Exercise Discrimination And Interpretation Using Canonical Correlation Analysis

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Abstract

Accurately identifying human activities in an interpretable manner is essential for developing automated rehabilitation and sports training systems. This poster proposes a motion classification approach based on Canonical Correlation Analysis(CCA) that can evaluate the relationship between different groups of landmark joints in humans and identify the unique correlation patterns to identify the exercise being performed. Assuming the dependence between joints in each data set, CCA is an efficient method to study these interrelationships. While neural networks have been shown to be effective in classification, they do not give interpretable results.

Exercise data used in this work are obtained from Microsoft Kinect and are in the form of 25 landmark joint locations in the x, y and z dimensions. For analysis these joints are organized into some multivariate data sets. The canonical correlation coefficients are calculated between all possible pairs of data sets for each exercise to study the correlation patterns. The correlation 'heat maps' provide an interpretable result which is the further used for classification. The canonical coefficients are unique for the joint group in each exercise. This can be used to identify and differentiate exercise types. We aim to use the canonical variables for diagnosing faults in exercises.

Introduction

Human Motion data

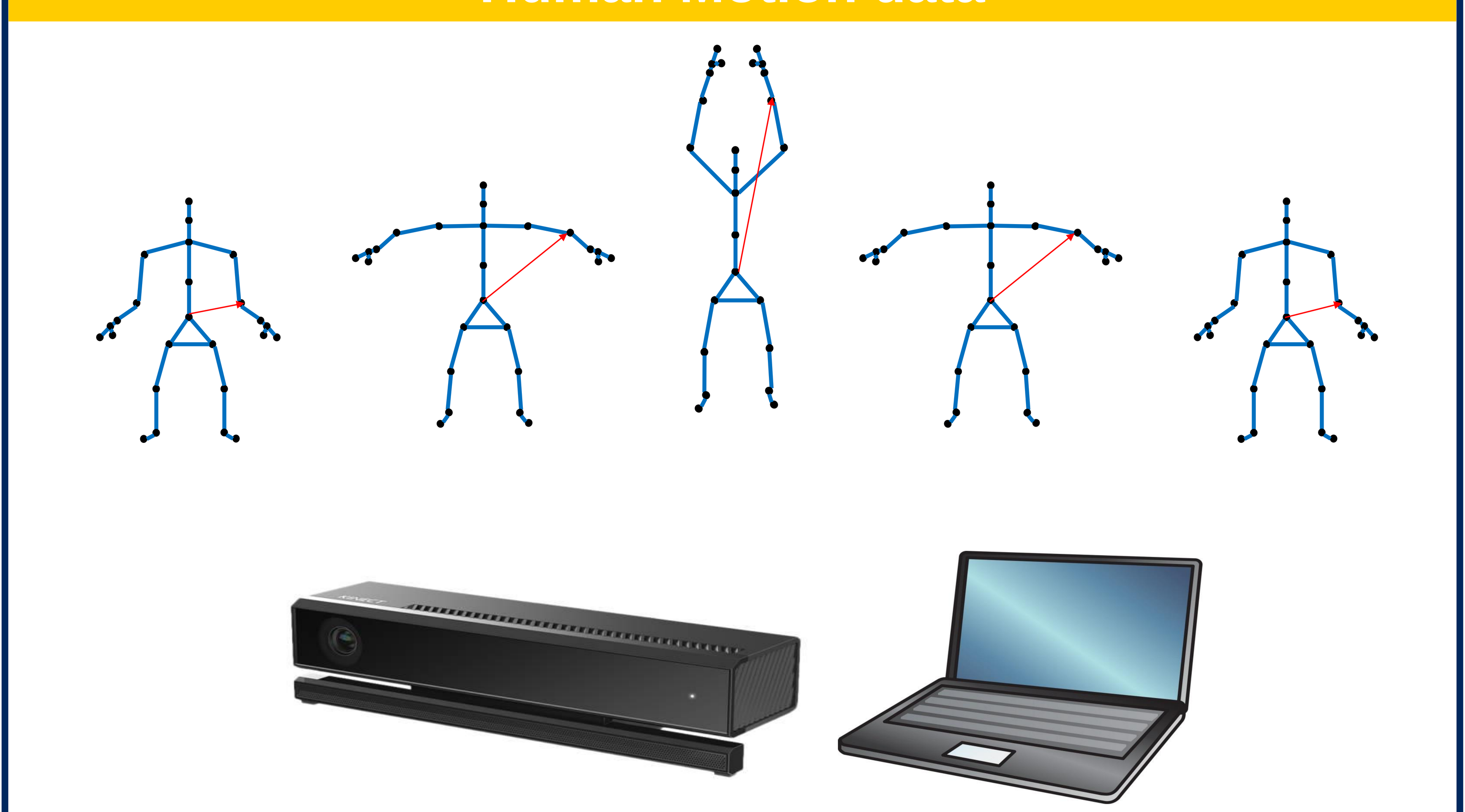


Figure 1: Kinect Camera 2.0 tracks the positions of 25 landmark human joints in x, y and z axes.

- Human activities can be quantified as temporal three dimensional joint-location data using a motion sensing camera.
- Kinect camera has built-in software to track and record 25 joints on the body at a sampling rate of ~33 fps.
- Raw data is collected using Java libraries.
- The code preforms mathematical operations to turn the raw data into more meaningful results to be interpreted.
- While we used Human exercise data, the proposed method can be expected to work for many time series classifications.

Methods

Canonical Correlation Analysis

