

Activity Recognition in a Physical Interactive RoboGame

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PAPER**



Goal

- In this paper, we propose a model which aims at classifying player's activity in a Physically Interactive RoboGame using a 3-axis custom accelerometer positioned on player's chest.
- We define a set of high level activity classes that are automatically classified relying on a supervised machine learning framework.
- Our methodology consists of transforming the raw input space into one that is able to capture variance of the signal to emphasize the recognition of target activities.
- Our main contribution is on the fact that we are able to obtain reasonable results in accuracy by applying a simple transformation.
- The results achieved are comparable, in terms of accuracy, with other sliding window approaches; this suggests that our method is feasible for real applications.
- We test our methodology on activity recognition during a real RoboGame scenario.

Game Scenario

Environment

- Human vs Holonomic Robot.
- 4m x 2m area.
- Towers placed at the corners.
 - 4 charging LEDs per tower.
 - Charging time: 2.5secs/LED
 - Push button on each tower.



Players role & win/lose condition

- Human player must be able to **secure all the existing towers without letting a single one be ruined down by the robot.**
- "Secure a tower" means turn on all 4 charging LEDs on each tower (using a tower charging button)
- If, at anytime, a tower falls (because of the robot or player) the game ends and the human player is defeated.
- Player can move across the entire playground.
- Human can block the robot's path by staying in front of it.
- Robot cannot try to put down an already captured tower, or one whose button is currently pressed by the human player.

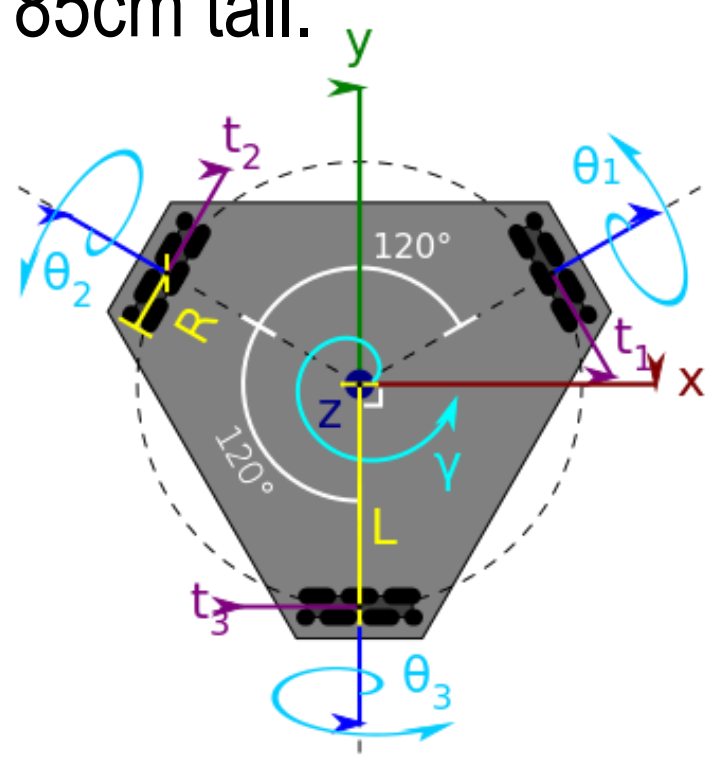
Notice that while the player is trying to capture a given tower the robot can try to put down another one!

Robot & Other Hardware Components



Robot

- Robust, triangular, omnidirectional base 5cm
- high (with 40 cm in diameter).
- Kinect sensor on top.
- Shuttle computer.
- Max velocity 1.4 m/sec.
- 85cm tall.

