Towards the Automatic Clasification of Movement Variability

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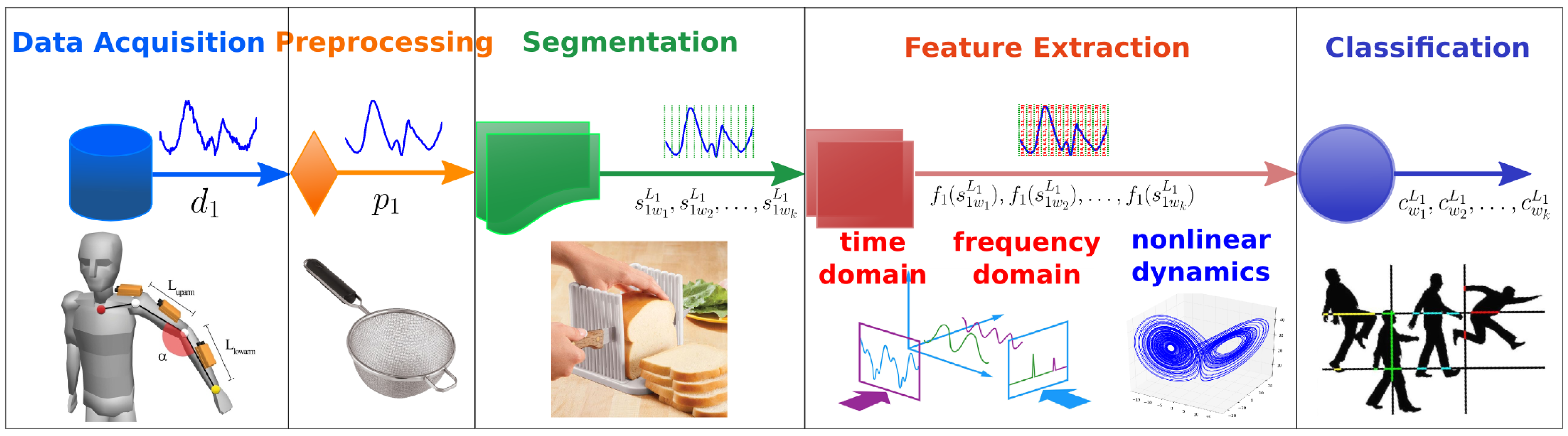
Introduction

Movement Variability is an inherent characteristic of human movement [1]. Generally, humans perform the same action slightly differently trial by trial which is a common challenge in Human Activity Recogtion (HAR). However, little research has been done in order to automatically measure such movement variability in HAR [2]. For the current work, I am focusing on the extraction of simple features in time-domain, frequency domain and nonlinear dynamics domain in order to provide insight into the movement variability across persons and inter-trial variability in dance activities.

Human Activity Recognition Chain

Bulling *et al.* [2] reviewed the state-of-the-art of HAR to identify activities from body-worn intertial sensors.

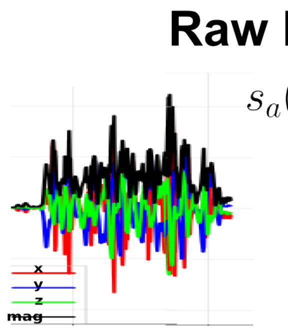


Adapated from Banõs *et al.* [5].

Materials and Methods

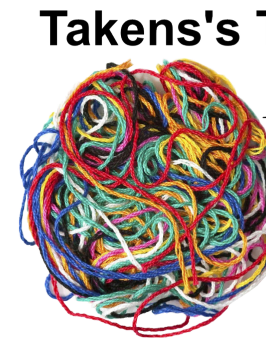
Raw data is collected from a triaxial accelerometer and gyroscope $(a_x, a_y, a_z, g_x, g_y, g_z)$. Then, a N samples length time-series, e.g. a_x, is used to obtain *(i)* mean and standard deviation; *(ii)* frequency DC component and Power Spectrum Energy and; *(iii)* the time-delay embedded matrix, $E\{a_x\}$, with $m = 20$ and $\tau = 3$ [3, 4], to which PCA is applied to $E\{a_x\}$ to compute the percentage cumulative energy (PCE) [6].

