Identifying Gestures through EMG signals

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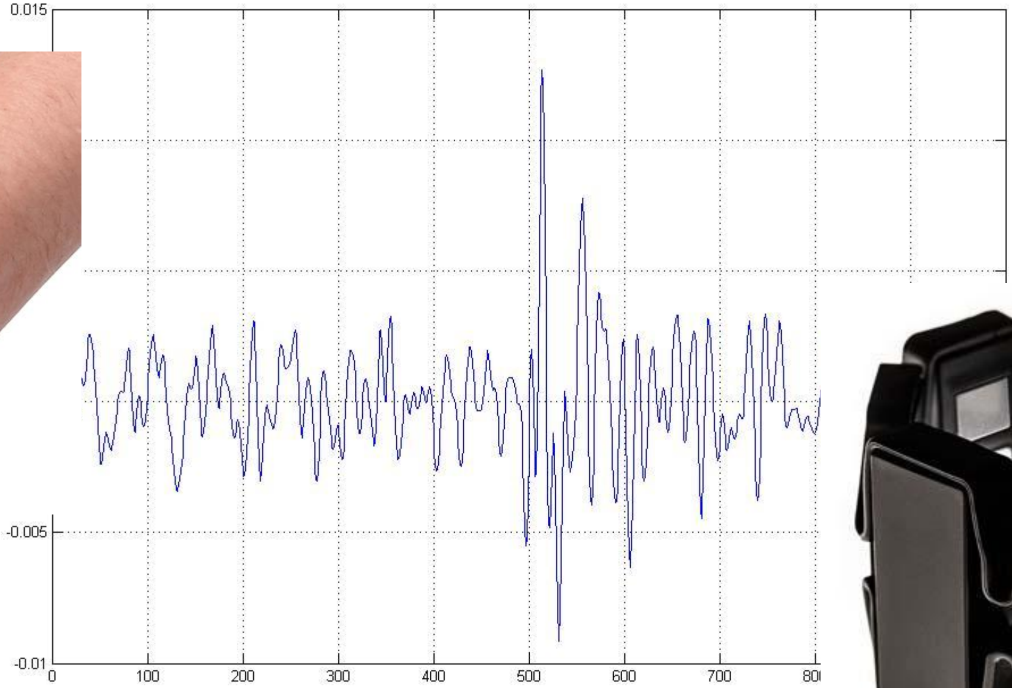
Background



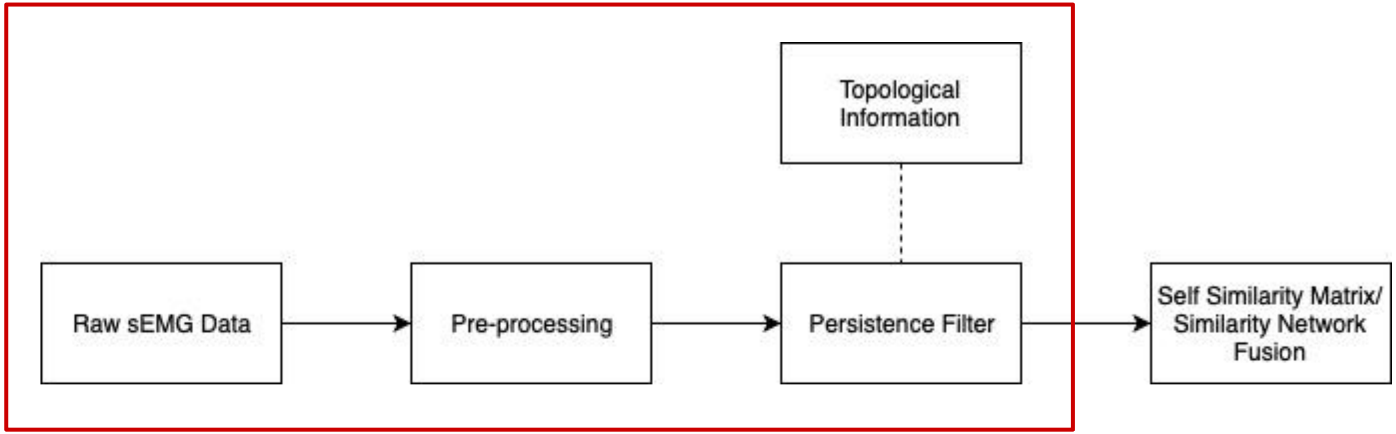
The Problem

- Dependable gesture recognition & prediction provides intuitive alternatives for a wide range of applications:
    1. Consumer – Prosthetics, Human-computer interface, etc.
    2. Military & industrial – Exoskeleton, remote robotic control, etc.

