Analysis of the Movement Variability in Dance Activities Using Wearable Sensors

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Outline

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Movement Variability

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

Inter-trial Movement Variability

[Preatoni et al., 2013] mentioned that inter-trial variability is a combination of

- noise in the neuro-musculo-skeletal system, and
- functional changes that might be associated with the exploration of different stragies to find the most effective one among many available.

Motor Variability is not noise

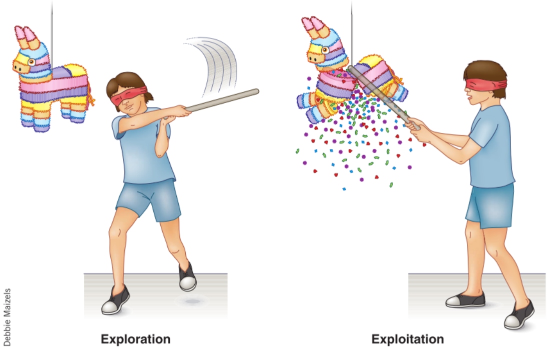

Figure 1: Find the piñata **[Herzfeld and Shadmehr, 2014]** .

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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Time-delay embedding theorem

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

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

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

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

where m is the **embedding dimension** and τ is the **embedding delay** **[Takens, 1981]** . False Nearest Neighborhood and Mutual Information algorithms are used to compute the optimal value of m and τ.

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Percentage Of Variance

The Percentage of variance (POV) is obtained by using the PCA.

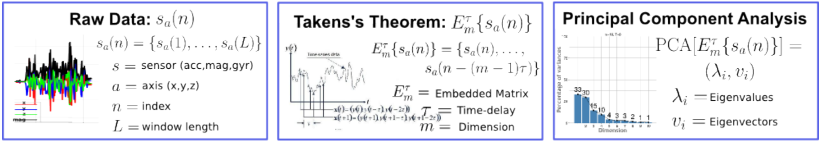

Figure 2: Percentage of Cummulative Energy

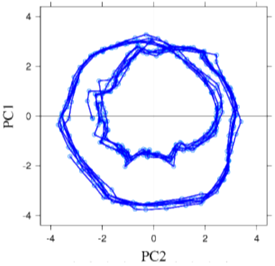

Figure 3: Reconstructed State Space

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Participants

Thirteen participants with different years of experience in dancing were invited to dance basic salsa steps:

- eleven (4 female, 7 male) novice dancers (none or less than two months of experience);
- one male intermediate (4 years of experience); and,
- one male expert (14 years of experience)

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Razor 9DOF IMU

Data collection from triaxial accelerometer, gyroscope and magnetometer sensors at a sampling rate of 50Hz for 20 seconds.

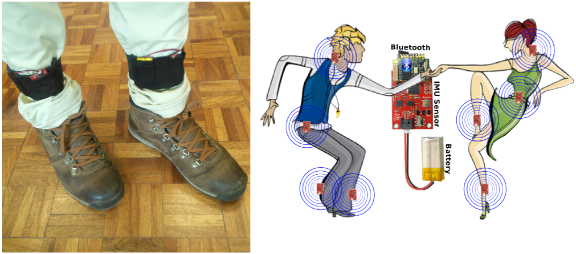

Figure 4: IMU sensors mounted on left and right ankle

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Basic Salsa Steps

Figure 5: Mambo and Side Cross-over Steps

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Visual levels of dexterity

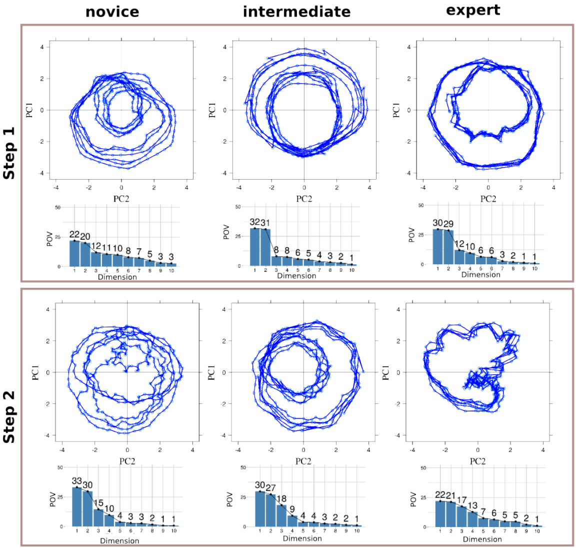

Figure 6: 2-D reconstructed state spaces and percentage of variance.

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Conclusions

- (+) Visual difference between levels of skillfulness in simple dance activities using the time-delay embedding technique.
- (+) Extending the understanding of human movement variability.

- (-) Time-delay embedding is subject to the embedded parameters (m and τ).
- (-) There is only one intermediate and one expert participant.

Future Work

- Collect data from a wider range of individuals (gender and age) performing different simple movements with additional inertial sensors
- Undertake a wider review of nonlinear dynamics techniques.
- Explore the use of Hidden Markov Models and Deep Neural Networks for the automatic classification of the movement variability.

Figure 7: Mirror Simple Movements Using NAO Robot

GRACIAS

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