Analysis of the Movement Variability in Dance Activities Using Wearable Sensors

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Outline

Why Movement Variablity in Dance?

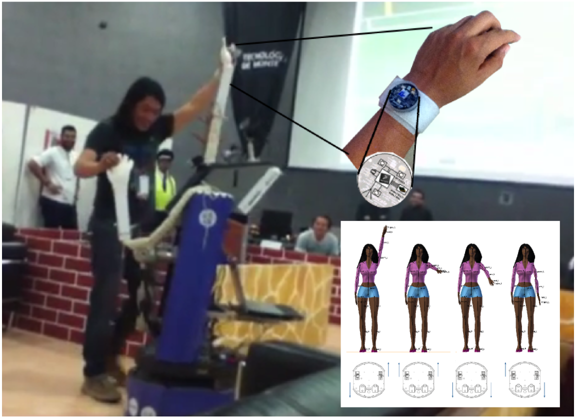

Figure 1: Dance Demo with a Robot at the Mexican Robotics Tournament 2013

Movement Variability

Movement Variability is an inherent feature that occurs not only across but within individuals and across systems of movement **[Newell and Corcos, 1993]** .

Inter-trial Movement Variability

Inter-trial variability (V_{tot}) is a combination of noise (V_e) in

- sensory information and motor output commands (V_{eb})
- changes in the enviromental conditions (V_{ee})
- measuring and data processing techniques (V_{em})

and functional changes that might be associated with the exploration of different stragies to find the most effective one among many available (V_{nl}) **[Preatoni et al., 2013]** .

$$V_{tot} = V_e + V_{nl}$$

Motor Variability is not noise

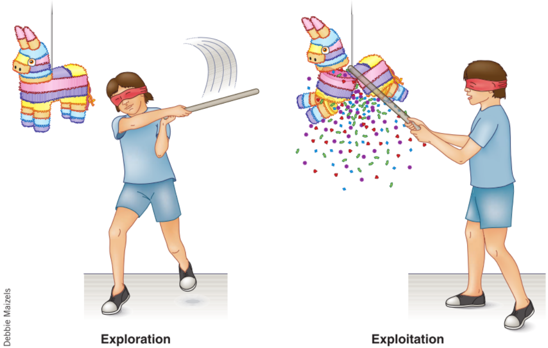

Figure 2: Find the piñata **[Herzfeld and Shadmehr, 2014]** .

Nonlinear Dynamics to Movement Variability

According to **[Preatoni et al., 2013]** , some nonlinear dynamics tools to explore the nature of movement variability and its relationship with skills development are:

- Phase Space Representation
- Lyapunov Exponent.

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Activity Recognition Chain for Inertial Sensors

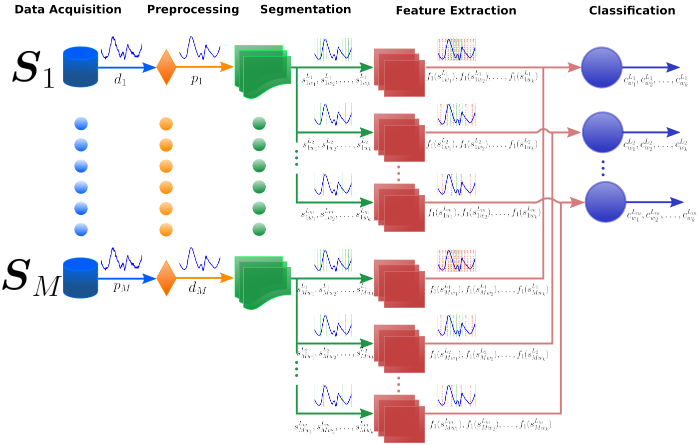

Figure 3: Window Size impact in ARC **[Banos et al., 2014]** .

Feature extraction Using Inertial Sensors

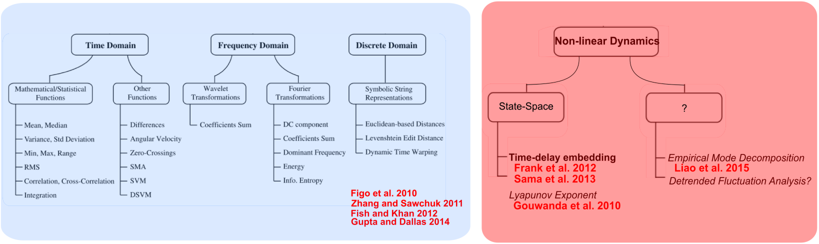

Figure 4: Techniques applied to accelerometer sensor signals for feature extraction [Figo et al., 2010, Liao et al., 2015, Gupta and Dallas, 2014, Fish and Khan, 2012, Zhang and Sawchuk, 2011] .