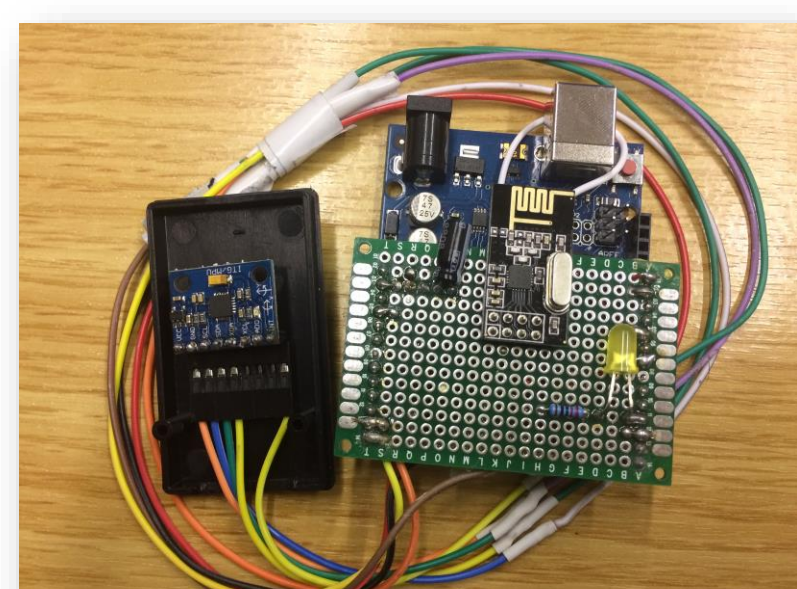


Software

- Native ROS integration

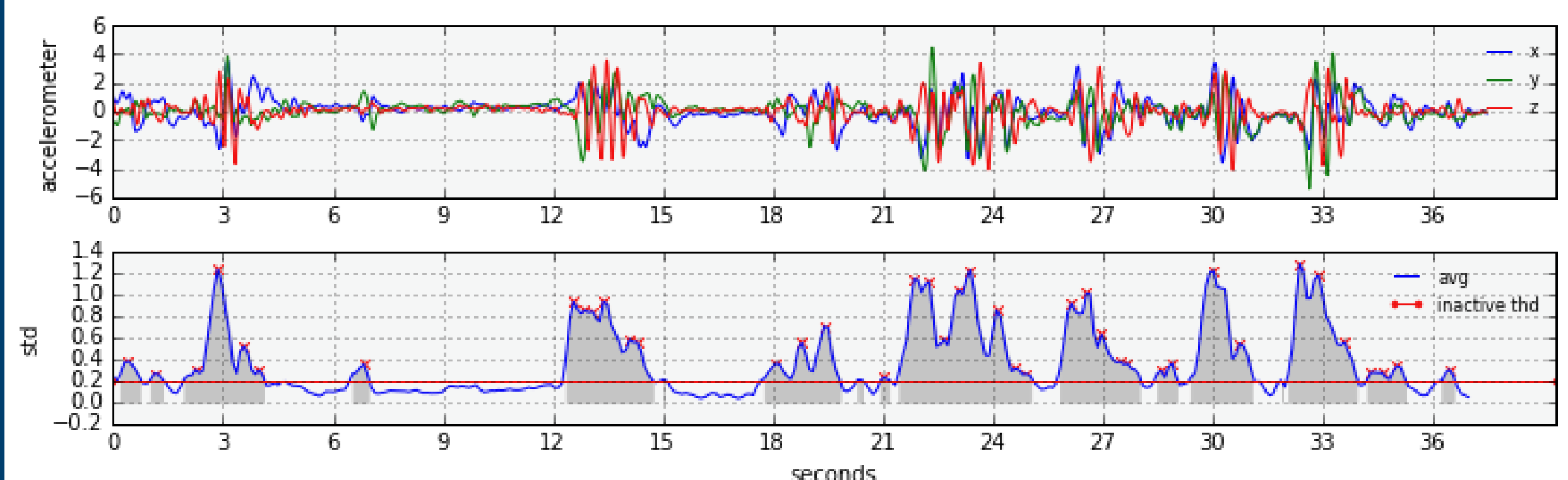
Accelerometer

- Custom device:
 - InvenSense MPU-6050
 - Arduino Uno
 - Nrf24I01 radio frequency