- Modest results despite ample researcher attention:
    1. Imprecise readings dependent on superficial user characteristics
    2. Incongruous data sets leads to small training sets & overfitting
    3. Onboard computing resources limited

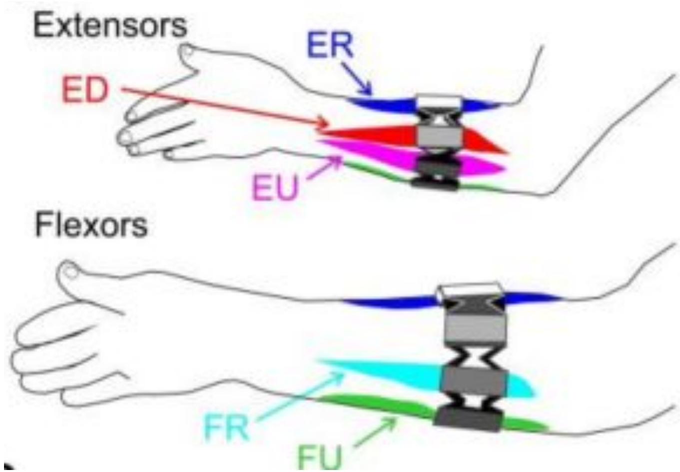
Solution

- Computationally feasible data pipeline comprised of two parts:
  - Filtering component: Remove superficial noise irrelevant to all gesture classes
  - Classifying component: Classify gesture as early as possible in cycle

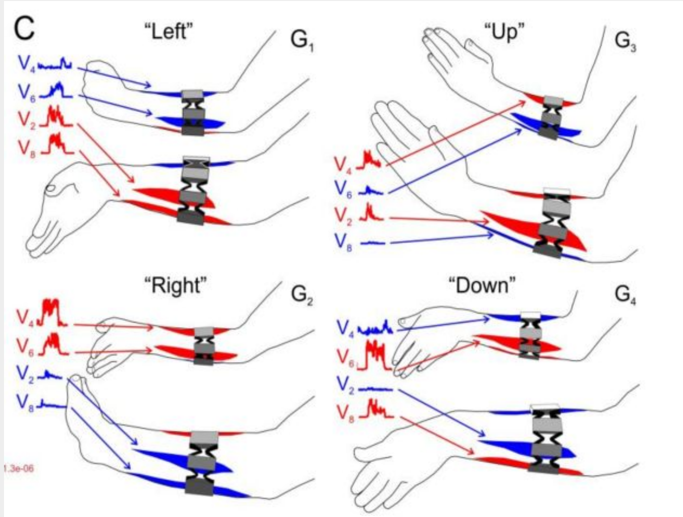


Data

- 36 Test Subjects
- 8 Sensors: 5 are placed directly on main muscles

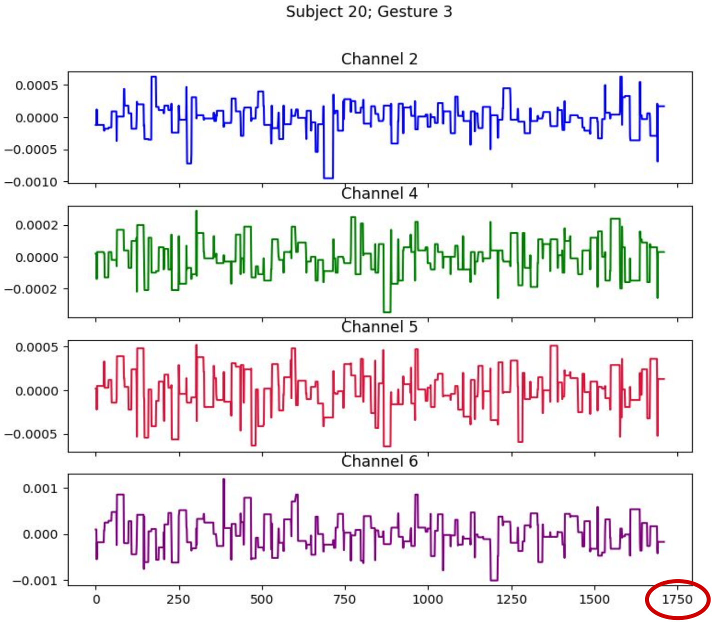


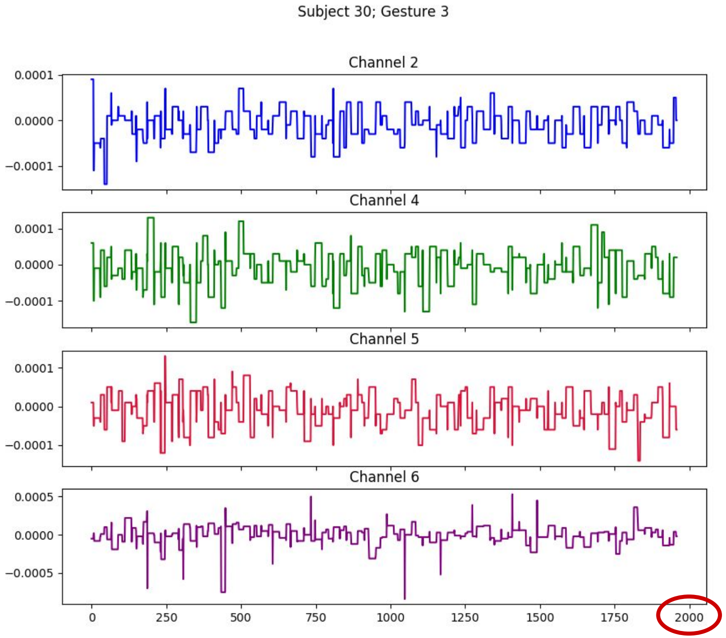
- 6 Gestures: 4 simple (e.g. “left”) and 2 compound (e.g. “left + up”)
- Perform gesture for 3 sec.