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Time-delay embedding theorem

For a given discrete time-series $x(n) = [x(1), x(2), \ldots, x(N)]$, a reconstructed state space can be created by

$$\overline{x}(n) = [x(n), x(n-\tau), x(n-2\tau), \ldots, x(n-(m-1)\tau)]$$

which creates a concatenated column-wise matrix of the time-delay versions of the original signal:

$$\mathbf{X} = \begin{pmatrix} x(1) & x(1-\tau) & x(1-2\tau) & \ldots & x(1-(m-1)\tau) \\ x(2) & x(2-\tau) & x(2-2\tau) & \ldots & x(2-(m-1)\tau) \\ \vdots & & & \ddots & \vdots \\ x(N) & x(N-\tau) & x(N-2\tau) & \ldots & x(N-(m-1)\tau) \end{pmatrix}$$

where m is the **embedding dimension** and τ is the **embedding delay** **[Takens, 1981]** .

Time-delay embedding theorem

The time-delay embeddings theorem states that for a large enough m is possible to unfold the attractor and $\tau > 0$ is chosen to maximize the information content of $x(n)$.
False Nearest Neighborhood and Mutual Information algorithms are used to compute the optimal value of m and τ. However, as pointed out by **[Samà et al., 2013]** the optimal values don't neccesarily represent the best rate of recognition.

Principal Component Analysis (PCA)

The Percentage of Cumulative Energy (PCE) is obtained by using the PCA [Hammerla et al., 2011] . For each eigenvalue λ_i, the cummulative energy is

$$C_i = \frac{\Sigma_{j=1}^{i} \lambda_j}{\Sigma_{k=1}^{m} \lambda_k}$$

then, the area under the curve is computed to obtain the PCE.

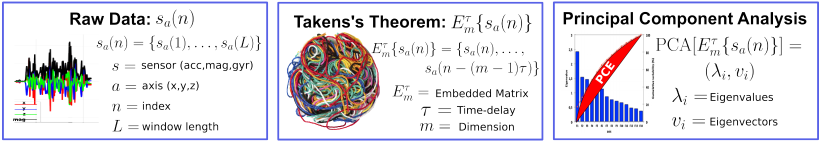

Figure 5: Percentage of Cummulative Energy

Time-delay embedding

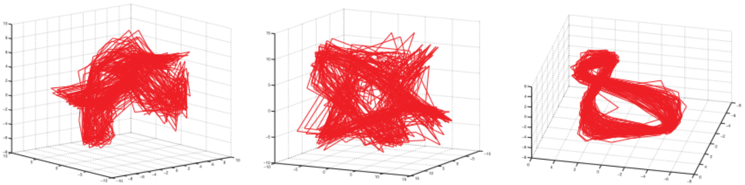

Figure 6: 3-D Reconstructed State Spaces for walking (left), running (middle), and cycling (right) $m = 3$, $\tau = 4$.
[Frank et al., 2010, Frank et al., 2012] .

Time-delay embedding

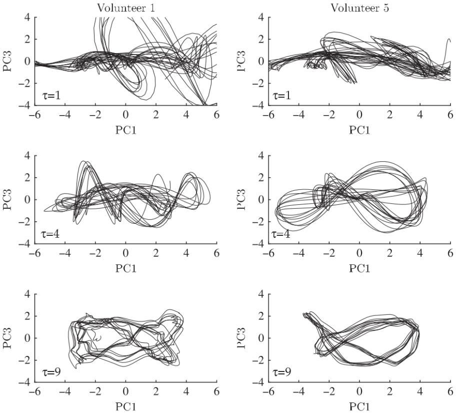

Figure 7: 2-D Reconstructed State Spaces for gait patterns of two persons ($m = 20$ for $\tau = 1$, $\tau = 4$ and $\tau = 9$, respectively). **[Samà et al., 2013]** .

[Time-delay embedding for Emotion Recognition]

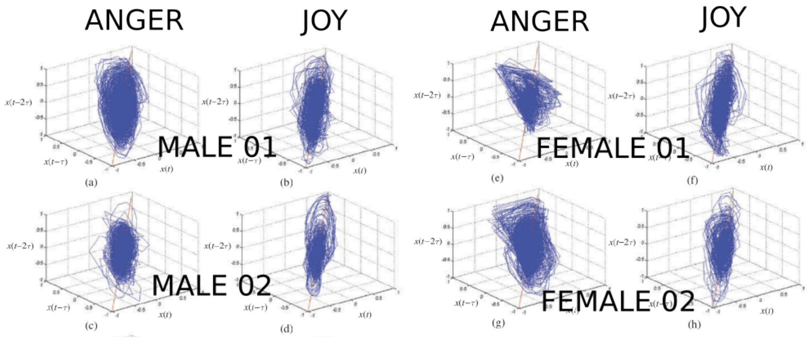

Figure 8: Time delay embeddings for two male and two female expresing sentences of anger and joy ($m = 3$ for $\tau = 1$) **[Harimi et al., 2015]** .