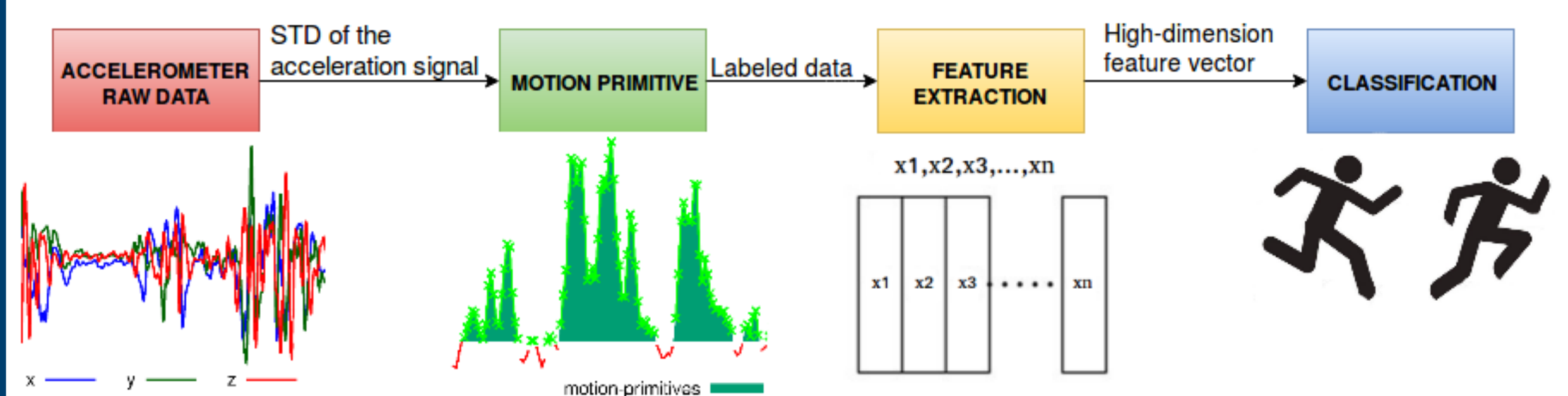


Method

Raw accelerometer signal & proposed transformation



Pipeline for training a classification model

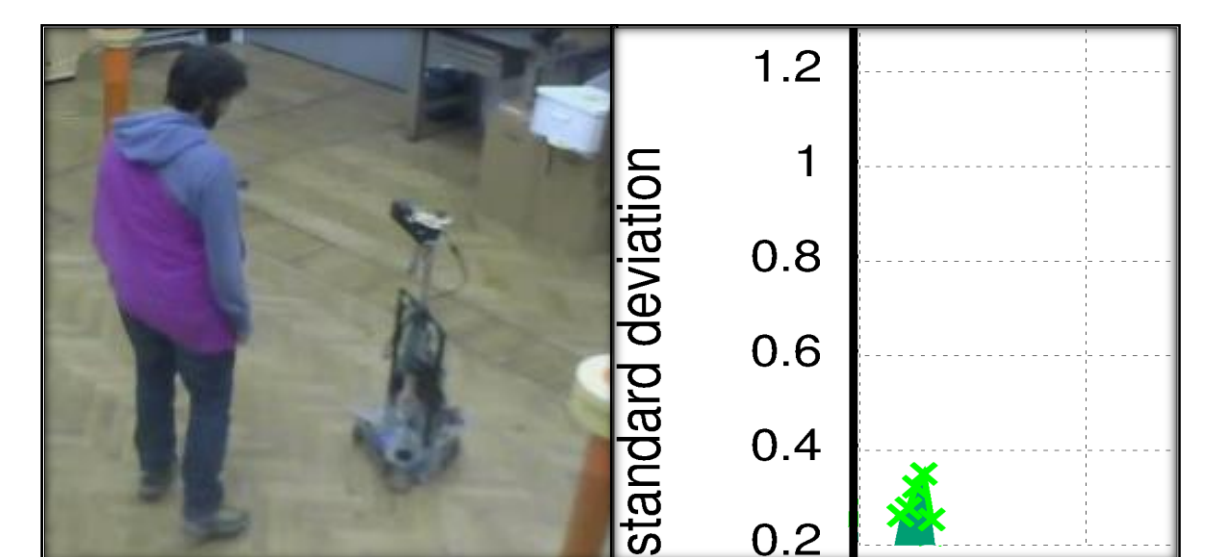


Motion primitive examples

Running



Standing/Locally moving



Results

Features

- Root mean square
- FFT energy
- Signal mag. area
- M. primitive mean
- Max peak

Class support

- 367 motion primitives
- "locally moving": 34%;
- "walking/dodging": 25%;
- "running": 41%.

