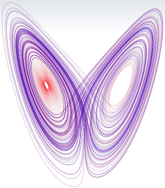

Chaos Theory Approach to Human Activity Recognition Using Inertial Sensors

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University of Birmingham, UK

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Presentation Outline

Open Challenge @ Mexican's Tournament of Robotics 2013

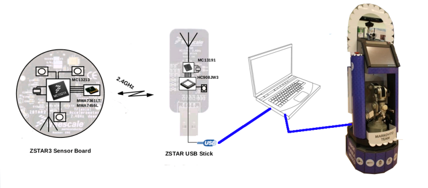


Figure 1: Human-Robot Interface

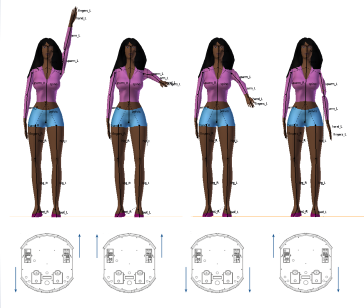
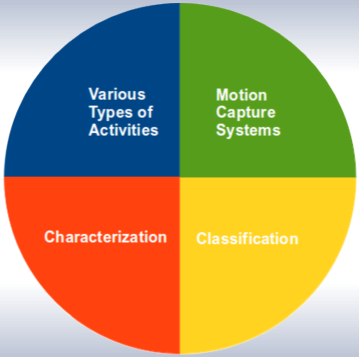


Figure 2: Human Body Gestures

Presentation Outline

Challenges in HAR



Various Types of Activities

Group	**Activities**
Ambulation	Walking, running, sitting, standing still, liying, climbing stairs descending stairs, riding escalator, and riding elevator.
Transportation	Riding a bus, cycling and driving.
Daily activities	Eating, drinking, working at the PC, watching TV, reading, brushing teeth, stretching, scrubbing, and vacuumming.
Exercise	Rowing, lifting weights, spinning, Nordic walking and doing push ups.
Military	Crawling, kneeling, situation assessment and openning a door.
Upper body	Chewing, speaking, swallwing, sighing, and moving the head
Others	Dancing different styles of music: latin, waltz, salsa, etc.

Table 1: Types of activities recognized by Human Activity Recognition Systems

Signal Characterization

Group	Methods
Time domain	Mean, standard deviation, variance, interquartile range, mean absolute deviation, correlation between axes, entropy, and kurtosis.
Frequency domain	Fourier Transform, and Discrete Cosine Transform
Others	Reconstructed State Space, Principal Component Analysis, Linear Discriminant Analysis, Autoregresive Model, and HAAR filters.

Table 2: Featured Extraction Methods[Lara and Labrador, 2013].

Lara, O. D. and Labrador, M. A. (2013).
A Survey on Human Activity Recognition using Wearable Sensors.

Classification

Group	**Classifiers**
Decision tree	C4.5 and ID3
Instance Based	k-nearest neighbors
Neural Networks	Multilayer Perceptron
Domain transform	Support Vector Machines
Fuzzy Logic	Fuzzy Basis Function and Fuzzy Interference System
Regression methods	MLR, ALR
Markov models	Hidden Markov Models and Conditional Random Fields
Classifier ensembles	Boosting and Bagging

Table 3: Classification Algorithms [Lara and Labrador, 2013].

Motion Capture Systems

- Vision-based,
- Floor-sensor based,
- Intertial-sensor based:
  - Human Body-sensed
  - Foot-sensed

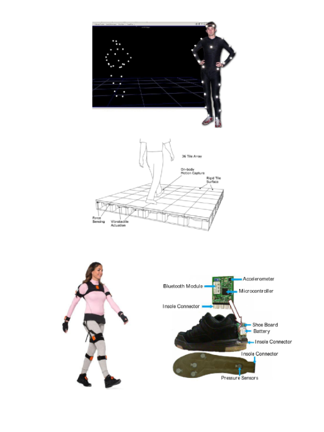


Figure 3: Motion Capture Systems

Presentation Outline

The Human Body as a Complex Dynamical System

Human Body Movement is the result of a complex dynamical system that include:

- Muscular system,
- Cardiovascular system,
- Skeletal system, and
- Nervous system.

