Action Classification from Motion Capture Data using Topological Data Analysis

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OUTLINE

- We propose a novel framework for activity recognition using topological data analysis (TDA)
- Time delay embedding is used to construct point clouds describing the oscillatory patterns of body joints
- Robust low dimensional features are extracted from persistence diagrams for classification of activities

DATASET

- Motion capture data was recorded for activities shown in Table 1. We collected individual activities as well as some transitions

Activity	Time (minute)
Bicycle	1
Walking	1
Sitting	1
Golf	1
Waving	1

Table 1. Protocol

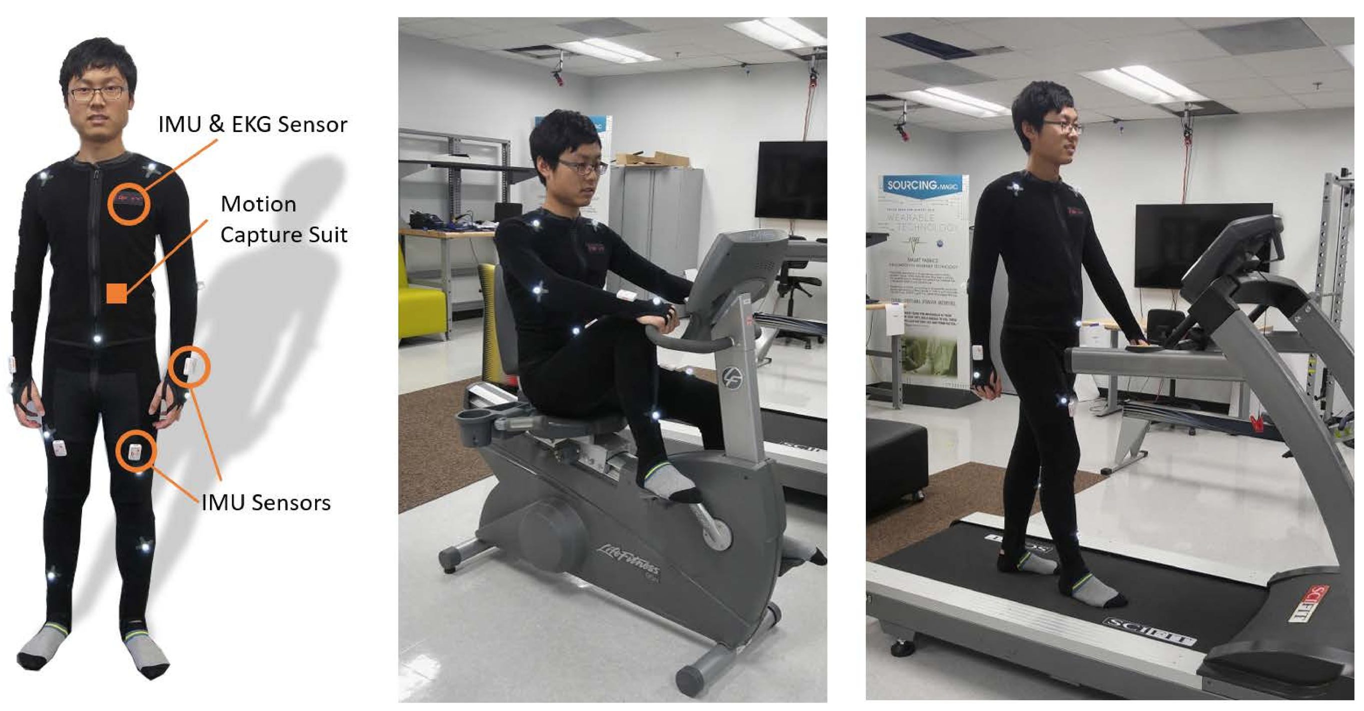

Fig 1. Data collection with motion capture system

METHOD: TIME DELAY EMBEDDING

- Given a time series $s_i(t)$, the Taken's delay embedding of the signal into an m-dimensional space is mapped as,

$$S_i(t) = [s_i(t), s_i(t+\tau), \ldots, s_i(t+(m-1)\,\tau)]$$

where τ is the delay embedding and m is the embedding dimension.

