USC University of Southern California

USC Viterbi School of Engineering

Ming Hsieh Department of Electrical Engineering

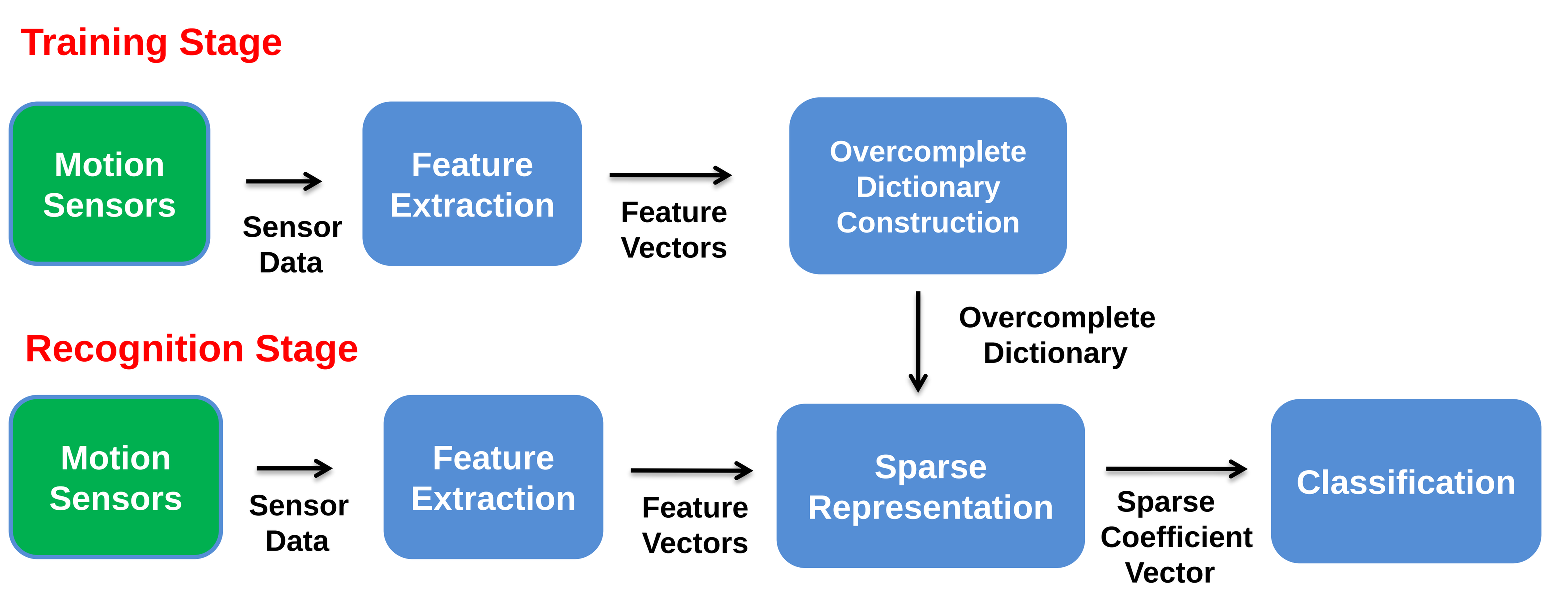
Sparse Representation for Reliable Human Activity Modeling and Recognition using Wearable Sensors

Mi Zhang, and Alexander A. Sawchuk

Motivation & Introduction

- Introduction
  - The recognition of various human activities using wearable sensing technology is important because it is the basis for a wide range of applications that would provide enormous benefits to our daily lives.
  - Example applications include long term physical fitness monitoring, sleep quality assessment, physical rehabilitation, and intelligent assistance for elderly and people with cognitive disorders.
- Challenges
  - Scalability to handle large amount of activity classes and style variation.
  - Performance highly dependent on features.

Our Method



- Feature Extraction
  - Sliding-Window based feature extraction
  - Features: Mean, Variance, Derivatives, Correlation, Crossing Rate, Energy, Entropy, Eigenvalues, etc.
- Overcomplete Dictionary Construction
  - The dictionary consists of the (selected) training samples from all activity classes.
- Sparse Recovery via L1 Minimization

$$\hat{\alpha} = \arg\min_{\alpha} \|\alpha\|_1 \qquad \text{subject to } \|A\alpha - y\|_2 \le \varepsilon$$

where $\mathbf{A}$ is the dictionary, $\mathbf{y}$ is the test sample, and α is the sparse coefficient vector whose non-zero entries encode the class membership.

- Classification
  - The test sample is classified to the activity class which has the smallest residual value.