Data

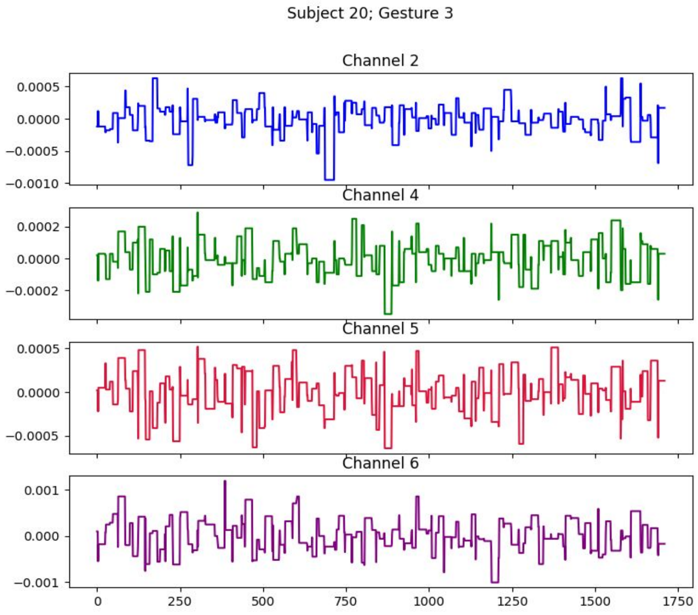
Between subject performance variability

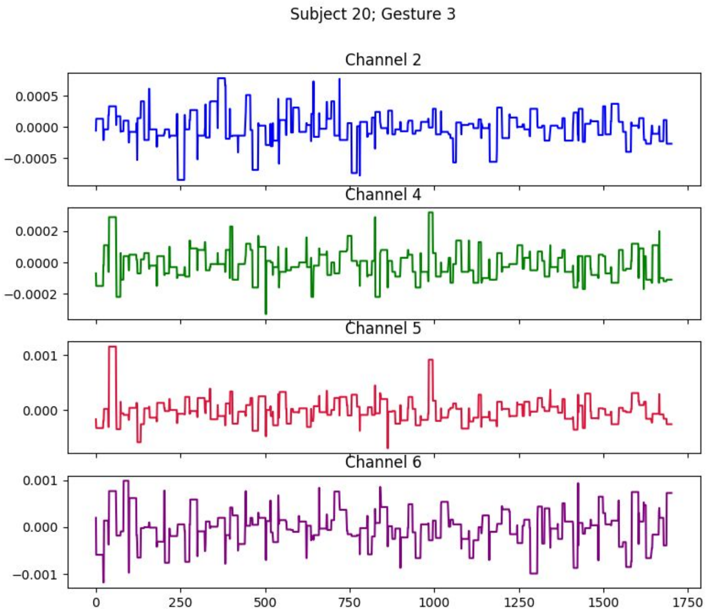




Data

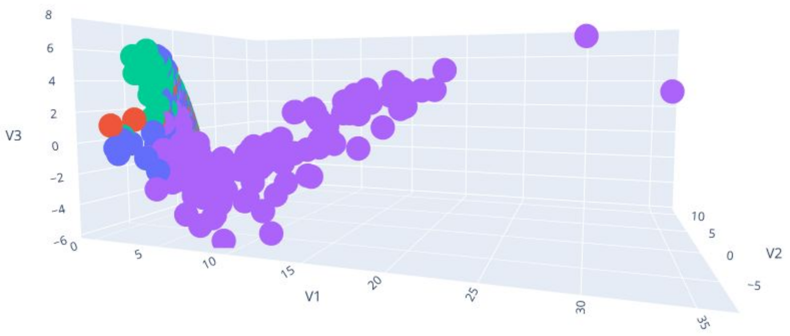
Within subject performance variability



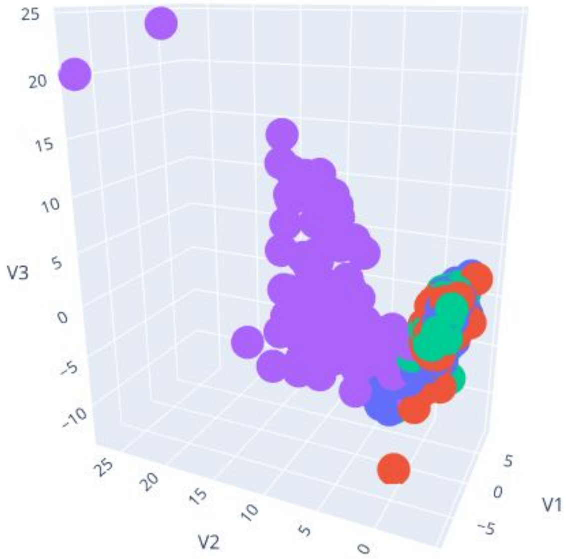


Exploratory Analysis - Dimension Reduction

- Principal Components Analysis:
  - First 3 PCs: 80% of variance

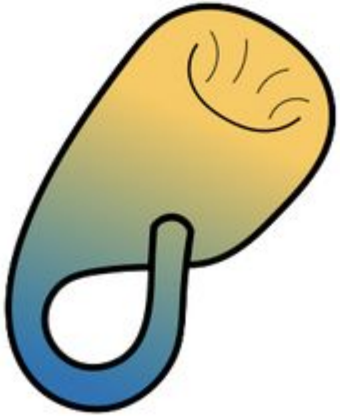


- Multidimensional Scaling

