Physical Activity Monitoring

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ABSTRACT

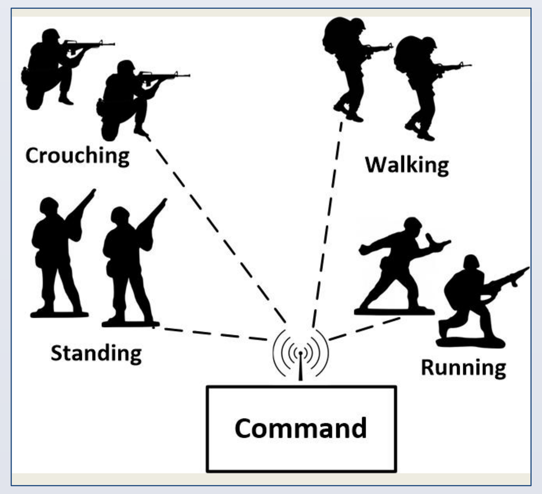
Physical activity monitoring is possible due to the advance of low cost and easy-to-use sensors that can record movements and heart rate. Maintaining a record of physical activity is a difficult task; knowledge of performed activities can help a subject make decisions toward a healthier lifestyle.

Our project applies machine learning approaches on a data set obtained from UCI Machine Learning Repository to classify activities performed by 8 subjects. Activities include exercise of varying intensities. DT, SVM, and LDA were implemented an achieved high accuracy in classifying activities and intensity. A combined DT-LDA approach is being implemented to adapt a classifier towards a particular subject.

MOTIVATION

Available technology and data sets will enable new applications in activity monitoring:

- Soldier Monitoring
- Personal Activity Recording
- Firefighter Monitoring
- Nursing Home



Machine learning approaches can improve monitoring

- More commercial use
- Use monitoring analysis to facilitate better decisions:
  - Amount of exercise per day
  - Call help for soldier or firefighter in distress

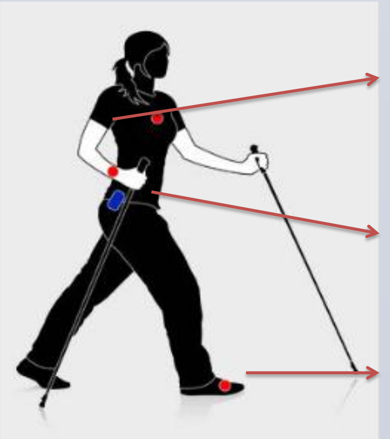
DATA

Inertial Measurement Units (IMU)

- Placed on Chest, Hand, and Ankle for 8 subjects
- Heart Rate, 3-axis Accelerometer, 3-axis Gyroscope, 3-axis Magnetometer data
- Sampled at 100 Hz

Activities

- Light Intensity – Lying, Standing, Walking, Ironing
- Moderate Intensity – Vacuuming, Descend Stairs, Nordic Walking, Cycling
- Vigorous Intensity – Running, Ascending Stairs, Rope Jumping



IMU Chest: Gyroscope *3 for XYZ, Accelerometer * 3 for XYZ, Magnetometer*3 for XYZ

IMU Hand: Gyroscope *3 for XYZ, Accelerometer * 3 for XYZ, Magnetometer*3 for XYZ

