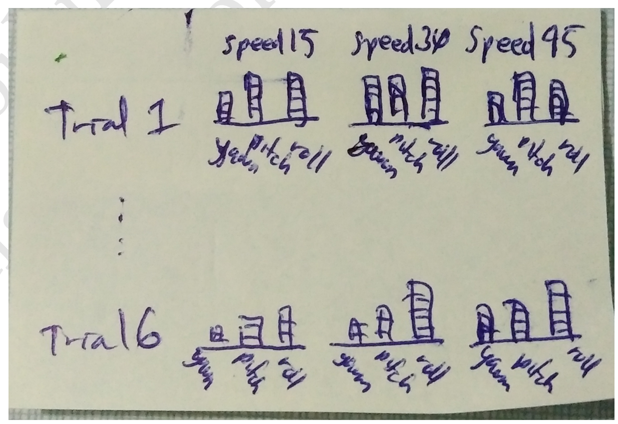

Figure 3: Head Pose Estimation of six trials at three speeds 15, 30 and 45

6 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.

7 CONCLUSIONS

This paragraph will end the body of this sample document. Remember that you might still have Acknowledgments or Appendices; brief samples of these follow. There is still the Bibliography to deal with; and we will make a disclaimer about that here: with the exception of the reference to the LaTeX book, the citations in this paper are to articles which have nothing to do with the present subject and are used as examples only.

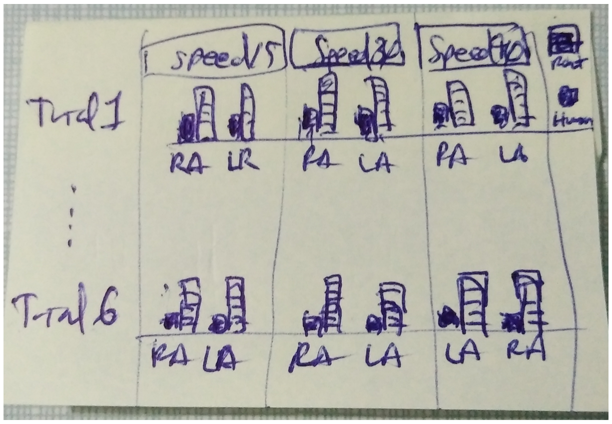

Figure 4: Right Arm (RA) and Left Arm (LA) from Human and robot arm movememtns of six trials at three speeds 15, 30 and 45

ACKNOWLEDGMENTS

The authors would like to thank Dr. Yuhua Li for providing the matlab code of the *BEPS* method.

The authors would also like to thank the anonymous referees for their valuable comments and helpful suggestions. The work is supported by the National Natural Science Foundation of China under Grant No.: 61273304 and Young Scientsts' Support Program (http://www.nnsf.cn/youngscientsts).

XXX gratefully acknowledges XXX for pursuing his doctoral studies at University of XXX. Special thanks is also extended to XXX from XXX at University of XXX for XXX acute critics and suitable comments that are helping the work to give a better shape to the scientific value of knowledge of my research endevours.

REFERENCES

[1] Author A, Author B, and Author C. 2017. Title. In *Booktitle*.

[2] 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*.

[3] R. Blake and M. Shiffrar. 2007. Perception of Human Motion. In *Annual Review of Psychology*, Vol. 9. Annual Reviews, 47–73.

[4] Ty W. Boyer, Josita Maouene, and Nitya Sethuraman. 2017. Attention to body-parts varies with visual preference and verb–effector associations. *Cognitive Processing* 18, 2 (2017), 195–203.

[5] J. F. Brown. 1931. The visual perception of velocity. *Psychologische Forschung* 14, 1 (1931), 199–232.

[6] Liangyue Cao. 1997. Practical method for determining the minimum embedding dimension of a scalar time series. *Physica D: Nonlinear Phenomena* 110 (1997), 43–50.

[7] Jordan Frank, Shie Mannor, and Doina Precup. 2010. Activity and Gait Recognition with Time-Delay Embeddings Time-Delay Embeddings. *AAAI Conference on Artificial Intelligence* (2010), 407–408.

[8] David J Herzfeld and Reza Shadmehr. 2014. Motor variability is not noise, but grist for the learning mill. *Nat Neurosci* 17, 1 (2014), 149–150.

[9] Barbara La Scaleia, Myrka Zago, Alessandro Moscatelli, Francesco Lacquaniti, and Paolo Viviani. 2014. Implied Dynamics Biases the Visual Perception of Velocity. *PLOS ONE* 9, 3 (03 2014), 1–15.

[10] S. Lemaignan, F. Garcia, A. Jacq, and P. Dillenbourg. 2016. From real-time attention assessment to "with-me-ness" in human-robot interaction. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 157–164.

[11] K.M. Newell and D.M. Corcos. 1993. *Variability and Motor Control*. Human Kinetics Publishers.

[12] Pierre Pica, Stuart Jackson, Randolph Blake, and Nikolaus F. Troje. 2011. Comparing Biological Motion Perception in Two Distinct Human Societies. *PLOS ONE* 6, 12 (12 2011), 1–6.

[13] Muhammad A.J. Qadri and Robert G. Cook. 2017. Pigeons and humans use action and pose information to categorize complex human behaviors. *Vision Research* 131 (2017), 16 – 25.

[14] Albert Samà, Francisco J. Ruiz, Núria Agell, Carlos Pérez-López, Andreu Català, and Joan Cabestany. 2013. Gait identification by means of box approximation geometry of reconstructed attractors in latent space. *Neurocomputing* 121 (2013), 79–88.

[15] 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).