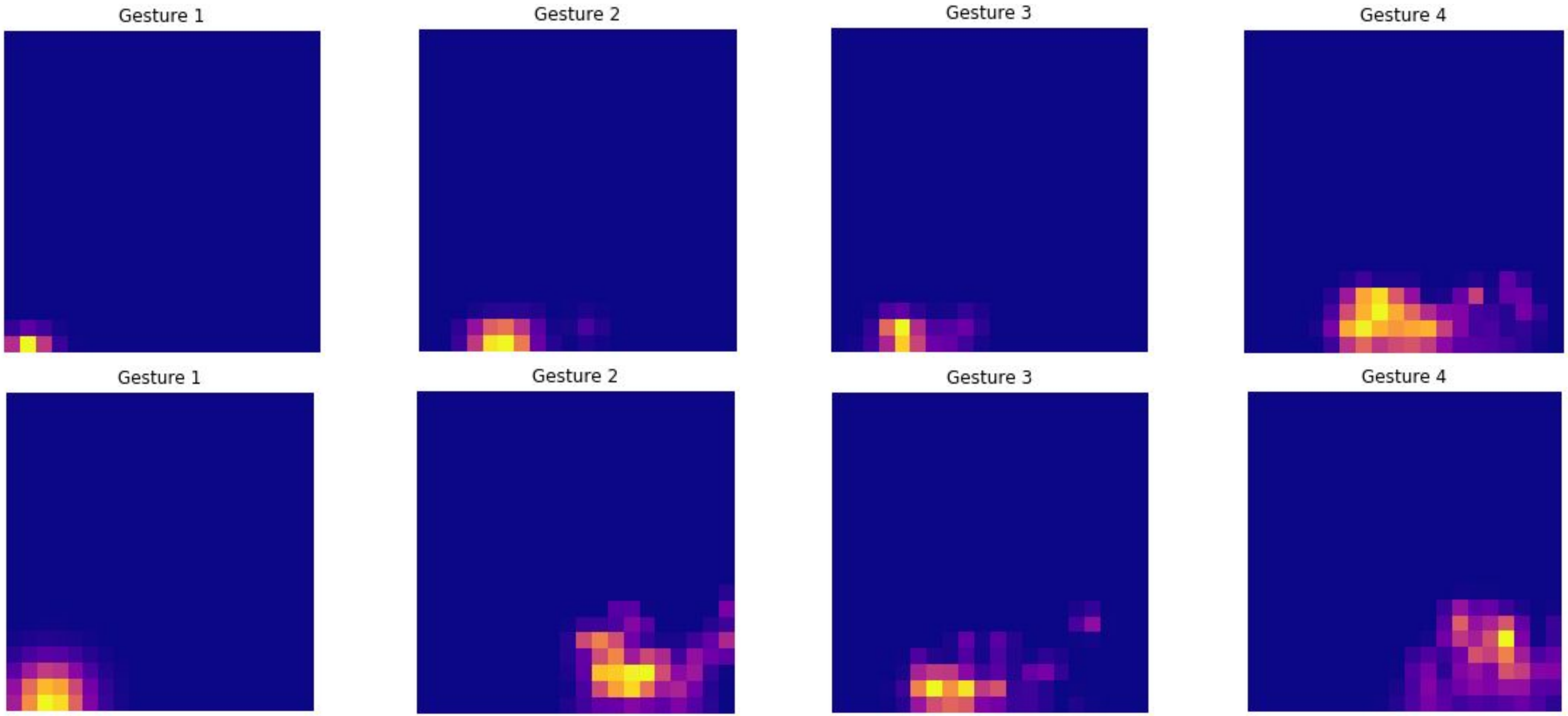


Identifying Important Characteristics

- What characteristics are important for classification?
  - Identifying peaks & valleys will be unique to a gesture
  - Characteristics common to all gestures may be removed without information loss
- Persistent homology may help to answer this question
  - Vietoris-Rips Complex calculated for 1-D homology group on 5-channel time series
  - 20x20 pixel persistence images generated with σ = 1e-5