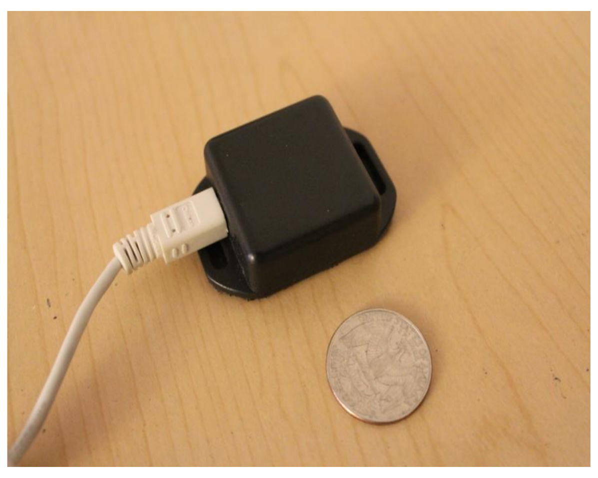
$$c = \arg\min_{i} r_i(y) \qquad \text{where } r_i(y) = \|y - A\delta_i(\hat{\alpha})\|_2$$

Future Work

Based on the promising results exhibited from this sparsity-based approach, we consider to implement it on the smart phones and build activity recognition centered applications on top of it for field studies in the future.

Sensors & Dataset

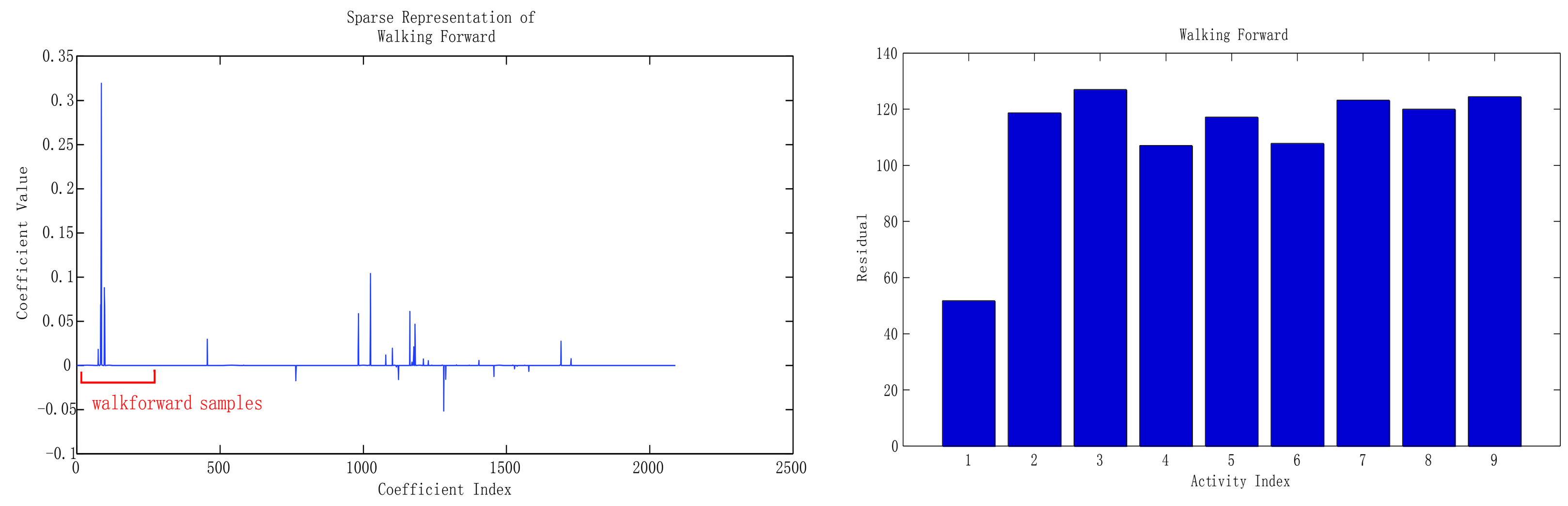
- Sensing Platform
  - MotionNode: A 6-DOF inertial measurement unit (IMU) that integrates a 3-axis accelerometer, a 3-axis gyroscope.



