

...Movement Variability in Human-Humanoid Imitation

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ABSTRACT

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ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; See <http://acm.org/about/class/1998/> for the full list of ACM classifiers. This section is required.

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 [8]. Recently, Herzfeld et al. [6] conducted experiments to argue that movement variability is not only noise but a source of movement exploration which at certain point is becoming a source of movement exploration. 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 movement variability.

...I AM READING THESE PAPERS TO COMPLETE THE INTRODUCTION: Perception of Human Motion [1]. Pigeons and humans use action and pose information to categorize complex human behaviors [10]. The visual perception of velocity [3]. Implied Dynamics Biases the Visual Perception of Velocity [7]. Attention to body-parts varies with visual preference and verb-effector associations [2]. Comparing Biological Motion Perception in Two Distinct Human Societies [9]

METHOD

Reconstructed State Space

In this work we follow the notation employed in [12]. 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).

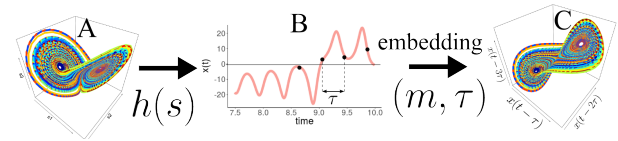


Figure 1. A. M -dimensional complex system $s(t)$; B. 1-dimensional measurement $x(t)$; and C. N -dimensional complex system $v(t)$ where $M \geq N$

Thus, the time delay reconstruction in m dimensions with a time delay τ is defined as: $\bar{x}(t) = (x(t), x(t-\tau), \dots, x(t-(m-1)\tau))$. 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. [11] estimated that the minimal embedded dimension (m_{min}) with False Nearest Neighbours (FNN) method. However, Cao [4] 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. [5] proposed a grid search method to find the minimal embedded parameters, but there are little details about their approach. Additionally, Sama et al. [11] 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

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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 [4].

CONCLUSION

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Sample text: We thank all the volunteers, and all publications support and staff, who wrote and provided helpful comments on previous versions of this document.

REFERENCES FORMAT

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REFERENCES

1. R. Blake and M. Shiffrar. 2007. Perception of Human Motion. In *Annual Review of Psychology*, Vol. 9. Annual Reviews, 47–73.
2. 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.
3. J. F. Brown. 1931. The visual perception of velocity. *Psychologische Forschung* 14, 1 (1931), 199–232.
4. Liangyue Cao. 1997. Practical method for determining the minimum embedding dimension of a scalar time series. *Physica D: Nonlinear Phenomena* 110 (1997), 43–50.
5. 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.
6. 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.
7. 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.
8. K.M. Newell and D.M. Corcos. 1993. *Variability and Motor Control*. Human Kinetics Publishers.
9. 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.
10. 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.
11. 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.
12. 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).