# Measuring the Movement Variability Using Wearable Sensors


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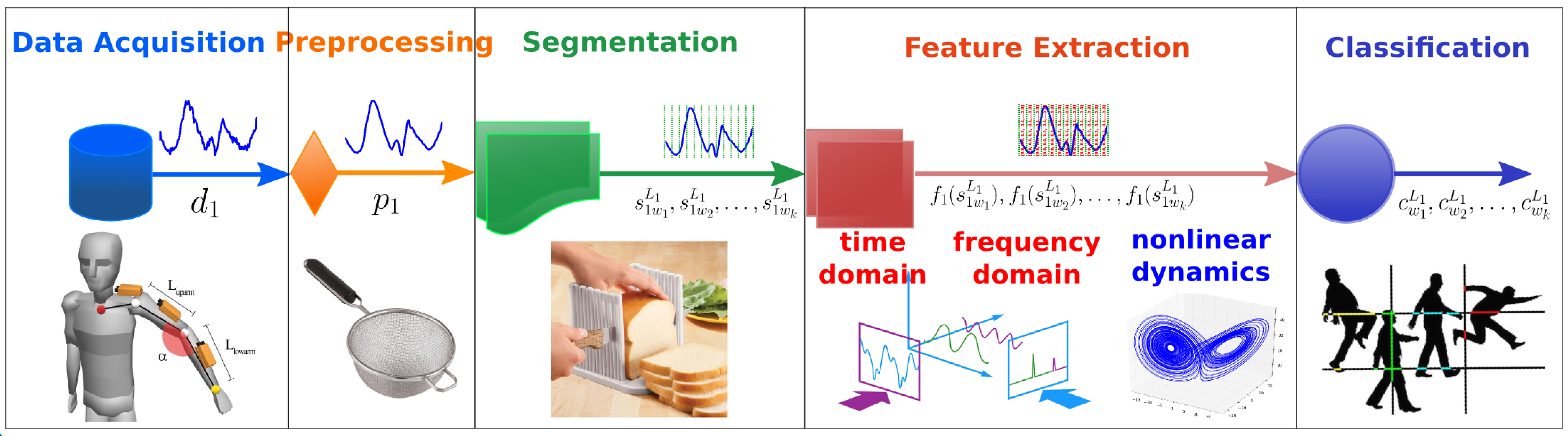
## Introduction

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 variability in HAR [2]. For the current work, I am focusing on a time-delay embedding theorem and Principal Component Analysis (PCA) which have proven to be reliable methods for feature extraction in HAR [3, 4]. I belive that those methods might provide insight into movement variability and be useful to automatically identify the variability of human activities.

## Human Activity Recognition Chain

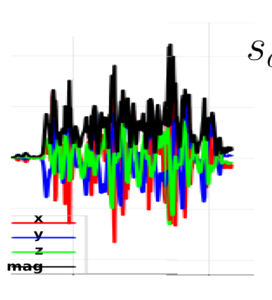
Bulling *et al.* [2] reviewed the state-of-the-art of HAR to identify activities from body-worn intertial sensors, they also illustrated an implementation of such systems with an educational example problem. The following diagram is replicated from the work of Banõs *et al.* [5].




## Materials and Methods

Raw time-series data is collected from a triaxial accelerometer $(a_x, a_y, a_z)$. Then, a $N$ samples length time-series, e.g. $a_x$, is used to obtain the time-delay embedded matrix, $E\{a_x\}$, with $m = 20$ and $\tau = 6$ [3, 4]. Finally, PCA is applied to $E\{a_x\}$ to compute the percentage cumulative energy (PCE) [6]. The method is then applied to six simple movements which were performed by five participants wearing a low-cost and commercial intertial sensor on their right wrist; each movement was continuously repeated for 10 seconds.