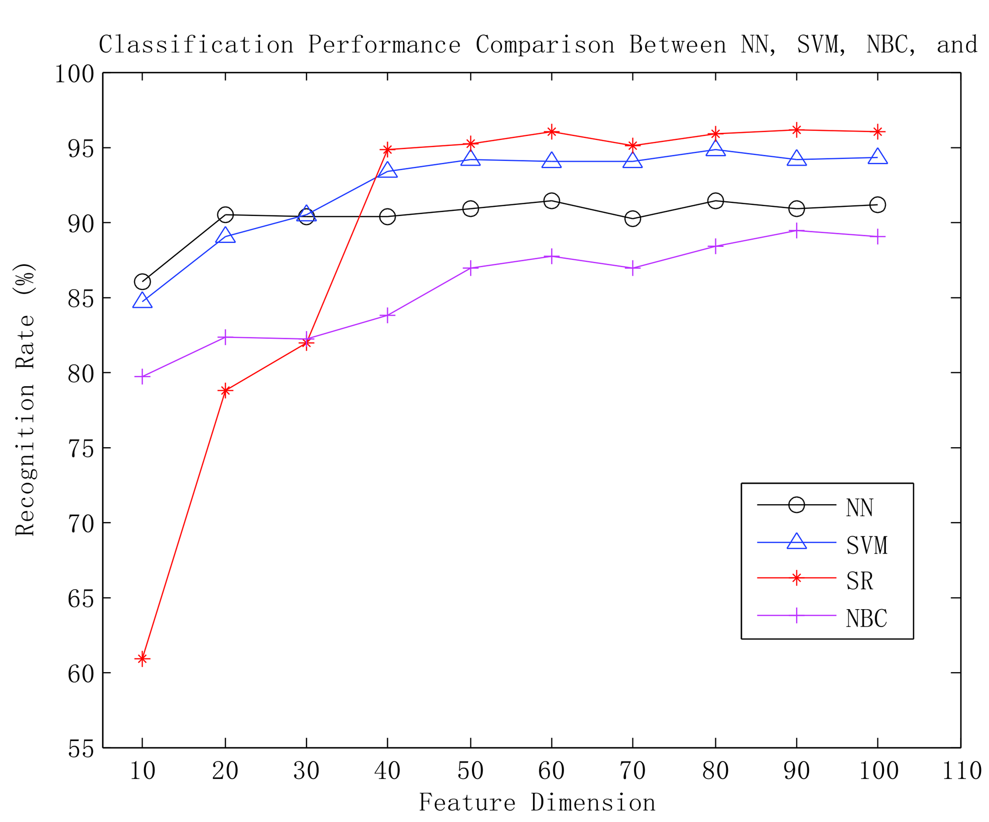
- Dataset
  - Fourteen subjects with diverse gender, age, height, and weight participated in this study.
  - Each subject performed nine most basic and common activities in daily life including *walk forward*, *walk left*, *walk right*, *go upstairs*, *go downstairs*, *jump up*, *run*, *stand*, and *sit*. A total of 42 hours of data is collected.

Experimental Results

- Sparse Representation

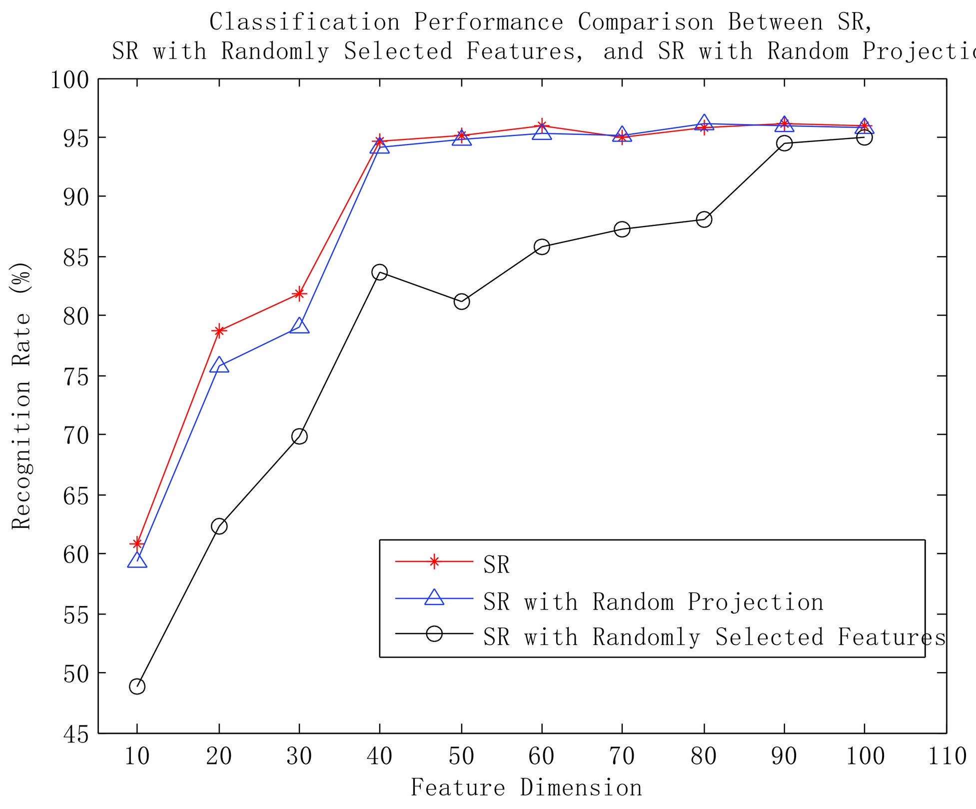


- Effect of the Feature Dimension



- Baseline Algorithms:
  - nearest neighbor (NN),
  - naive Bayes classifier (NBC), and
  - linear SVM
- Observation: When feature dimension is equal or larger than 40, our approach (SR in red curve) achieves a steady performance and beats all the other three methods, achieving a maximum recognition rate of 96.1%.

- Effect of the Choice of Features and Random Projection



- Feature Selection / Projection Algorithms:
  - random selection,
  - sequential forward selection (SFS), and
  - random projection
- Observation: By using random projection, the task of looking for “optimal features” to achieve the best performance is less important.

For more information, please contact Mi Zhang via mizhang@usc.edu

Ming Hsieh Institute
Ming Hsieh Department of Electrical Engineering