Figure 4: Human Body Systems

Nonlinear Dynamics in the Human Body

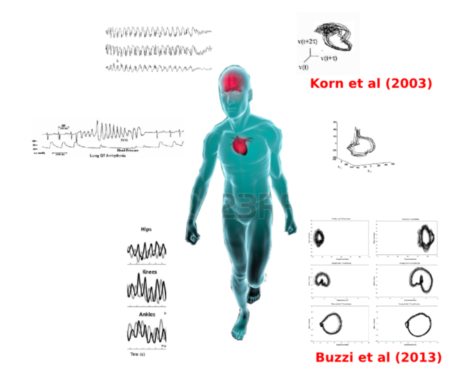


Figure 5: Some Captured Time-Series from the Human Body

Time-Delay Embedding in HAR

[Jordan et al., 2010] and [Samà et al., 2013] have proposed the use of Taken's Theorem so as to indenfity primitive human activities such as walking, cycling, and running. However, little has been done regarding the identification of complex activities that, for example, involve dance.

Jordan, F., Mannor, S., and Precup, D. (2010).
Activity and Gait Recognition with Time-Delay Embeddings.

Samà, A., Ruiz, F. J., Agell, 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.

Presentation Outline

Lorenz System

$$
\begin{aligned}
\frac{dx}{dt} &= \sigma(x-y),\\
\frac{dx}{dt} &= x(\rho - z) - y,\\
\frac{dx}{dt} &= xy - \beta z.
\end{aligned}
$$

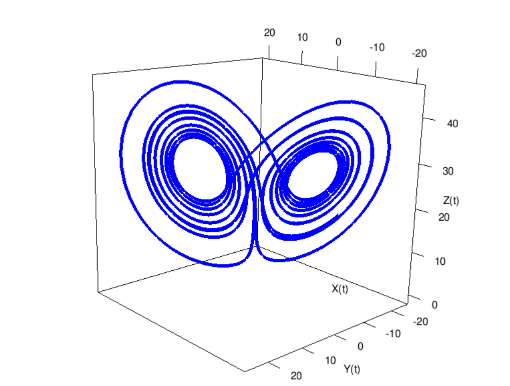


Figure 6: $\sigma = 10$, $\rho = 28$ and $\beta = 3/8$

Time-Delay Reconstruction

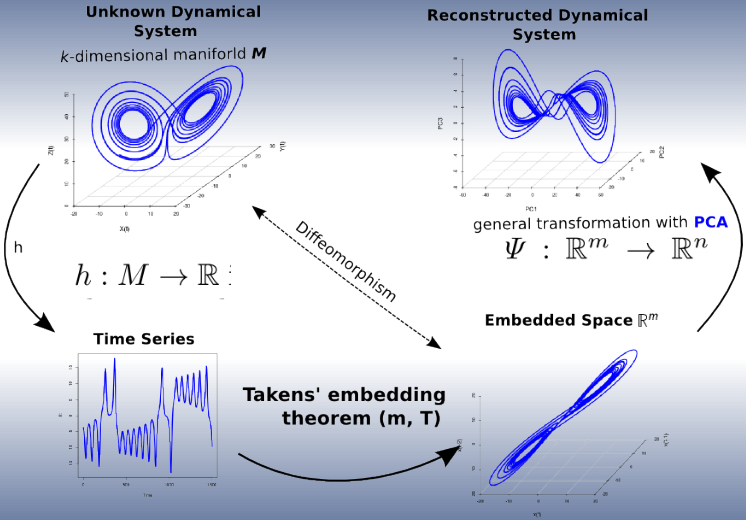


Figure 7: Reconstructed State Space Via Taken's Theorem

Takens' Theorem (1981)

According to Takens' Theorem, the reconstructed state space in m **embedding dimension** with τ **embedding delay** of the original system is given by the delay coordinate (DC) vector

$$\overline{x(t)} = (x(t), x(t-\tau), x(t-2\tau), ..., x(t-(m-1)\tau).$$

Takens' Theorem, also knows as time-delay embeddings method, states that for a large enough m to unfold the attractor and $\tau > 0$ chosen to maximize the information content of $x(t)$, this method provides a one-to-one reconstruction of the true dimension k system ($\mathbb{R}^k$).