Raw Data: $s_a(n)$



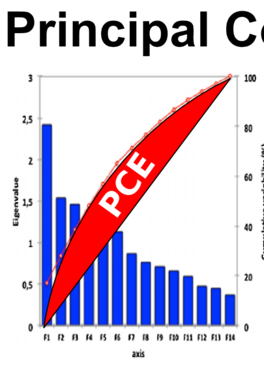
$s_a(n) = \{s_a(1), \ldots, s_a(L)\}$
$s =$ sensor (acc,mag,gyr)
$a =$ axis (x,y,z)
$n =$ index
$L =$ window length

Takens's Theorem: $E^{\tau}_m\{s_a(n)\}$



$E^{\tau}_m\{s_a(n)\} = \{s_a(n), \ldots, s_a(n-(m-1)\tau)\}$
$E^{\tau}_m =$ Embedded Matrix
$\tau =$ Time-delay
$m =$ Dimension

Principal Component Analysis



$\mathrm{PCA}[E^{\tau}_m\{s_a(n)\}] = (\lambda_i, v_i)$
$\lambda_i =$ Eigenvalues
$v_i =$ Eigenvectors

Conclusion and Outlook

Although the time-delay embedding technique is subject to different m and τ values which are related to the length and complexity of the time-series, the reconstructed state spaces are giving us insights into movement variability for simple dance steps of thirteen novice dancers.

We showed that the use of time-domain, frequency domain and nonlinear dymanics are giving us insight into the movement variability across participants.

From this, there are three areas that we are going to investigate:

- Collect data from a wider range of individuals (gender and age) and from additional sensors,
- Undertake a wider review of nonlinear techniques that can be used for the assessment of variability using wearable sensors, and
- Explore the use of Hidden Markov Models (HMM) and Deep Neural Networks (DNN) for automatic recognition of the movement variability.

References

[1] Karl M. Newell and Daniel M. Corcos. 1993. Variability and motor control. Human Kinetics Publishers.

[2] Andreas Bulling, Ulf Blanke and Bernt Schiele. 2014. A tutorial on human activity recognition using body-worn inertial sensors. In *ACM Computing Surveys (CSUR)*, vol. 6, 1-33.

[3] Jordan Frank, Shie Mannor and Doina Precup. 2010. Activity and Gait Recognition with Time-Delay Embeddings. In *Proceedings of the 24-th AAAI Conference on Artificial Intelligence*, 1581-1586.

[4] 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. In *Neurocomputing*, vol. 121, 79-88.