- Canonical Correlation Analysis explores the linear relationship between two multivariate sets $\underline{X}$ and $\underline{Y}$

$$\underline{X} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix} \quad \underline{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_q \end{bmatrix} \qquad \underline{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix} \quad \underline{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{bmatrix}$$

- Linear combinations of $\underline{X}$ and $\underline{Y}$ with scalar vectors $\underline{a}$ and $\underline{b}$, give us their projections on vectors $\underline{a}$ and $\underline{b}$: $\underline{U}$ and $\underline{V}$

$$\underline{U} = \underline{a}'.\underline{X} \qquad \underline{V} = \underline{b}'.\underline{Y}$$

- The correlation coefficient between $\underline{U}$ and $\underline{V}$ is given by:

$$r_{XY} = \frac{\underline{a}'\Sigma_{XY}\underline{b}}{\sqrt{\underline{a}'\Sigma_{XX}\underline{a}}\sqrt{\underline{b}'\Sigma_{YY}\underline{b}}}$$

- CCA finds the pair of vectors $\underline{a}$ and $\underline{b}$ that maximize the correlation r_{XY} between variate pairs $\underline{U}$ and $\underline{V}$.

Implementation

- Joint location data are separated into 5 semantically meaningful groups: left arm, right arm, left leg, right leg, torso
- Each sets of data contains the measured positions in x, y and z axes.
- The position of each joint in each axis can be considered as a random variable.
- $\underline{\boldsymbol{S}_x}$, $\underline{\boldsymbol{S}_y}$, $\underline{\boldsymbol{S}_z}$ denotes the x, y and z-position of $\boldsymbol{p}$ joints in set $\boldsymbol{S}$.

$$\underline{\boldsymbol{S}_x} = \begin{bmatrix} S_{1x} \\ S_{2x} \\ \cdots \\ S_{\boldsymbol{p}x} \end{bmatrix} \qquad \underline{\boldsymbol{S}_y} = \begin{bmatrix} S_{1y} \\ S_{2y} \\ \cdots \\ S_{\boldsymbol{p}y} \end{bmatrix} \qquad \underline{\boldsymbol{S}_z} = \begin{bmatrix} S_{1z} \\ S_{2z} \\ \cdots \\ S_{\boldsymbol{p}z} \end{bmatrix}$$

- The canonical correlation between the $\boldsymbol{S}$ and $\boldsymbol{R}$ data set can be expressed in the form of a matrix:

$$r_{S,R} = \begin{bmatrix} r_{S_xR_x} & r_{S_xR_y} & r_{S_xR_z} \\ r_{S_yR_x} & r_{S_yR_y} & r_{S_yR_z} \\ r_{S_zR_x} & r_{S_zR_y} & r_{S_zR_z} \end{bmatrix}$$