Persistence Images

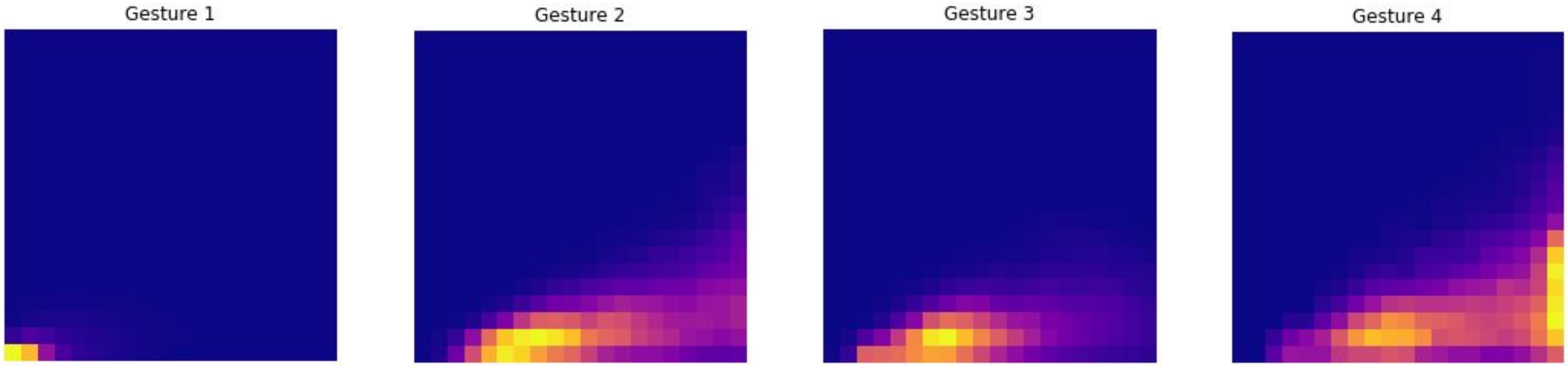


Combining Persistence Images

- Want to determine which qualities are shared within a gesture class
- Normalized sum of normalized persistence images, P_n

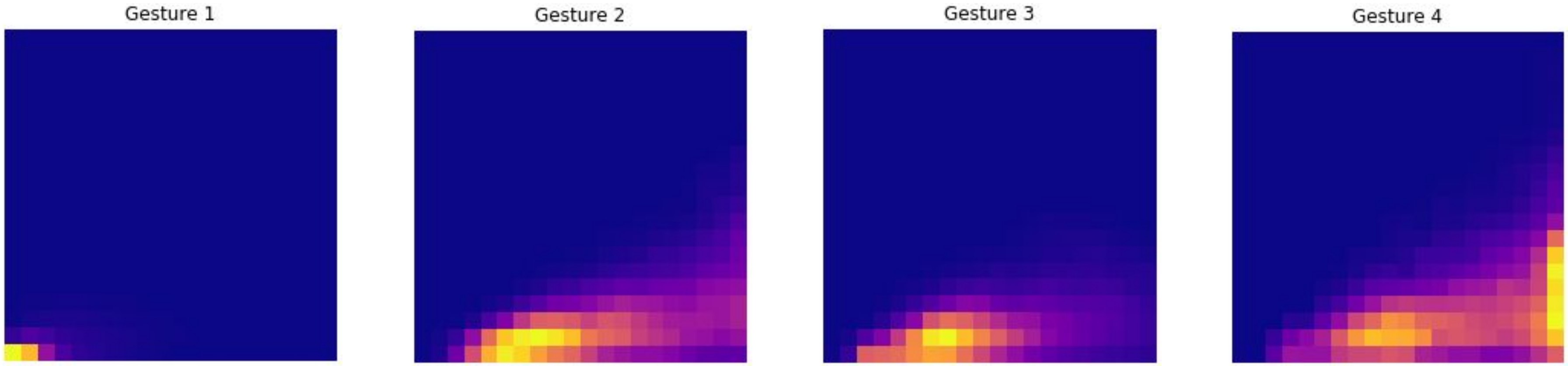
Let $\mathbf{v}_k$ be a persistence image of class $k \in \mathcal{K}$.
Let K be the set of observations from $\mathcal{K}$.

$$\mathbf{u}_k := \frac{\mathbf{v}_k}{\sum_i \mathbf{v}_k} \qquad P_n = \frac{\sum_{k \in K} \mathbf{u}_k}{\sum_i \sum_{k \in K} \mathbf{u}_{k,i}}$$



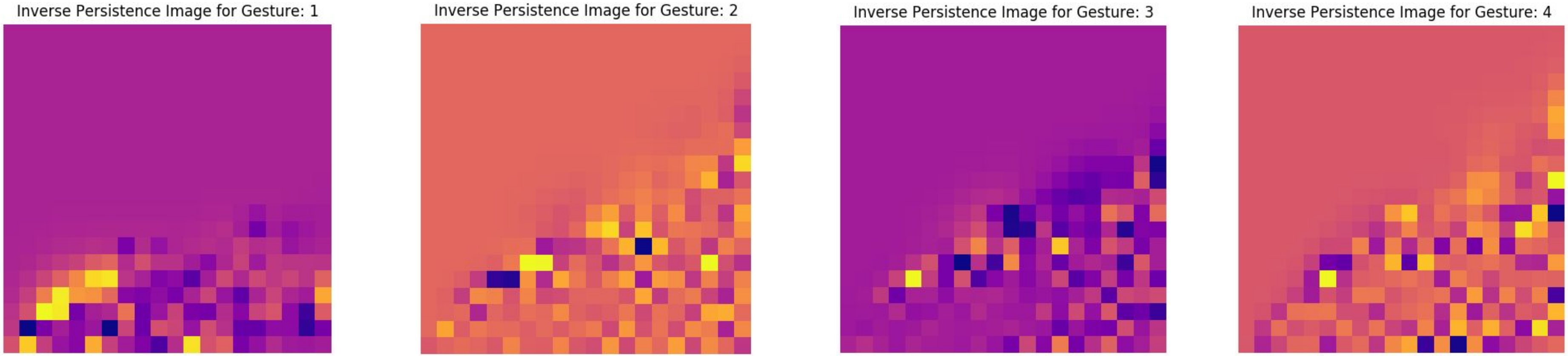
Aside: Using P_n to classify persistence images