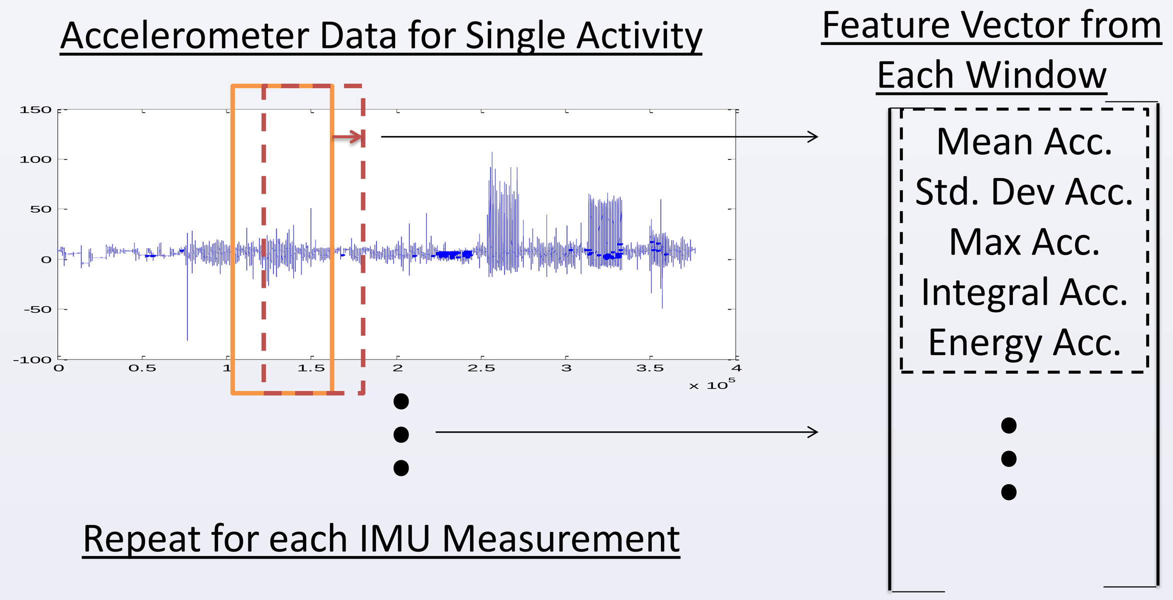
IMU Ankle: Gyroscope *3 for XYZ, Accelerometer * 3 for XYZ, Magnetometer*3 for XYZ

DATA PRE-PROCESSING

Total – 20,108 examples. 140 features

Windowing

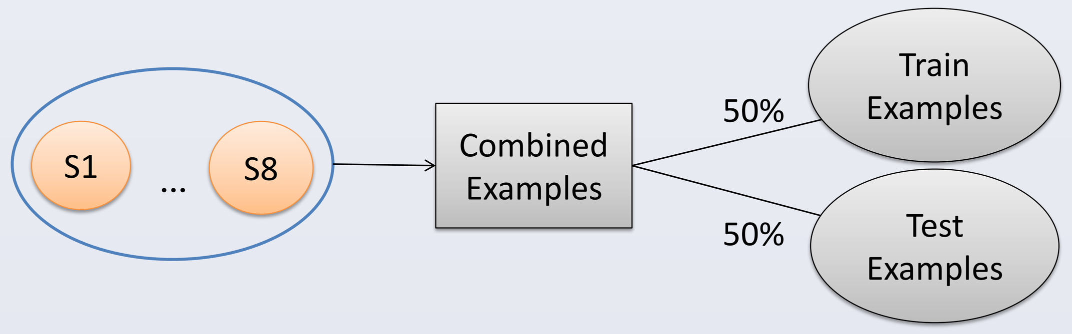
- 5 second windows were taken from raw data to get meaningful range
- Time domain features were calculated from window
- Features include mean, std. dev, max, integral, energy
- **Calculated for each axis of each IMU for heart rate, accelerometer, gyroscope, magnetometer**
- Each window = 1 example
- Windows shifted by 1 second



CLASSIFICATION TASKS

1 – Classify Specific Activity - Lying, Standing, Walking, Ironing, Vacuuming, Descend Stair, Ascend Stair Nordic Walking, Cycling, Running, Rope Jumping