Time-Dalay Embedding Example

With time signal $x(i) = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$, we let $m = 3$, $\tau = 2$, and $N = 9$.

$$
\begin{aligned}
\overline{x(1)} &= [1, \quad 3, \quad 5] \\
\overline{x(2)} &= [2, \quad 4, \quad 6] \\
\overline{x(3)} &= [3, \quad 5, \quad 7] \\
\overline{x(4)} &= [4, \quad 6, \quad 8] \\
\overline{x(5)} &= [5, \quad 7, \quad 9]
\end{aligned}
$$

Let $M = N - (m-1)\tau$. The reconstructed state space consist of a $m \times M$ matrix.

Optimal embedding parameters

[Cao, 1997] proposed a method to determine the optimal embedding dimmension from time-series based on Taken's theorem.

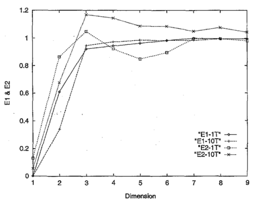


Figure 8: The values E1 and E2 for the data from chaotic Lorenz attractor

Cao, L. (1997).
Practical method for determining the minimum embedding dimension of a scalar time series.

Time-Delay Embedding in HAR

[Jordan et al., 2010] and [Samà et al., 2013] have proposed the use Taken's Theorems so as to indenfity primitive human activities such as walking, cycling, and running. However, little has been done regarding the identification of complex activities that, for example, involve dance.

Jordan, F., Mannor, S., and Precup, D. (2010).
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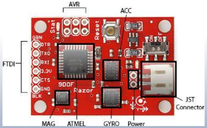
Gait identification by means of box approximation geometry of reconstructed attractors in latent space.

Presentation Outline

Procedure

9DOF Razor IMU



Accelerometer X Y Z |m|

Magnetometer X Y Z |m|

Gyroscope X Y Z |m|

Yaw
Pitch
Roll

DECIMUS Class in C++

*time-**D**elay **E**mbedding theorem for*
*Re**C**onstructing state spaces*
*Using **I**nertial **M**easurement **U**nit**S***

Time-Delay Embedding Parameters

```
DataAnalysis.Set_SpaceReconstructionParameters(50,10,5); // (lengthwindowframe, dim, tau)
```

Decimus DataAnalysis
Kind: *Variable* definition
Decl.: main.cpp :66 Show uses
DataAnalysis Object

Principal Component Analysis

```
mat A;

A= EmbeddedMatrix.t() * EmbeddedMatrix; // generate a symmetric matrix --- mat B = A.t()*A;


vec eigval_original, eigval;
mat eigvec_original, eigvec, transformedData;
eig_sym(eigval_original, eigvec_original, A.t(), "dc"); // divide-and-conquer

eigval = flipud(eigval_original);
eigvec = fliplr(eigvec_original);
transformedData = fliplr(eigvec_original).t()*EmbeddedMatrix.t();

cout << "DIY:eigenvalues \n" << eigval << endl;
cout << "DIY:eigenvectors \n" << eigvec << endl;
cout << "DIY:transformedData \n" << transformedData << endl;
```