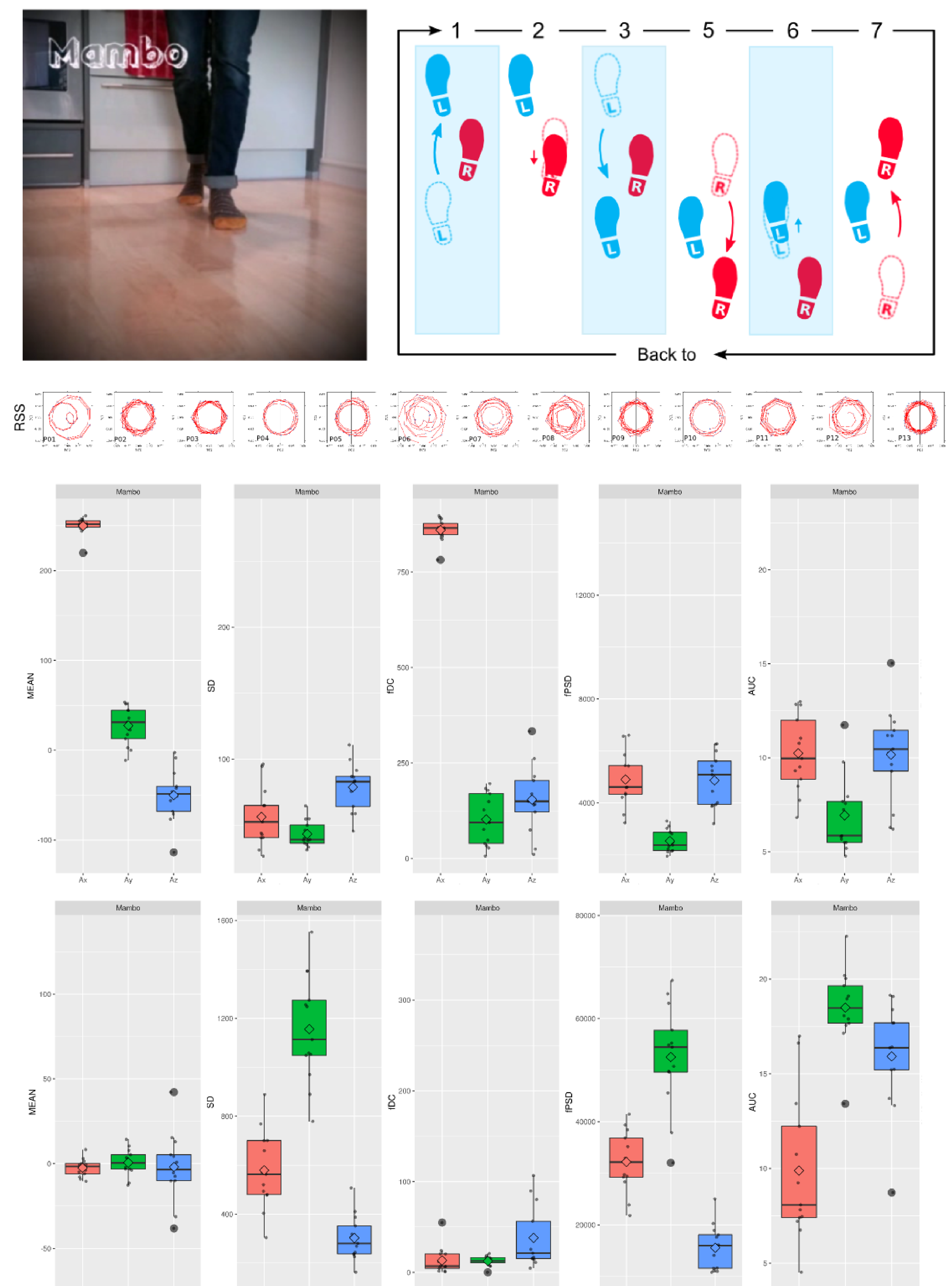
[5] Oresti Banos, Juan-Manuel Galvez, Miguel Damas, Hector Pomares and , Ignacio Rojas. 2014. Window size impact in human activity recognition. In *Sensors (Basel, Switzerland)*, 14, 6474-99

[6] Nils Y Hammerla, Thomas Plötz, Peter Andras and Patrick Olivier. 2011. Assessing Motor Performance with pca. In *International Workshop on Frontiers in Activity Recognition using Pervasive Sensing*, 18-23.