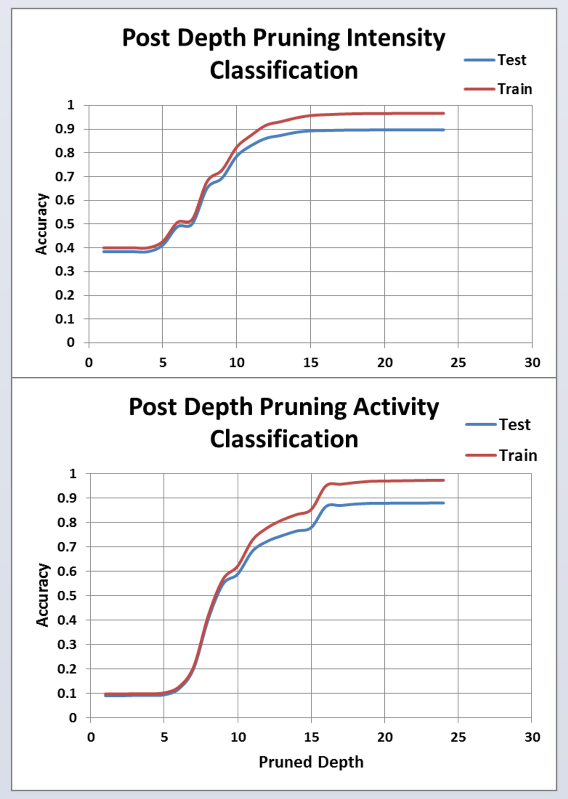
2 – Classify Intensity of Activity - Light, Moderate, Vigorous



RESULTS

Decision Tree

- **ID3 + incorporated the ability of our learner to handle missing features**
- Large Train Time ~ 9 hours (due to dataset and simple algorithm)
- Top nodes all split on different maximum values from our time domain analysis
  - Maximum Chest Acceleration In y-Direction
  - Maximum Chest Acceleration In z-Direction
  - Maximum Hand Acceleration In y-Direction
  - Maximum Heart Rate

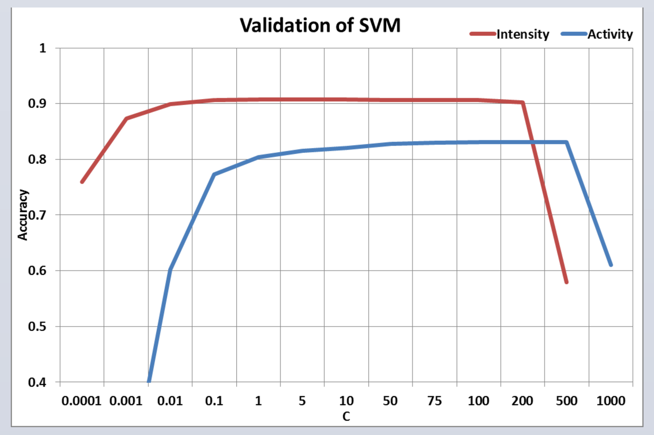


Intensity	Test Accuracy [%]
Light	98.36
Moderate	87.21
Vigorous	73.84

Activity	Test Accuracy [%]
Lying	98.57
Sitting	97.63
Standing	97.21
Walking	98.29
Running	96.34
Cycling	97.78
Nordic Walking	96.46
Ascending Stairs	41.98
Descending Stairs	46.77
Vacuum Cleaning	87.38
Ironing	95.25
Rope Jumping	95.20

SVM

- **1 vs. All approach used for both classification tasks**
- 12 classifiers for activities, 3 classifiers for intensity
- Validation – C= 500 Activities, C=10 Intensity
- Train time ~ 10 minutes for 12 classifiers
- SVMlight used



Linear Discriminant Analysis

- **Since our examples exhibited overlap from the windows, we performed Leave One Subject Out Tests to see if accuracy decreased**
- Fast train time, fairly accurate
- Rule calculated for each activity or intensity

$$h_{LDA}(\boldsymbol{x}) = \underset{y \in \{activities\}}{\arg\max} \{\log(P_y) - \frac{1}{2}(\boldsymbol{x} - \boldsymbol{u}_y)^2\}$$

Leave One Subject Out Test

S1	S2	S3		S8
Test	Train	Train	...	Train
Test	Test	Train	...	Train
Test	Train	Test	...	Train
		...		
Test	Train	Train	...	Test