Figure 9: IMU, Axes and C++ Class

Experiments

Cycling

Dancing Latin Styles:
Salsa, Cumbia and Bachata

Figure 10: Human Body Activities

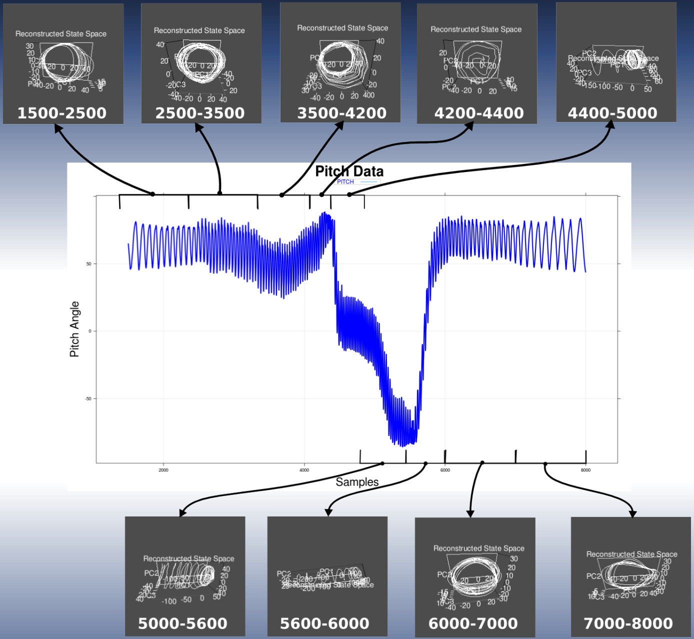


Figure 11: 3D Reconstructed State Spaces ($m = 9, \tau = 4$) for pitch angle data from cylcling activity

Basic Dance Foot Patterns

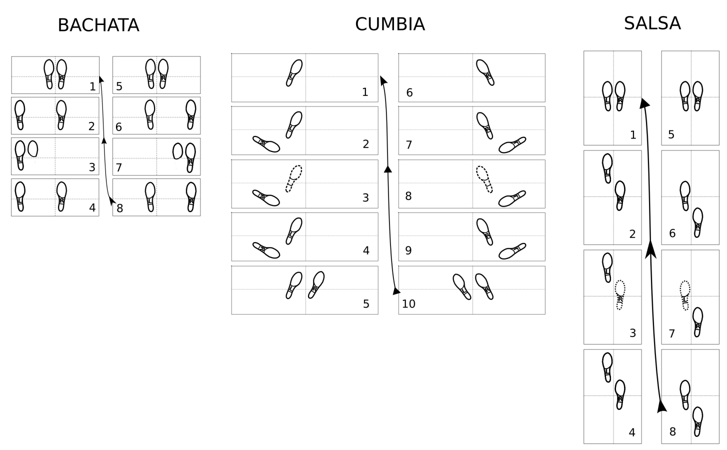


Figure 12: Latin Dance Foot Patterns

Optimal embedding parameters

Using the method proposed by [Cao, 1997], it has been obtained the values of E1 and E2 to determine the optimal embedding dimmension with $\tau = 5$ from pitch data.

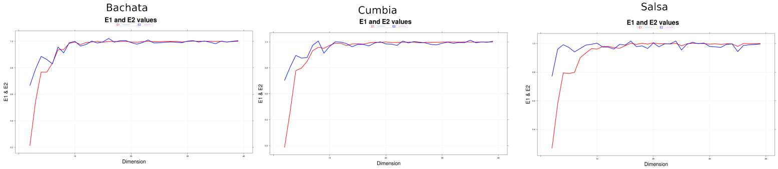


Figure 13: The values E1 and E2 for the data from latin dacen foot patterns

Reconstructed State Spaces

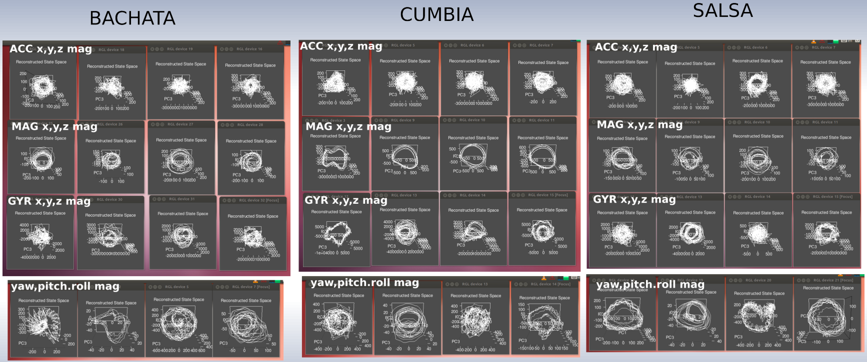


Figure 14: 3D Reconstructed State Space with $m = 20$ and $\tau = 5$ for a WF=1000.