- τ was selected from the first zero-crossing of the auto-correlation of the signal.
- $m = 3$ was selected empirically from the data using the false nearest-neighbors algorithms

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METHOD: OVERVIEW

Data streams $\gamma_j(t): \mathbb{R} \to \mathbb{R}^3$ from joints → Pick 10-second Window → Project to PC Directions to obtain $s_{j,p}(t): \mathbb{R} \to \mathbb{R}$ → TDE: Compute $\tau_{j,p}$ and delay embedding for each j and p → Obtain point cloud $X_{j,p}$ by subsampling delay embedding → TDA: Compute PD_1 from $X_{j,p}$ and maximum persistent interval length $L_{j,p}$ → Features $F_w = \left[L_{1,1} \; \ldots \; L_{N_j,N_p}\right]$ are used for classification using k-NN

Compute PCs for each joint that explain 95% of the variation

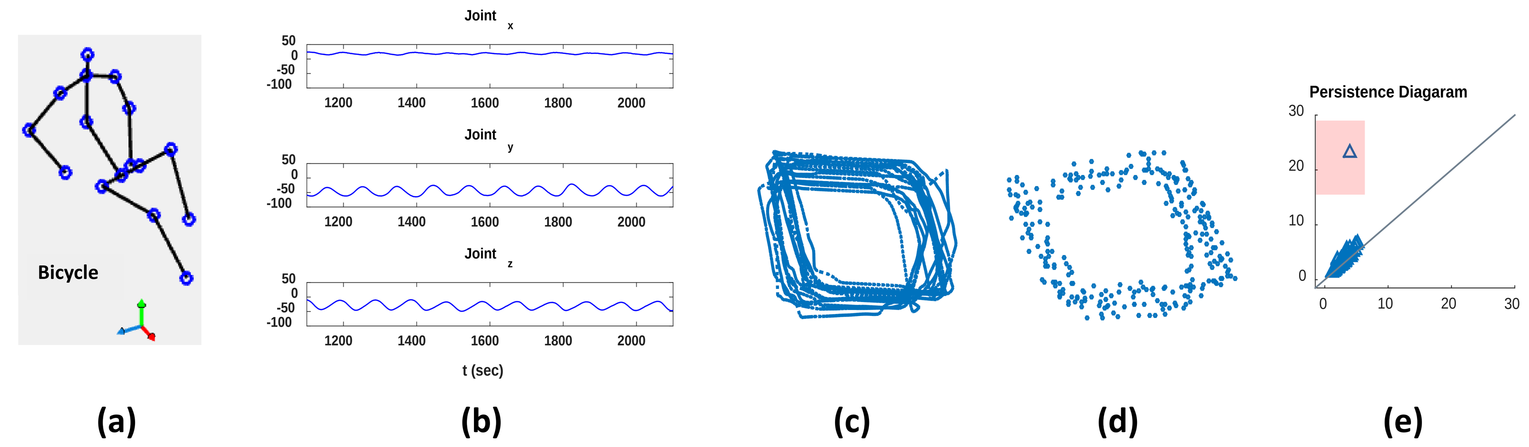

Fig 2. Snapshot of the skeleton data for bicycling (a), x, y, z time series from left ankle (b), time delay embedding of the principal components of the signals (c), subsampled point cloud (d) and the persistence diagram (e).

METHOD: PERSISTENT TOPOLOGY

- Given a point cloud $X = \{x_1, \ldots . . x_n\}$, sampled from a manifold M, we can construct a filtration by increasing the ϵ (radius of the balls) and plot the persistence diagrams to get information of the connected components and holes

