Intel-NTU Heterogeneous Sensor Network Project:
Champion Meeting

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Outline

• Body Sensor Network Contest
  – Description and Approach
  – Results and Conclusions

• Establishment of in-house wireless sensor network test-bed
  – Hardware Infrastructure
  – Sensor Node Software and Backend Support
Body Sensor Network

• Sensors (accelerometers, gyroscopes) record activities such as shelving a book, walking, sitting up, etc.
• Multiple datasets, each with unique sensor configurations
• Tasks include such things as classifying activity type and determining average stride time.
BSN: Binary Activity Classification*

• Sit to stand detection
  – For this task, the algorithm needs to be able to distinguish trials of “sit to stand” from trials of different types

• Training & testing
  – involved all three datasets
  – The data is accelerometer and gyroscope reading over time
  – Each dataset had different formats and numbers of features
  – A bonus: Segmentation is known

• Evaluation:
  – For each of the testing trials, the algorithm must classify an action as “sit to stand” or “not sit to stand”
  – Objective function to maximize: number of correct classifications

*Internal to contest, this known as “Task #3”
Analysis

- Size of training dataset is small, but feature size is large (avg of 60 for each class)
  - Reduce the dimensions to avoid overfitting
- There only a few subjects, but there are many subjects in test set
- The length of raw features is not fixed
- Different action have unique waveforms, some complementary

BSN: Binary Activity Classification

Task #3
Approach

• Raw features: the sensor values collected in time intervals
• Linear scale the raw feature
  – Actions of the same type may be performed at different speeds
  – Data must be scaled to the same absolute length in order to perform feature-based learning
• Perform Fast Fourier transform on the data from a single sensor
  – Filter high-frequency noise
• Training model & predict by SVM
  – Used linear kernel
Conclusion

• Testing error using each of the three datasets provided achieves an accuracy of 97~98%
  – FFT, wavelet or raw data were used as features.
  – FFT features proved to be most useful for this task
BSN: Multi-Class Action Segmentation/Classification*

- 4 sensor nodes attached to each test subject, each with 5 sensors (measure acceleration, rotation).
- Goal: Given a testing sequence, detect 9 kinds of actions along with begin and end times of the detected action within a tolerance of 0.5 seconds

Testing Sequence:

prediction: 1 2 9 9 9

- Provided Training Data:

  In all, there were 9 actions performed by 3 test subjects.

*Internal to contest, this known as “Task #1”
Analysis

• Since the test subjects used in the creation of the testing and training were different, high *generality* of the model was required.

• For each label, we had (4 sensor)*(5 readings/sensor)*Length features, while there were only (3 person)*(10 example/person) training examples. *Overfitting* may be an issue.

• There may be *unknown actions* performed in the testing sequence. Thus, negative examples in testing can be much more diverse than in training.
  — But after we studied the testing sequence, we found there were actually no unknown actions performed.
Approach

• Model Selection:
  – After trying different classifiers, we found SVM with a linear kernel and large margin can yield stable and generalizable performance compared with other approaches we tried.

• Feature Extraction:
  – Raw Features: Scale windows to length of 64 data points
  – FFT Features: Transform sequence into Fourier Coefficients, use low frequency portion (top 16), e.g. low-pass filter.
  – Wavelet Features: Transform sequence into wavelet coefficients.

• Window Selection:
  – Strategy 1: Move sliding window with different sizes, classify each window, and select those with most confidence.
  – Strategy 2: Find those segments with significant vibration and use the classifier to determine which actions they are. Here we need to assume vibration is not caused by unknown actions.
Conclusion

• Competition-driven:
  – If the sensors are in a stable state most of the time, or for a dataset like the one in this competition, strategy 2 is better for its simplicity and efficiency.

• Research value:
  – Strategy 1 is closer to real world applications.
  – How to design a algorithm that deals with segmentation and classification at the same time is a valuable research topic.
BSN: Average Stride Time Calculation*

- Find the average stride time = \( \frac{\text{Time}_{\text{Total}}}{\text{Num}_{\text{Stride}}} \)

- Details:
  - Three different datasets, each having a different sensor configuration and with different test subjects at distinct locations
  - One of the datasets included trials at different walking speeds and inclinations
  - Calculate the full cycle of sensor reading on one leg

*Internal to contest, this known as “Task #2”
BSN: Avg Stride Time Calculation

Analysis

Data: not all sensor readings are distinguishable, only certain sensor readings are needed

Detecting peaks and valleys for cycle recognition
Our Method

1. Perform a moving average to smooth the raw time series data

2. Estimate the probable range of the periodical interval $R_{pi}$ according to the most frequent distance between peak points

3. Count stride number $N_s$ and accumulate total stride time $T_{total}$ by searching peak points in the sliding window with the range of size $R_{pi}$

4. Average Stride Time = $T_{total} / N_s$
Conclusion & Possible Improvements

• The estimated range of periodical interval may be hard to detect and become lost in the noise.

• A possible solution is to convert the raw time series into a different representation form to filter out the highest-frequency peaks before beginning the estimation process.

• It is crucial to automatically detect and focus on the most significant set of time series data in the sensor network with respect to a desired event of interest.
BSN Contest Overall Conclusion

The First Body Sensor Network Contest
In Conjunction with BSN 2011

Second Place

is awarded to

National Taiwan University Team
National Taiwan University

On Behalf of the Organizing Committee
Roozbeh Jafari, John Lach