Pitch Angle Time Series for Bachata

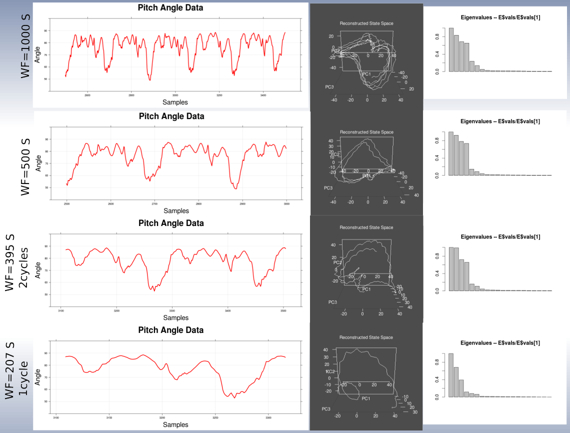


Figure 15: 3D Reconstructed State Space and Eigenvalues

Pitch Angle Time Series for Cumbia

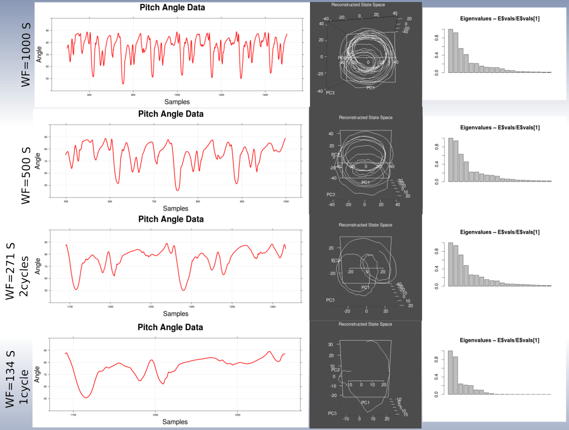


Figure 16: 3D Reconstructed State Space and Eigenvalues

Pitch Angle Time Series for Salsa

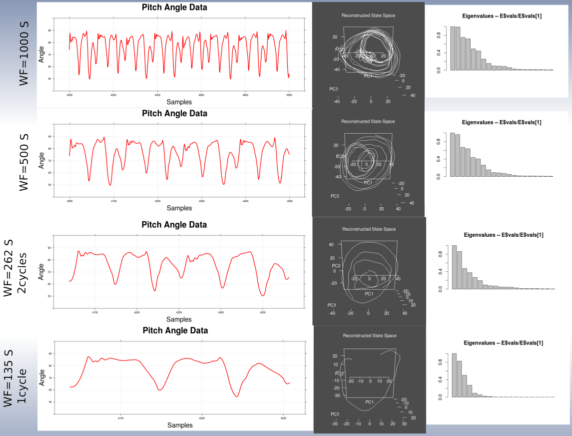


Figure 17: 3D Reconstructed State Space and Eigenvalues

Presentation Outline

??????????????????????

TECHNICAL CHALLENGES

- Build a body sensor network and determine how many sensors and where are the optimal places to wear this sensors [Mannini et al. 2013].
- Create its c++ library as a open source software for the human motion capture system
- Implement machine learning algorithms and evaluate the human activity recognition in a real-time performance.

RESEARCHABLE CHALLENGES

- Which non-reported concepts from nonlinear dynamics can be used to obtain features in the human body analysis?
- Does the use of concepts from nonlinear dynamics using Inertial Measurement Units can recognise up to 50 human activities as reported in [Reddy et al. 2012]?

QUESTIONS?

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