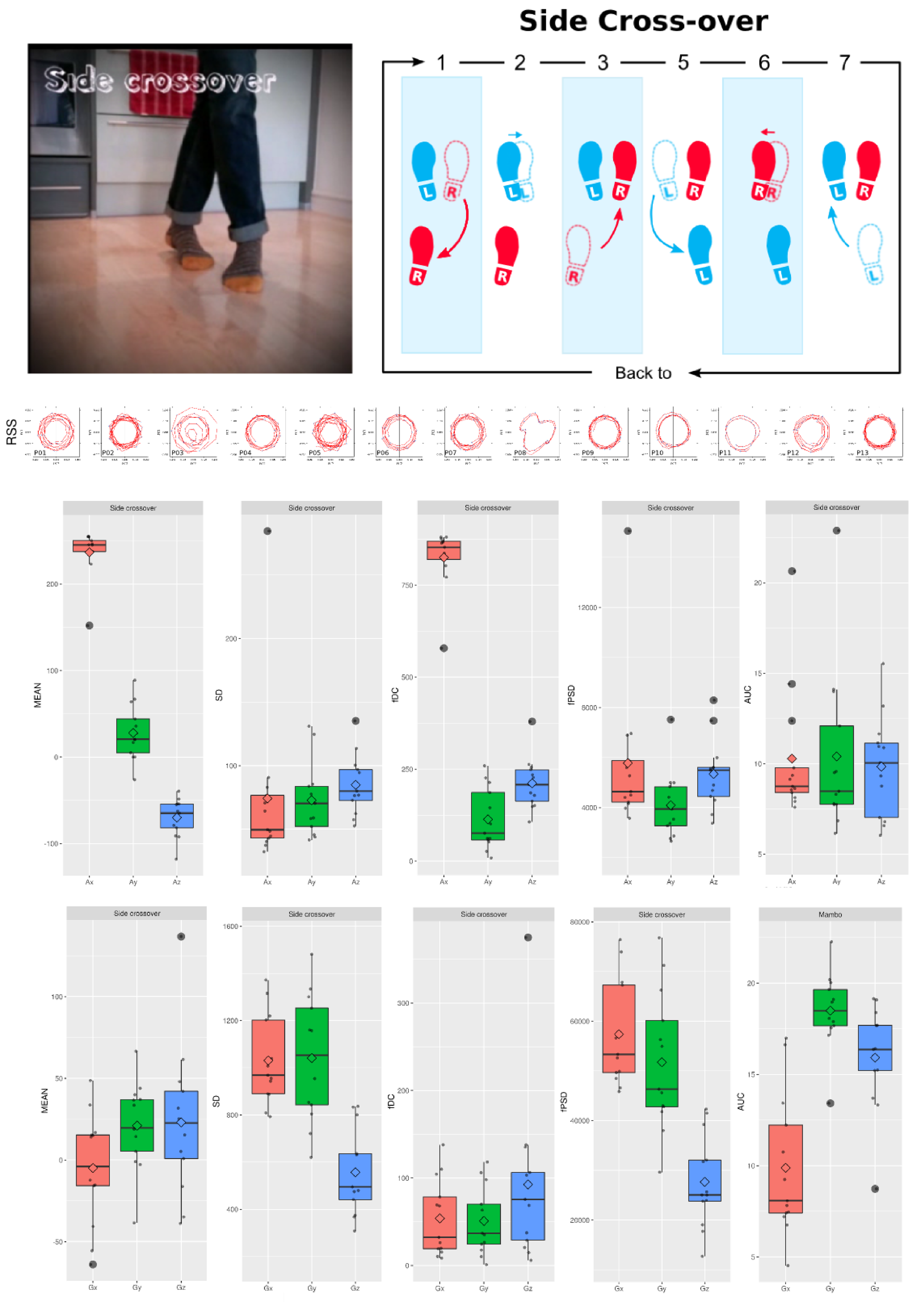
Results

Simple salsa mambo step and side cross-over step were danced by thirteen participans. Reconstructed State Spaces (RSS) are shown for all the novice participants dancing both steps. Similarly, error bars are presented for mean, standard deviadtion (SD), DC frequency (fDC), power spectral density (fPSD) and Area Under the Curve (AUC) of the PCE using the triaxial accelerometer (a_x, a_y, a_z) and triaxial gyroscope (g_x, g_y, g_z) for both steps.

Mambo



Side Cross-over



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