Dataset Characteristics

- 29 matches
- 15 males
- Ages: 7-10; 26-40.
- Dur: ~1m30sec

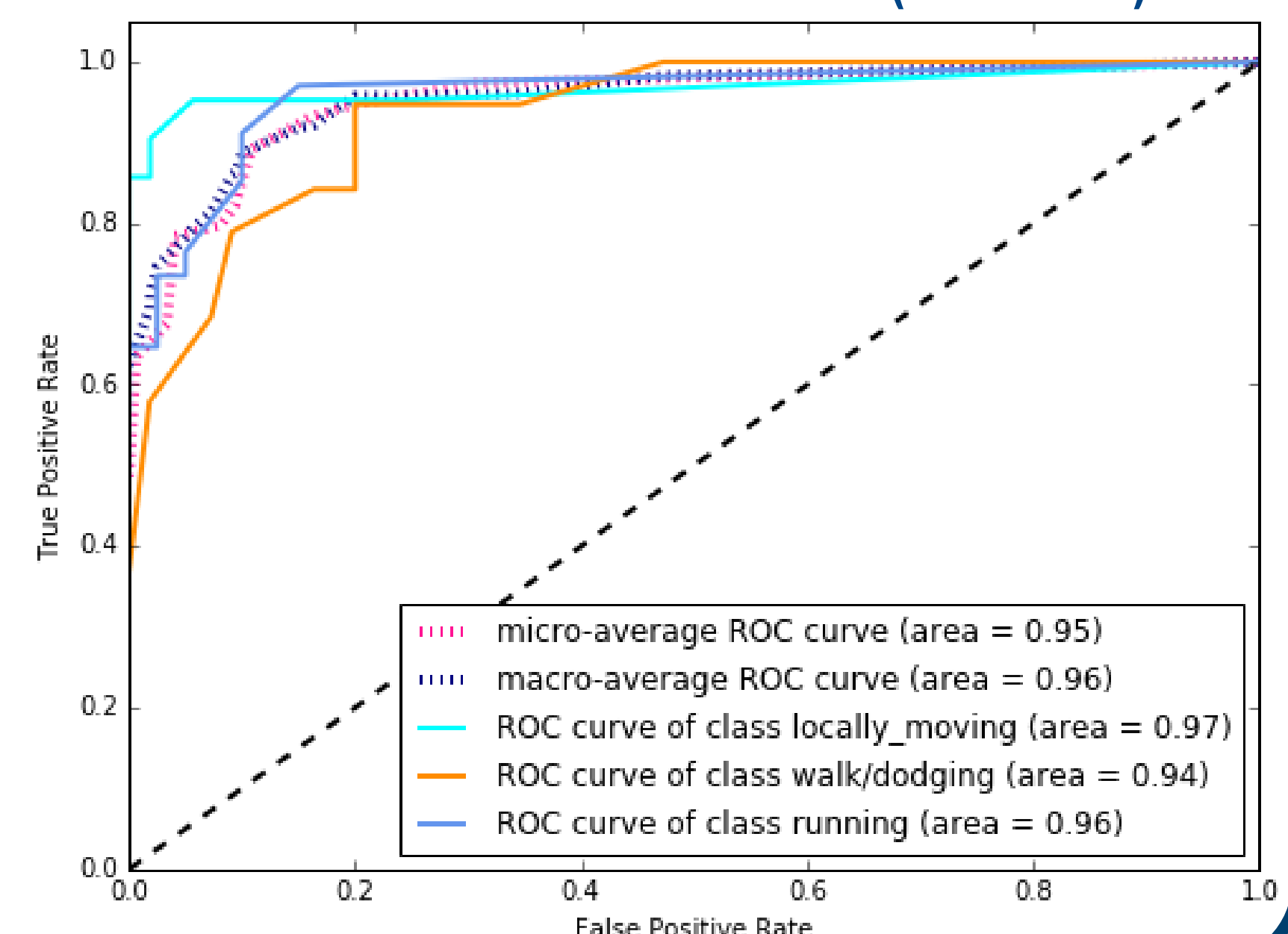
Advantages

- Low complexity.
- Simple to implement.
- Easy to tag.
- Good accuracy.

Limitations

- Multiple activities may be associated with a single motion primitive.

ROC curve for the trained Random Forest Ensemble method (100 trees)



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