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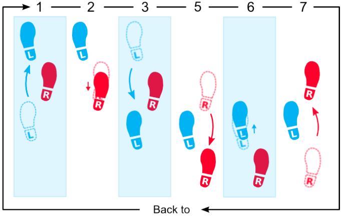
Basic Salsa Steps

Mambo



Side Cross-over

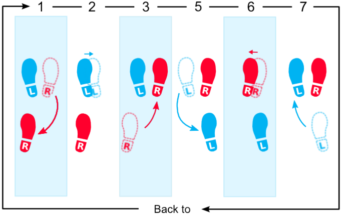


Figure 9:

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Dancers time-series

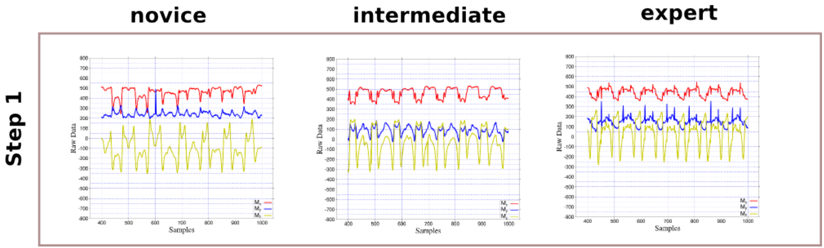

Figure 10:

2-D R

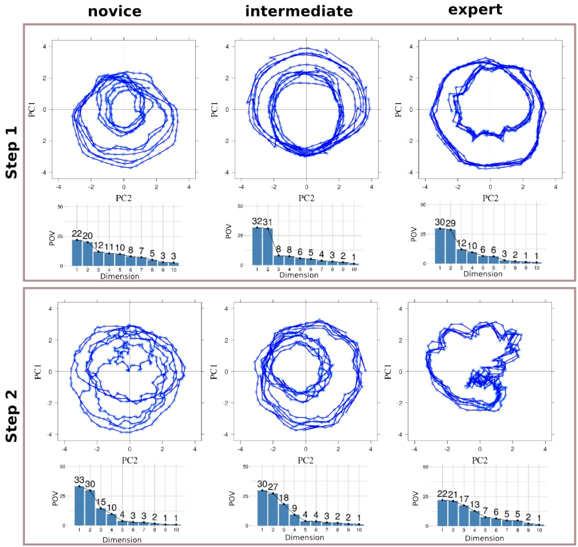

Figure 11:

Segmentation Analysis

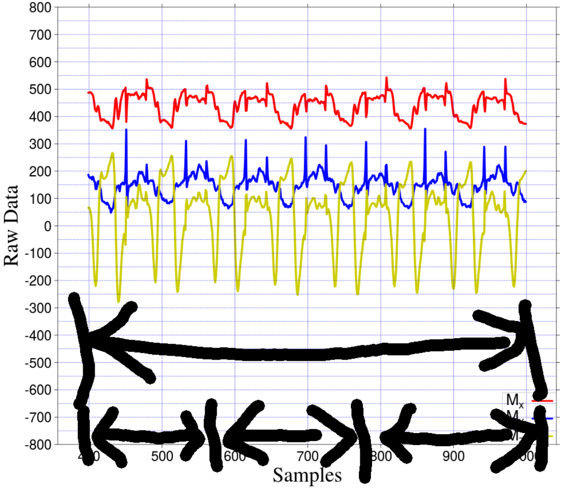

Figure 12:

Novice Dancers time-series

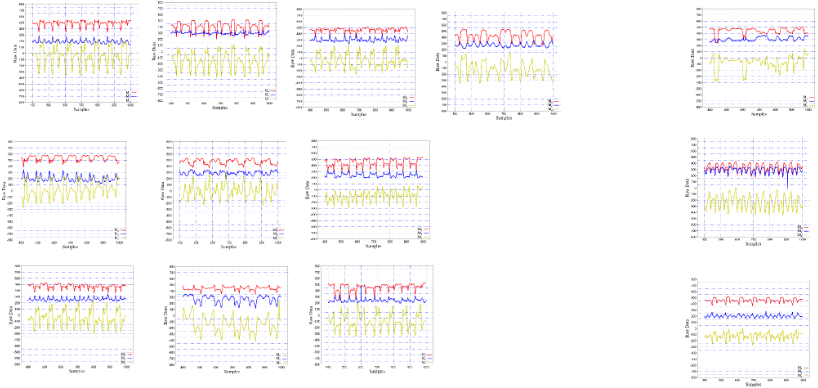

Figure 13:

Future Work

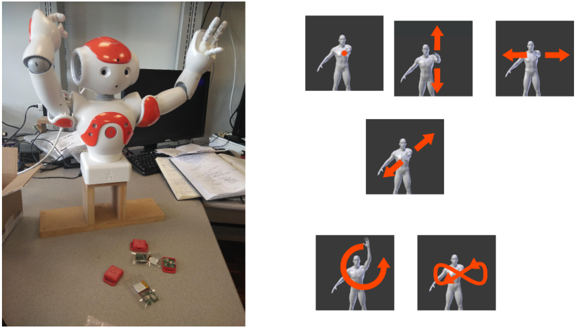

Figure 14: Testing variability across participants

References I

Banos, O., Galvez, J.-M., Damas, M., Pomares, H., and Rojas, I. (2014).
Window size impact in human activity recognition.
Sensors (Basel, Switzerland), 14(4):6474–99.

Bulling, A., Blanke, U., and Schiele, B. (2014).
A tutorial on human activity recognition using body-worn inertial sensors.
ACM Computing Surveys (CSUR), 46(3):1–33.

Figo, D., Diniz, P. C., Ferreira, D. R., and Cardoso, J. M. P. (2010).
Preprocessing techniques for context recognition from accelerometer data.
Personal and Ubiquitous Computing, 14(7):645–662.

Fish, B. and Khan, a. (2012).
Feature selection based on mutual information for human activity recognition.
. . . , Speech and Signal . . ., pages 1729–1732.

Frank, J., Mannor, S., Pineau, J., and Precup, D. (2012).
Time Series Analysis Using Geometric Template Matching.
IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(3):1–1.

References II

Frank, J., Mannor, S., and Precup, D. (2010).
Activity and Gait Recognition with Time-Delay Embeddings.
AAAI Conference on Artificial Intelligence, pages 407–408.

Gouwanda, D. and Senanayake, A. (2012).
Non-linear Time Analysis to Estimate Gait Stability Using Wearable Gyroscopes Network.
Journal of Robotics and ..., 24(4):1–22.

Gupta, P. and Dallas, T. (2014).
Feature selection and activity recognition system using a single triaxial accelerometer.
IEEE Transactions on Biomedical Engineering, 61(6):1780–1786.

Hammerla, N., Ploetz, T., Andras, P., and Olivier, P. (2011).
Assessing Motor Performance with PCA.
Proceedings of the International Workshop on Frontiers in Activity Recognition using Pervasive Sensing (in conjunction with Pervasive 2011), pages 18–23.

References III

Harimi, A., AhmadyFard, A., Shahzadi, A., and Yaghmaie, K. (2015).
Anger or Joy? Emotion Recognition Using Nonlinear Dynamics of Speech.
Applied Artificial Intelligence, 29(7):675–696.

Herzfeld, D. J. and Shadmehr, R. (2014).
Motor variability is not noise, but grist for the learning mill.
Nature neuroscience, 17(2):149–50.

Liao, M., Guo, Y., Qin, Y., and Wang, Y. (2015).
The application of EMD in activity recognition based on a single triaxial accelerometer.
Bio-Medical Materials and Engineering, 26(s1):S1533–S1539.

Newell, K. and Corcos, D. (1993).
Variability and Motor Control.
Human Kinetics Publishers.

References IV

Plötz, T., Chen, C., Hammerla, N. Y., and Abowd, G. D. (2012).
Automatic synchronization of wearable sensors and video-cameras for ground truth annotation - A practical approach.
Proceedings - International Symposium on Wearable Computers, ISWC, pages 100–103.

Preatoni, E., Hamill, J., Harrison, A. J., Hayes, K., Emmerik, R. E. A. V., Wilson, C., and Rodado, R. (2013).
Movement variability and skills monitoring in sports.
Sports Biomechanics, 12(2):69–92.

Samà, A., Ruiz, F. J., Agell, N., Pérez-López, C., Català, A., and Cabestany, J. (2013).
Gait identification by means of box approximation geometry of reconstructed attractors in latent space.
Neurocomputing, 121:79–88.

Takens, F. (1981).
Detecting strange attractors in turbulence.
Dynamical Systems and Turbulence, Warwick 1980, 898:366–381.

References V

Zhang, M. and Sawchuk, A. A. (2011).
A Feature Selection-Based Framework for Human Activity Recognition Using Wearable Multimodal Sensors.
International Conference on Body Area Networks (BodyNets), 1:92–98.

QUESTIONS?

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