- These vectors provide a baseline classification rate
- In-sample accuracy: 57.1%
  - Remarkably high for extremely low compute cost
  - Expect 25% for random assignment
  - Out-of-sample accuracy is hit & miss - some subjects have more influence than others



Inverse Images - Logistic Regression

- Another method for determining feature importance: Fit logistic regression; extract coefficients and reform as inverse persistence image



- In-sample performance: 99.57% accuracy
- Out-of-sample performance: 52.59% accuracy

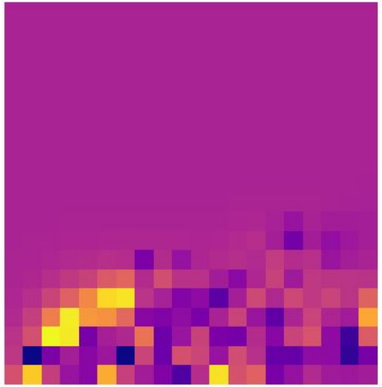
Inverse Images - LASSO

- Regularize & sparsify with L_1 penalty: $\underset{\beta \in \mathbb{R}^p}{\text{argmin}} \; f(Y|X,\beta) + \lambda||\beta||_1$
- More aggressive filtering

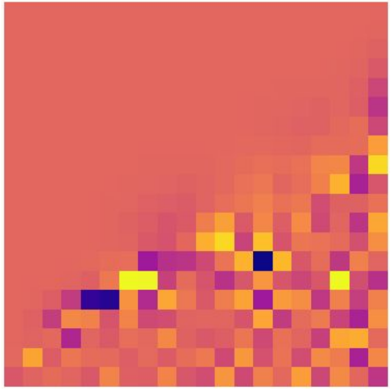
- In-sample performance: 81.96% accuracy
- Out-of-sample performance: 59.48% accuracy

Inverse Images - Compare

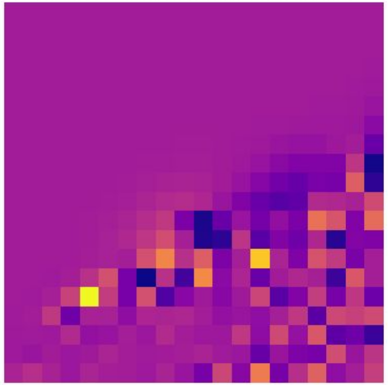
Inverse Persistence Image for Gesture: 1



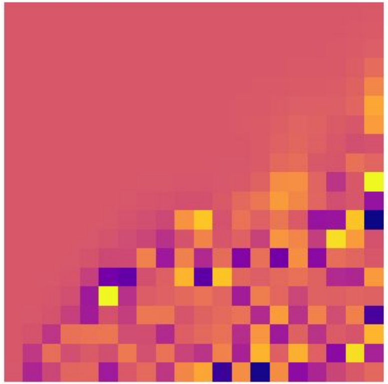
Inverse Persistence Image for Gesture: 2



Inverse Persistence Image for Gesture: 3



Inverse Persistence Image for Gesture: 4



Inverse Persistence Image for Gesture: 1

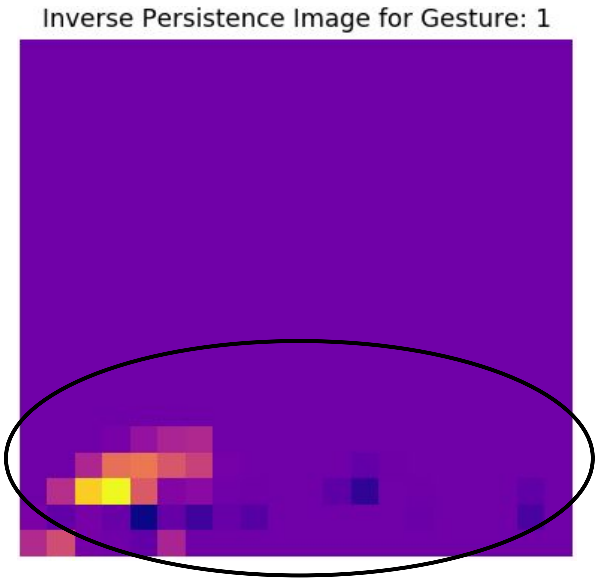
Inverse Persistence Image for Gesture: 4

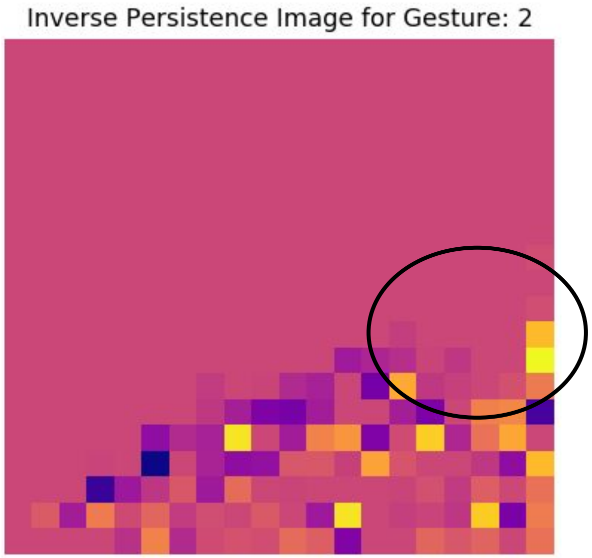
Inverse Persistence Image for Gesture: 3

Inverse Persistence Image for Gesture: 2

Persistence Filter

- Is it possible to construct a filter in this manner?
- Important information provided by less persistent 1-cycles.
- Cannot remove larger 1-cycles without loss of critical 1-cycles.