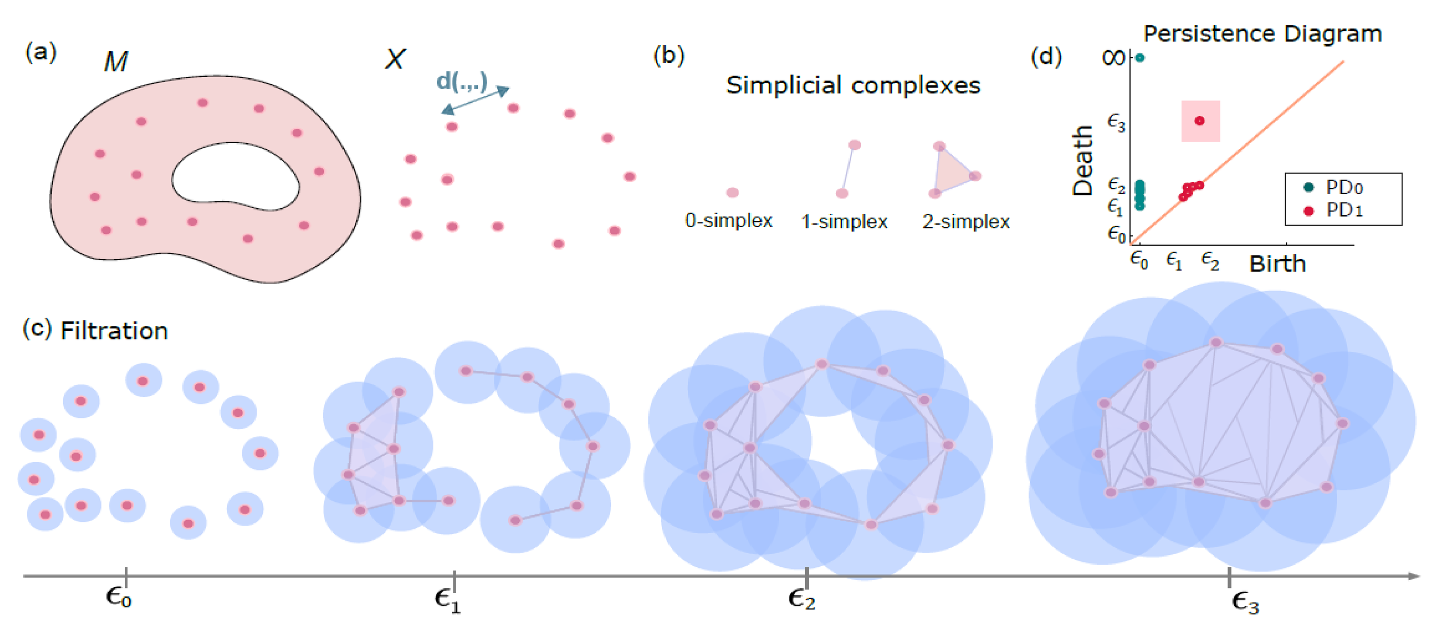

Fig. 3 shows the concept of topological persistence.

- Point cloud of TDA is obtained from delay embedding by subsampling 300 points using a k-NN density estimation with a max-min strategy. The value of k was set to 15 and the threshold on density was 0.90.
- We use the maximal length of the persistence intervals associated with PD_1 as a feature:

$$L = \max_{(b_i, d_i) \in PD_1} |d_i - b_i|$$

RESULTS

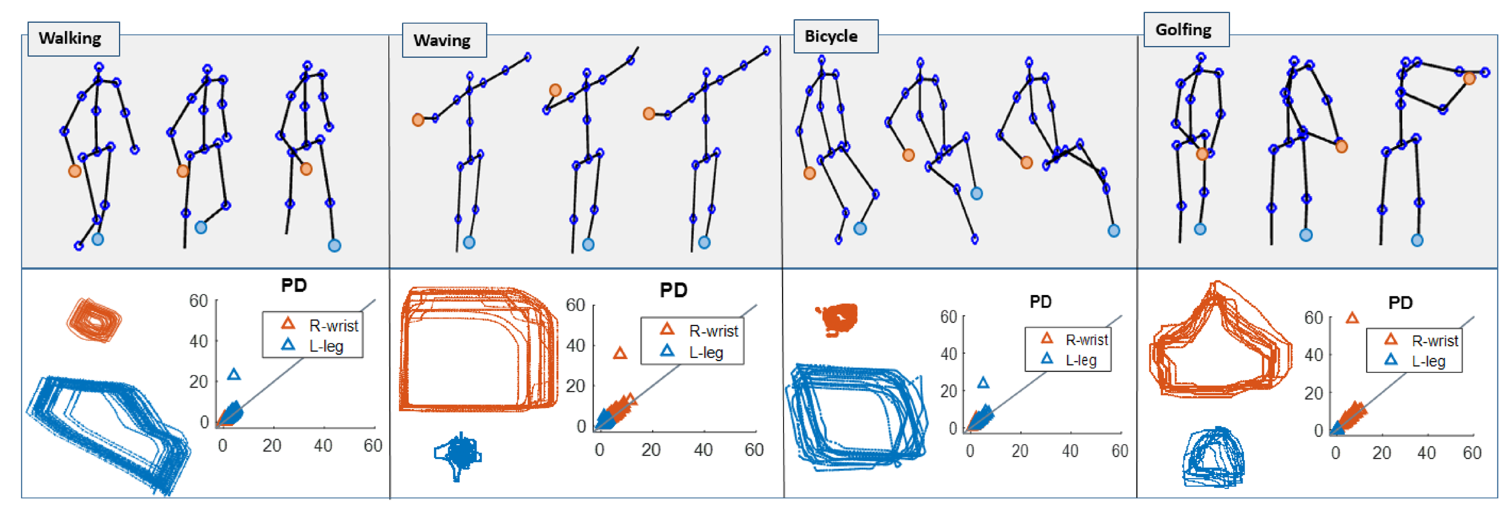

Fig 4. Delay embedding and persistence diagrams for the activities

- We used a sliding window of 10 seconds with a 50% overlap over the time series data, perform a k-fold cross validation and report the average class accuracy.
- A k-nearest neighbor search return the $k = 9$ closest points for a given test point and a majority voting rule gives the prediction label for the test point.
- Computation times (sec) : Delay embedding (0.10), subsampling (0.20), persistent homology (1.25 sec), kNN classification (0.03)

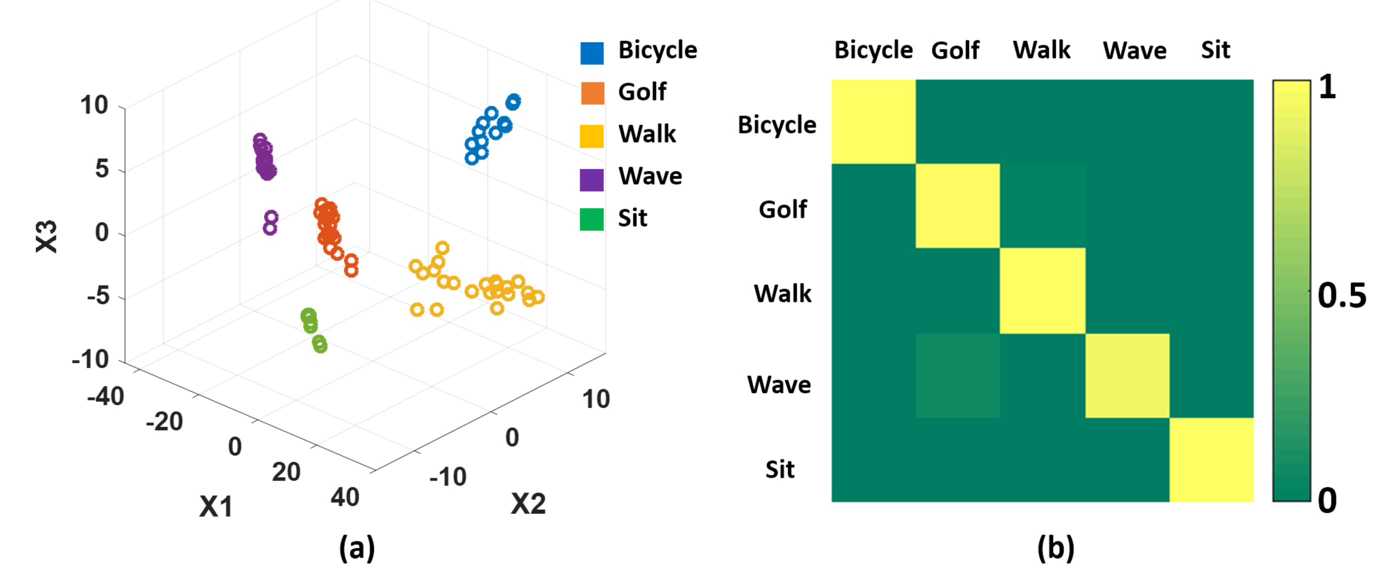

Fig 5, (a) shows separation of the classes from the training set, (b) confusion matrix over the predicted and true classes

CONCLUSION

- We demonstrate a successful classification of human activities on a motion capture dataset using our computationally efficient, robust and low dimensional topological feature generation procedure.
- The computation time for each stage shows the potential of the method to be used for real time applications