Results & Discussion

CCA correlation

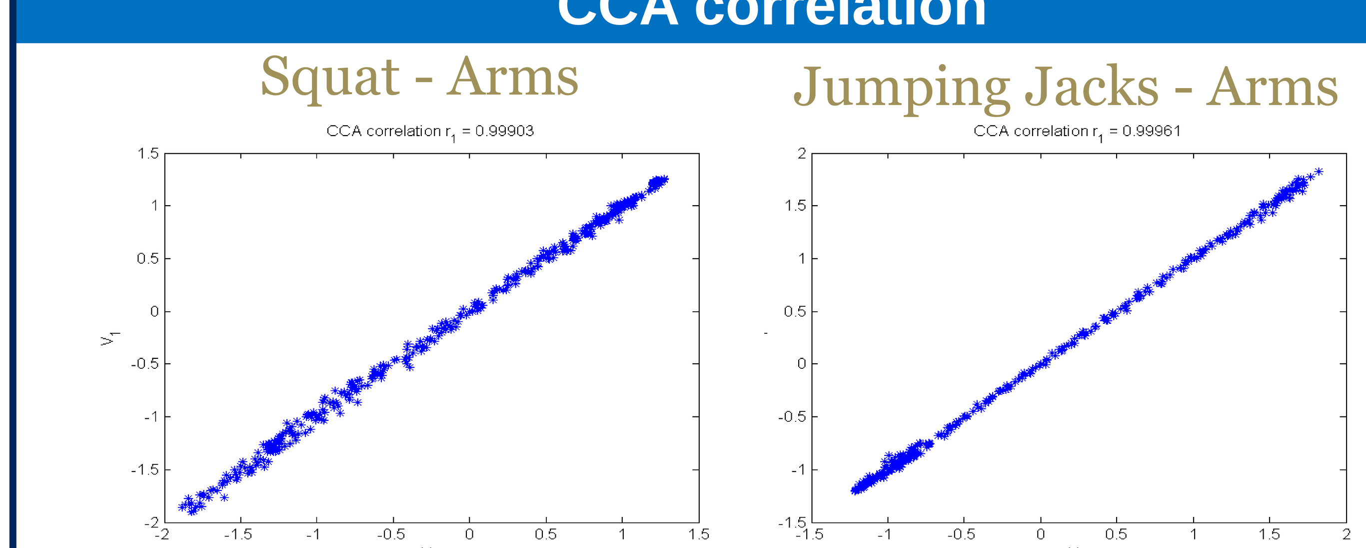


Figure 2: First variate pair corresponding to highest correlation values

Results & Discussion

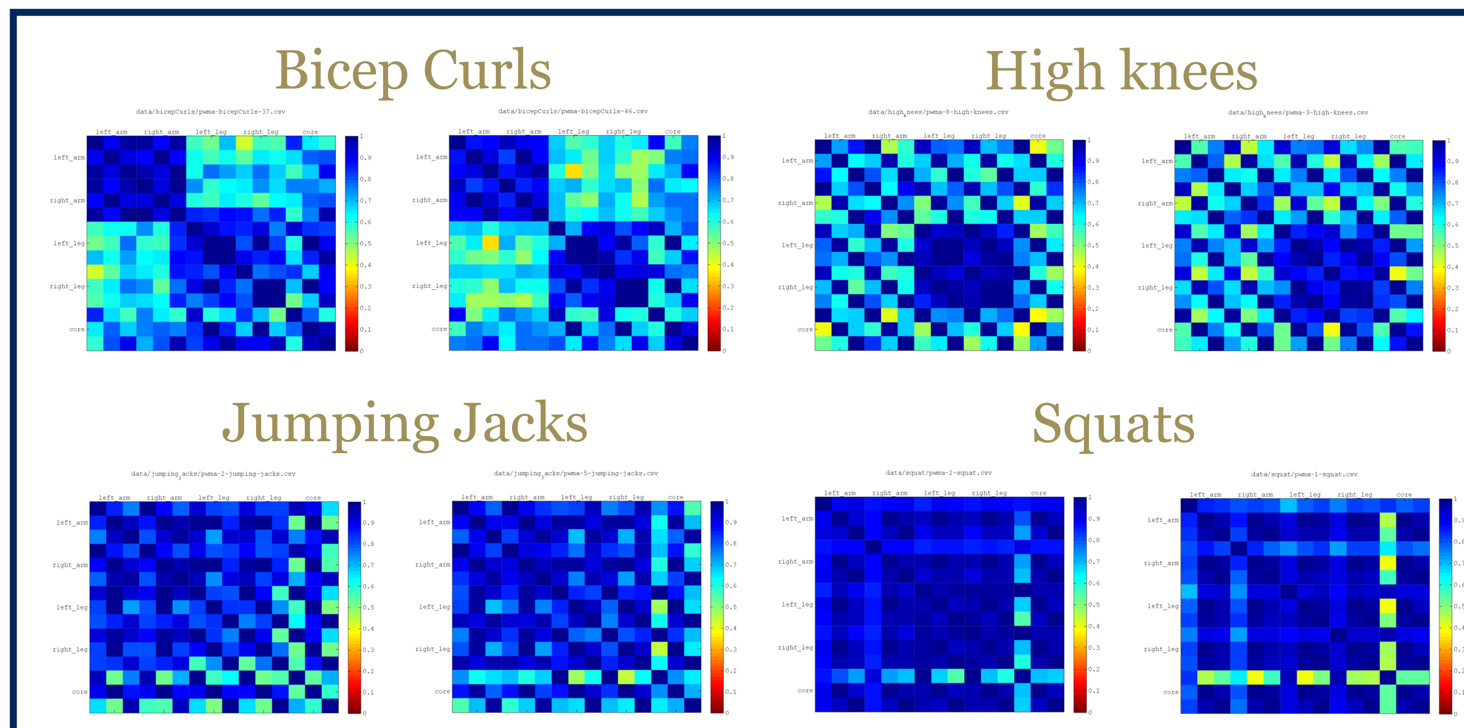
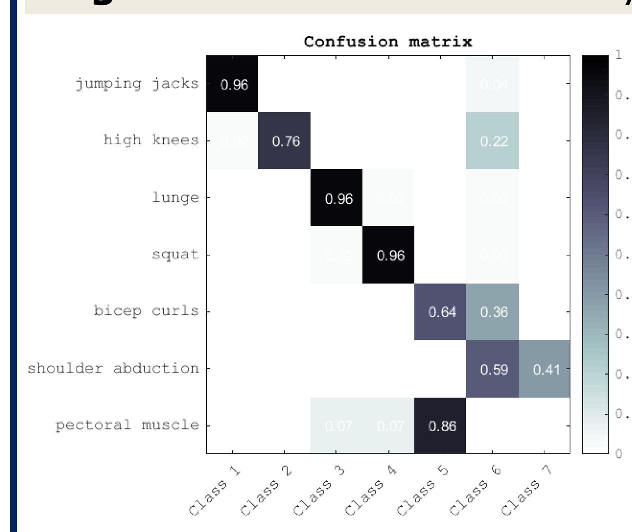


Figure 3: Intra class similarity and inter class variability in CCA Heatmaps.



- Since this method is unsupervised, the classes themselves are unnamed. However, the confusion matrix shows that CCA can be used for classification into exercise groups based on similarity.

Figure 3: Confusion matrix shows good discrimination for most exercises

Comparison with State of the Art Neural Networks

- Neural Networks achieve similar and occasionally higher discrimination(Our analysis indicates ~95% discrimination using DNN), in comparison to CCA's they lack in the following:

1. Interpretability of data. NN's are infamous for their 'black box' approach and it is notoriously difficult to associate any meaning with the weights and biases.

2. Ability to work on data of any number of timesteps. For every data, NNs require the input to be of the same format and would need to be trained all over again for a different size(~3000 epochs). CCA can work with any size due to compressing the temporal aspect of the data.

Future Work

- CCA can be used to obtain interpretable classification from semantically meaningful joint groups.
- This could be build upon further to diagnose errors in exercise activity automatically. The sources of low correlations in the map are of special interest.

References

[1] Alpaydin, Ethem. *Introduction to machine learning*. MIT press, 2014.

Acknowledgements

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