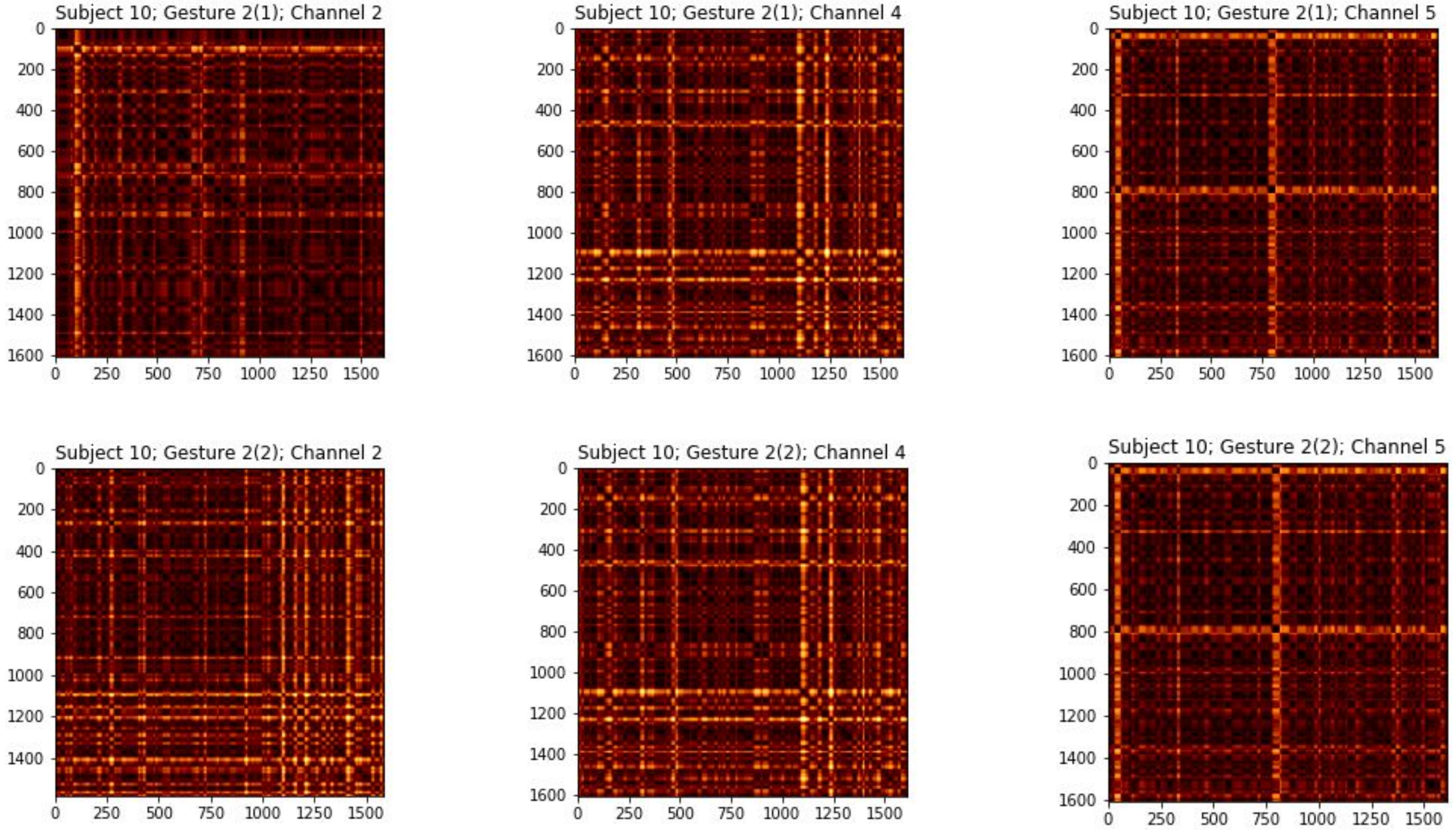


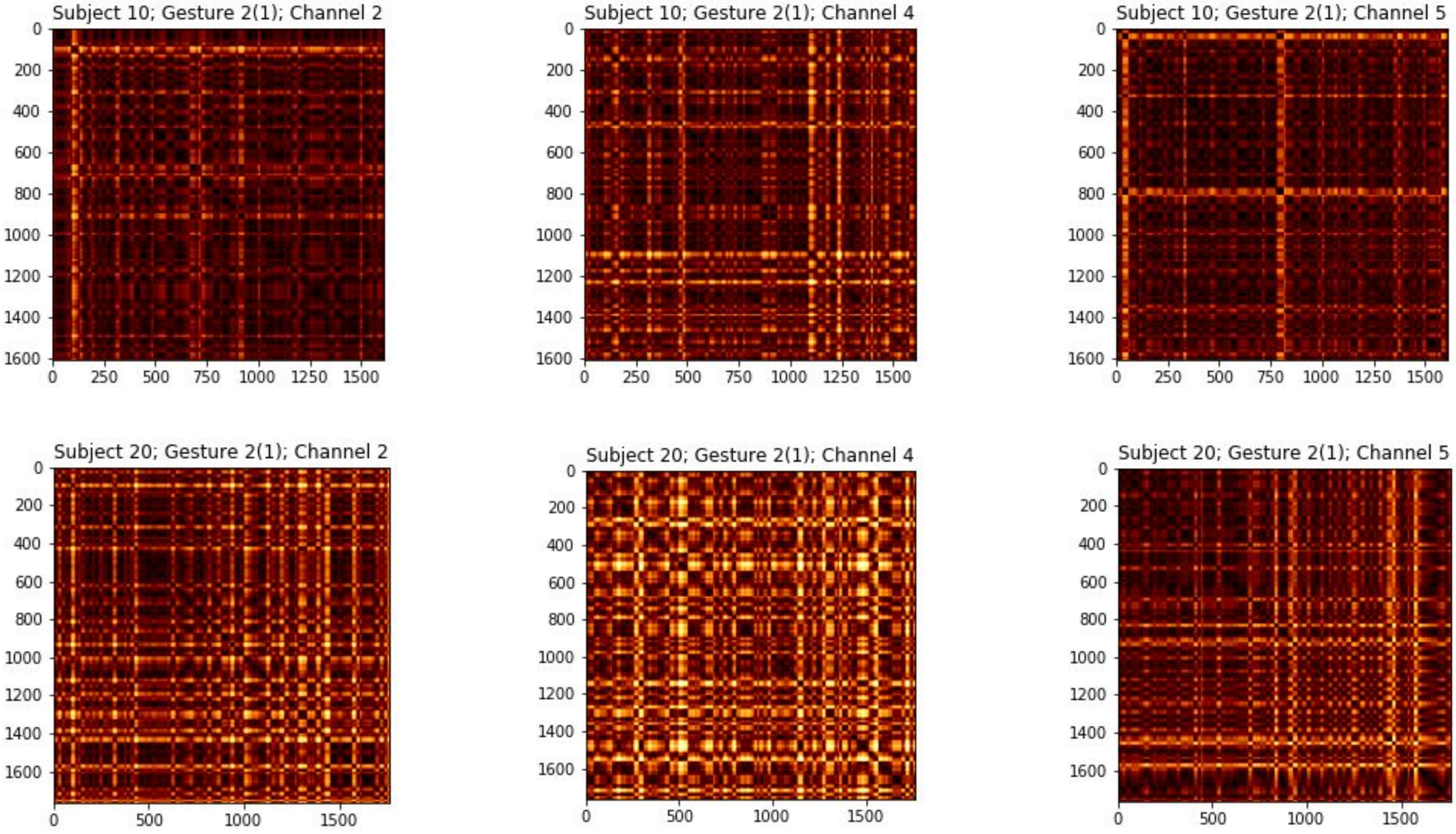


SSM - Classifier

What and How?

- Generate self-similarity matrix (SSMs) for time-ordered point cloud (TOPC) for each channel (modality)
- Derive self-similarity template through similarity network fusion (SNF); Use normalized SSMs to randomly walk over TOPC as a graph.
- Use features of fused SSMs to classify gestures.


Subject 10; Gesture 2(1); Channel 2
Subject 10; Gesture 2(1); Channel 4
Subject 10; Gesture 2(1); Channel 5
Subject 10; Gesture 2(2); Channel 2
Subject 10; Gesture 2(2); Channel 4
Subject 10; Gesture 2(2); Channel 5
0
200
400
600
800
1000
1200
1400
1600
0
250
500
750
1000
1250
1500


Subject 10; Gesture 2(1); Channel 2
Subject 10; Gesture 2(1); Channel 4
Subject 10; Gesture 2(1); Channel 5
Subject 20; Gesture 2(1); Channel 2
Subject 20; Gesture 2(1); Channel 4
Subject 20; Gesture 2(1); Channel 5
0 200 400 600 800 1000 1200 1400 1600
0 250 500 750 1000 1250 1500
0 500 1000 1500

Classifier - Challenges

- High one-time compute cost (size & time complexity)
    - 36 x 5 x 4 = 720 SSMs of size $(n \times n)$

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---------------------------------------------------------------------------
MemoryError                               Traceback (most recent call last)
<ipython-input-25-49496fc66e13> in <module>
----> 1 np.zeros(xdat)

MemoryError:
```

- Varying sized TOPCs require dynamic time-warping
    - Complexity: $\mathcal{O}(n^2)$ where $1500 < n < 3000$

Moving Forward

- Separate gestures into phases: begin, hold, release
- Perform sparse sampling of time series
- More work with SW1Pers:
  - Difficult to obtain topological evidence of cycles due to noise
  - More work needed to tune sliding window parameters
- Computing resources are available for SNF
  - Duke cluster
  - Google cloud environments

Sources

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