Ensemble Approach for Sensor-Based Human Activity Recognition

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Abstract
This poster discussed our ensemble based approach to detect Human Activity for the Sussex-Huawei Locomotion Transportation(SHL) recognition challenge. The objective was to recognize 8 modes of transportation: 1-Still, 2- Walk, 3-Run, 4-Bike, 5-Car, 6-Bus, 7-Train, 8-Subway in user and position independent manner. We trained Random Forest model on combined and shuffled SHL-Training and SHL-Validation data. To improve accuracy and prevent over-fitting, hyperparameter tuning was done with 10-fold cross validation. The model with best oob_score of 85.12% was selected as final one. The estimators were trained parallelly to reduce training time using all logical cores.

Methodology
• Missing values in every sample of 5 seconds replaced by mean in the frame
• To overcome the impact of position and orientation, magnitude for each sensor was calculated. √x²+y²+z²
• SHL-Training and SHL-validation dataset was combined and shuffled then split into 70% training and 30% test data
• 65 statistical features derived in Time-domain and Frequency domain for each frame of 5 seconds
  ○ Time-domain: mean, median, max, min, variance, standard deviation, interquartile range
  ○ Frequency-domain: mean frequency, energy, entropy, kurtosis, skewness, peak frequency
• For each frame of 5 seconds, corresponding label determined using mode of labels provided in that frame
• Out of SVM, KNN, XGBoost and Random Forest, we found Random Forest to have the best combination of accuracy and training time, making it suitable for our analysis.
• Ensemble of Decision Trees-Random forest model was trained parallelly thus reducing training time.
• Output of each decision tree combined by averaging the probabilistic prediction instead of classifier vote for one class

Dataset and Features
• The SHL Recognition Challenge 2020 focused on identifying 8 modes of transportation - Still, Walk, Run, Bike, Car, Bus, Train, Subway using inertial sensor data of a smartphone. The dataset was acquired from three users wearing four smartphones at positions - Hips, Bag, Hand and Torso simultaneously.
• The Dataset [1][2] was divided into 3 parts - SHL- Training, SHL-Validation and SHL-Test dataset. The SHL-Training dataset contained labeled data over 59 days, SHL-Validation data over 6 days and SHL-Test data over 48 days. SHL-Training data was the largest, containing raw sensor data at four positions from User 1. The SHL-Validation contained data for User 2 and User 3 at 4 positions while, SHL-Test contained data for User 2 and User 3 at a position, which was kept unknown. The raw sensor data was sampled at frequency of 100Hz and included data from following sensors: acceleration (x, y and z), linear acceleration (x, y and z), magnetic field (x, y and z), gravity (x, y and z), gyroscope (x, y and z), Orientation (x, y, z, w) and Pressure. Data was segmented with a non-overlapping sliding window of 5 seconds and labels were provided per sample.
• Acceleration, Linear Acceleration, Magnetic field, Gyroscope and Pressure were used as raw features.

Conclusions
• The F1-Score for the final model on Test dataset is: Still-88%, Walk-94%, Run-99%, Bike-94%, Car-84%, Bus-77%, Train- 80%, Subway-81%
• To overcome the issue of imbalanced dataset, weighted random forest model can be evaluated on this dataset. Furthermore, the window size has been considered of a fixed length of 5 seconds. It is possible that adjusting the window size to be of a shorter duration 2-3 seconds might yield better results.

References