LOSO Activity Average Accuracy – 76.45%

LOSO Intensity Average Accuracy – 86.65%

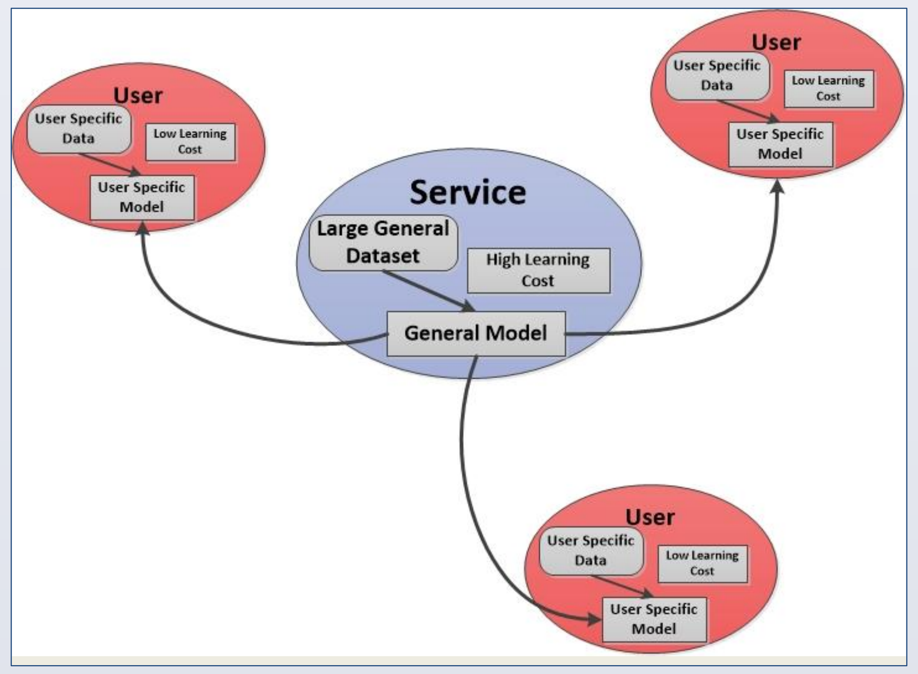
SUMMARY TABLE

Classifier	Train Activity	Test Activity	Train Intensity	Test Intensity
Decision Tree	97.27%	87.95%	96.69%	89.70%
SVM	79.08%	77.71%	88.85%	88.00%
LDA	80.36%	79.86%	86.83%	87.15%

DT LDA

We foresee applications such as personal activity recording needing a more complicated learning scheme:

- One that works right out of the package without user specific data
- One that gradually takes the user specific data from application use and creates a better model for that individual



DT-LDA Learner

- Create Decision Tree and LDA for General Dataset
- New User Specific Data Available - Retrain LDA Weighing New Examples More

DT-LDA Classifier

- $if\ h_{LDA} = h_{DT}$
  - $then\ classify\ as\ h_{LDA/DT}$
- $else\ if, \boldsymbol{x}\ close\ to\ a\ LDA\ mean$
  - $then\ classify\ as\ h_{LDA}$
- $else$
  - $classify\ as\ h_{DT}$

CONCLUSIONS AND FUTURE WORK

- High accuracy obtained with ML approaches – data is separable
- Decision Tree seems to perform best, future work will use McNemar's and confidence intervals to quantify
- Best features take maximum of accelerometer and heart rate
- LOSO analysis shows that classifier can be used on new subjects
- DT-LDA as an approach to tailor classifier for a particular subject

REFERENCES

[1] A. Reiss and D. Stricker. Introducing a New Benchmarked Dataset for Activity Monitoring. The 16th IEEE International Symposium on Wearable Computers (ISWC), 2012.

[2] A. Reiss and D. Stricker. Creating and Benchmarking a New Dataset for Physical Activity Monitoring. The 5th Workshop on Affect and Behaviour Related Assistance (ABRA), 2012.