**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:** $E^{\tau}_{m}\{s_a(n)\}$

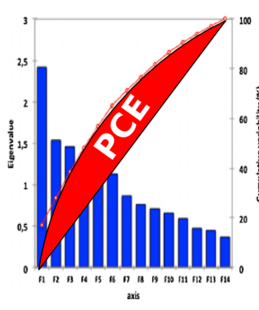
$E^{\tau}_{m}\{s_a(n)\} = \{s_a(n), \ldots, s_a(n-(m-1)\tau)\}$

$E^{\tau}_{m} =$ 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 $\tau$ values which are related to the length and complexity of the time-series, the technique is giving us insights into movement variability for simplistic movements. We showed with the current technique that it is possible to have simiar result when participant performed six simplistic movements wearing the low-cost and commercial sensor. 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 variability.

## References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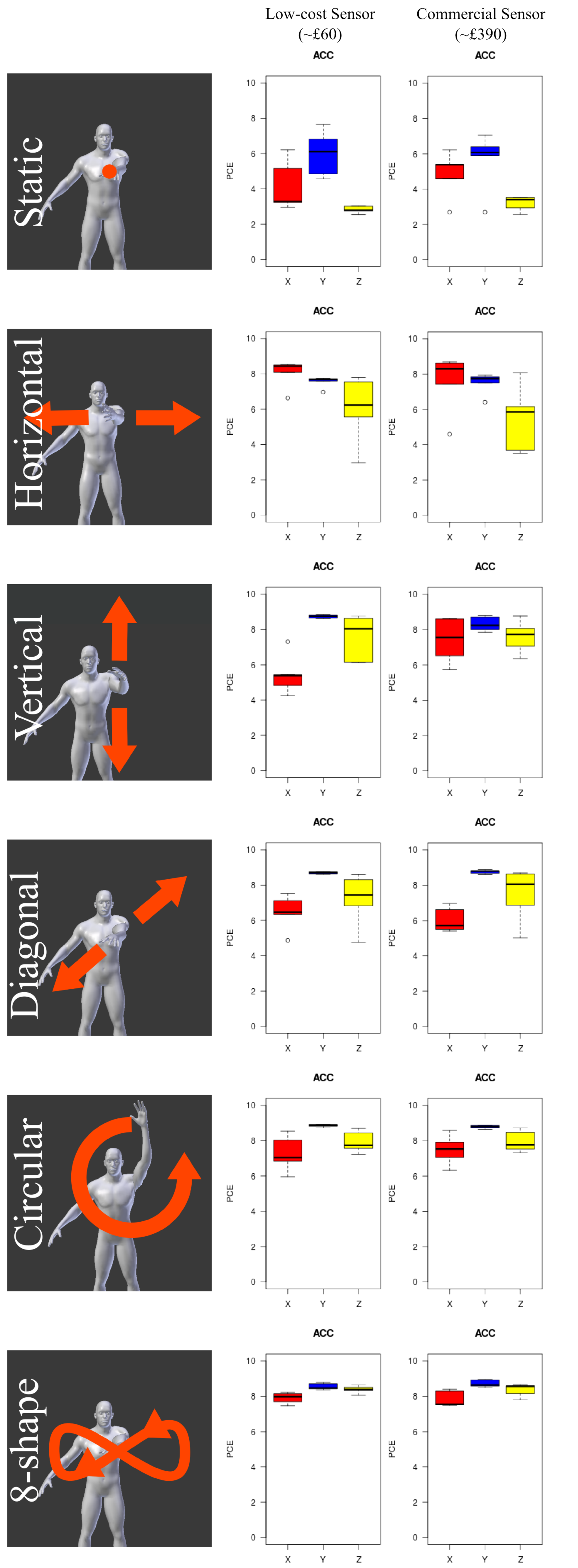
## Results

The values for percentage cumulative energy (PCE) from five participants are presented using boxplots for both low-cost and commercial triaxial accelerometer (ACC). It is visually evident that both sensors present similar results for each movement. It is highlighted that the circular movement shows the least variation per component compare to other movements.

We assume that the evident variability of the movements is due to the flexibility in the experiment where participants were only asked to perform the movements at a comfortable speed.

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