Hand gestures recognition with surface electromyogram and inertial sensors

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Abstract

This MScEng Thesis confronts with the real-world problem of hand gesture recognition. Data from 4 types of sensors, surface electromyogram, accelerometer, gyroscope and magnetometer which are placed on a subject's forearm, are analyzed, in order to recognize a gesture. These data are publicly available on the Ninapro-project's website in the Database 7. To achieve satisfactory recognition for 40 gestures of 22 subjects (2 of whom are amputees) we use machine learning models, deep learning models and ensemble learning. Due to the nature of the biosignals we process, we provide an intra-subject analysis. Our results follow the literature and are competitive.

Data

- We focus on the sensors "1-8" that are positioned 3 cm under the elbow and are equally spaced around the forearm.
- The repetitions of a gesture are considered in their full length.
- The data are immediately split in Train Set (repetitions "1", "3", "4", "5", "6") and Test Set (repetition "2").

Preprocessing

- The problem is simplified by focusing only in the most muscularly activated area of the hand, and the most active channel of each sensor (the channel with the greatest variance).
- The resulted signals are filtered according to the literature.
- Features are extracted from the signals.
- Feature standardization is applied.
- The best subset of features is selected with feature selection methods.

Performance Measures

Per subject analysis score:

- $Classification\ Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$
  - All moves are represented by the same number of repetitions.
  - Chance level: 2.5%

Per move analysis score:

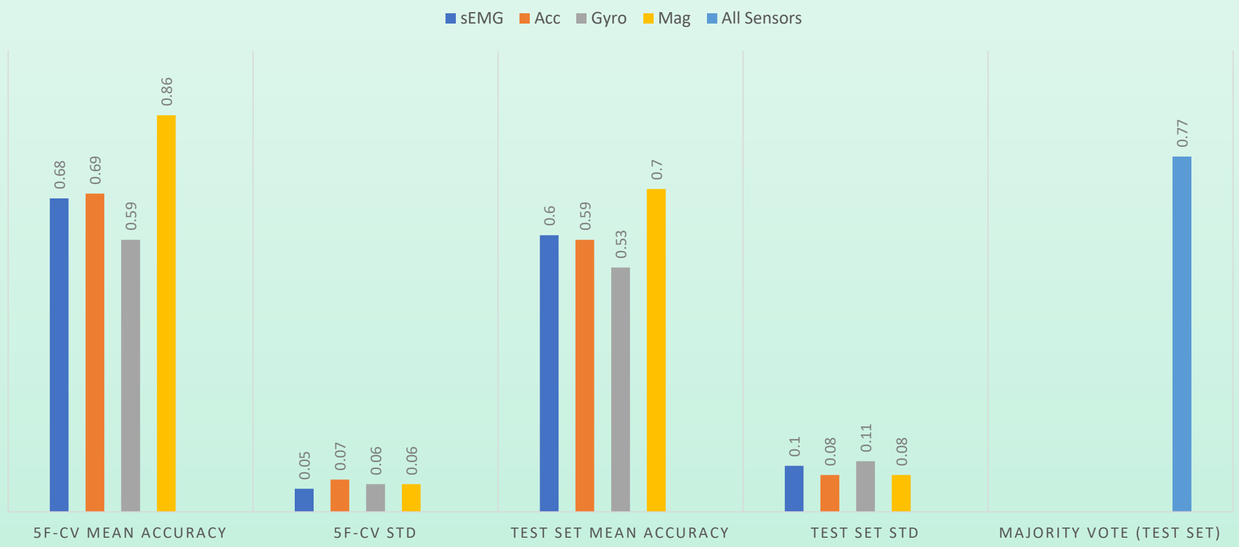
- $F_{1\,\text{score}} = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} = \frac{true\ positives}{true\ positives+\frac{1}{2}(false\ positives+false\ negatives)}$
  - Robust system with high precision and high recall.

Models

- LDA, RBF kernel Support Vector Machines, Random Forests, Soft Voting Clfs[LDA, RBF SVM, RF], Hard Voting Clfs[LDA, RBF SVM, RF], Neural Networks.
- Each classifier is optimized per subject and per type of sensor.
- We grid (or random) search parameters and use 5f-CV to pick the best classifier.
- Each classifier is trained per subject and per sensor with the selected parameters.

Results

- $F1_{score} > 0.7$, for 30 of the total 40 gestures (20 subjects).
- Example: 20 subjects, 40 gestures, Highly Optimized Machine Learning Models



Conclusions

- The combination of different sensors results in the highest classification accuracy.
- The highest accuracy between the single sensors was achieved by the magnetometer's signals. This result agrees with the literature that exists around the Database 7. However, we expect these results to have occurred due to bias in the way the gestures were sampled.
- The surface electromyogram have achieved close results to those of the accelerometer. The gyroscope signals have resulted in the worst performance.
- There is high variability in the classification accuracy results of different subjects.
- It is harder to recognize the gestures of the amputees group.

Suggestions for Future Research

- Can much better results be achieved by analyzing more data from a single subject?
- Can a move be recognized with only few msec of its onset?