7th International Electronic Conference on Sensors and Applications – S2 Wearable Sensors

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Inclusive Human Intention Prediction with Wearable Sensors: Machine Learning Techniques for the Reaching Task Use Case

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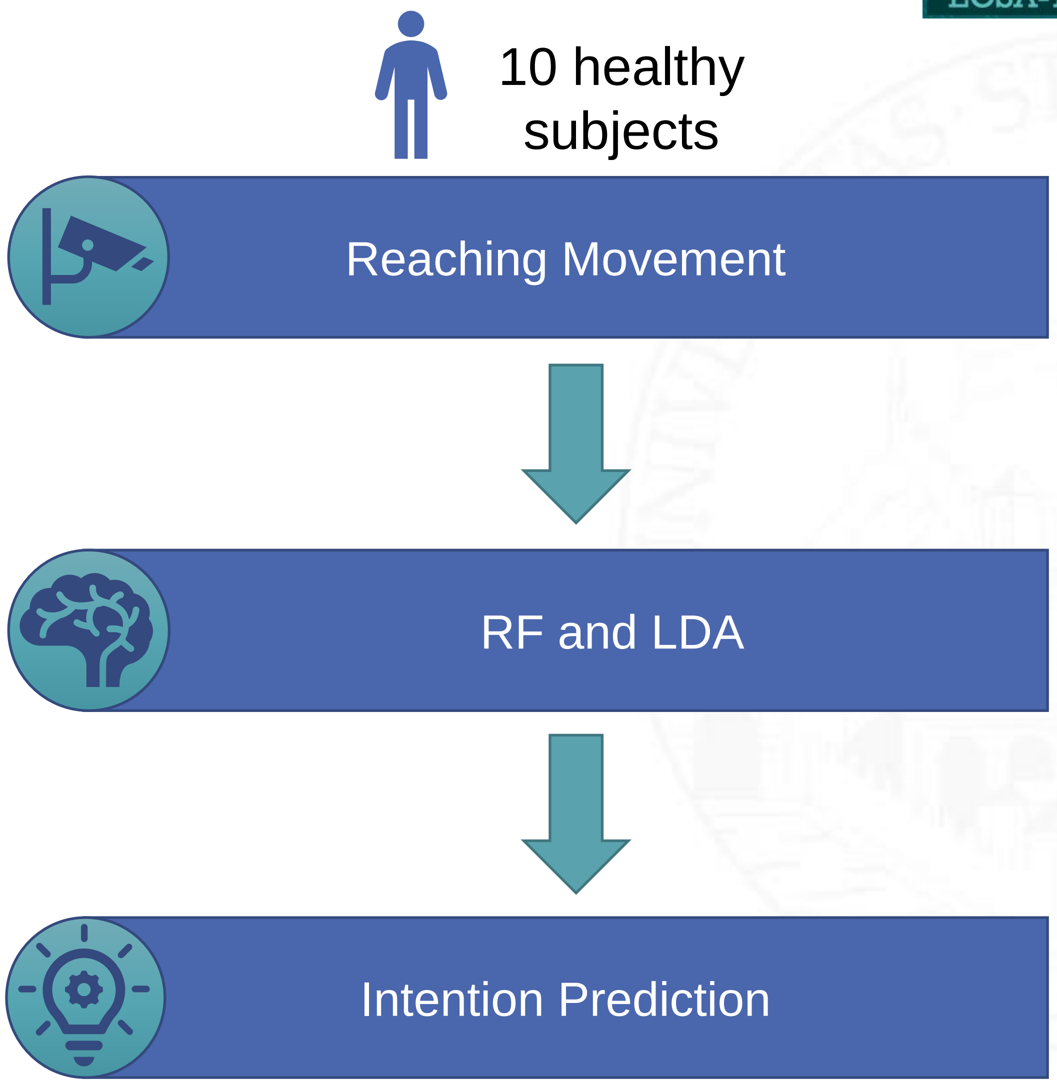
Agenda

- Objective
- Materials
- Methods
- Results
- Conclusions
- Future developments

Objective

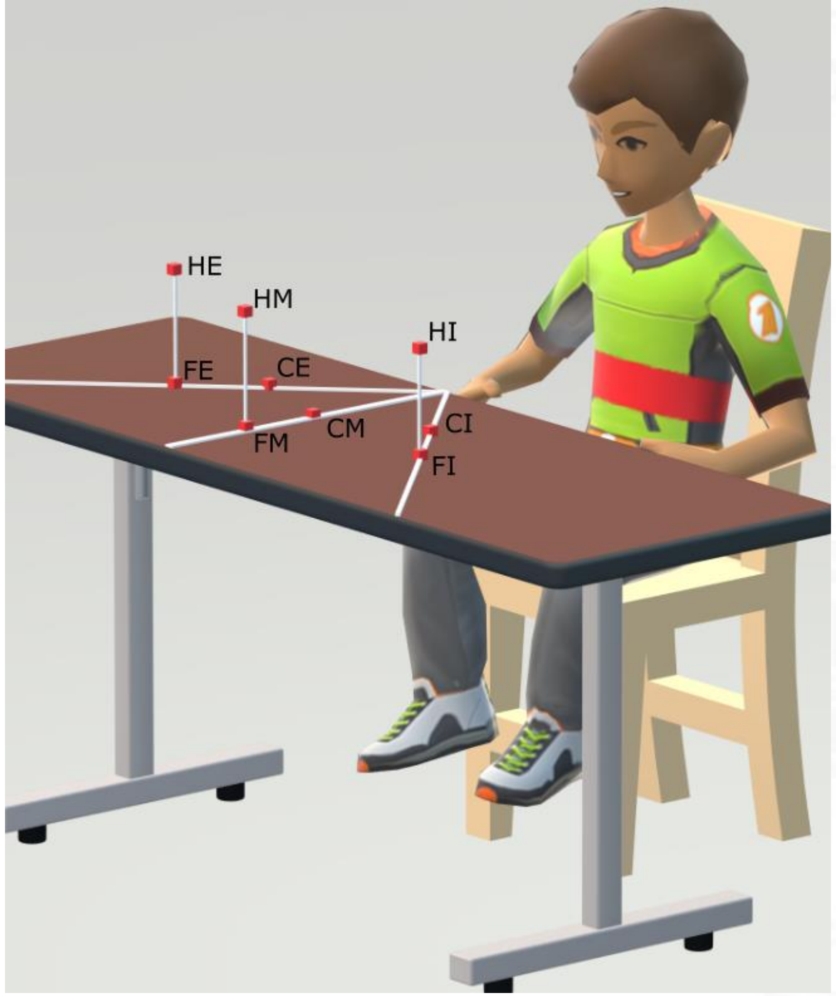
Analyse the reaching movement of 10 healthy subjects developing and training **Machine Learning Algorithms** able to predict subjects' **intention.**

Performances of **Random Forest** (RF) and **Linear Discriminant Analysis** (LDA) are compared.



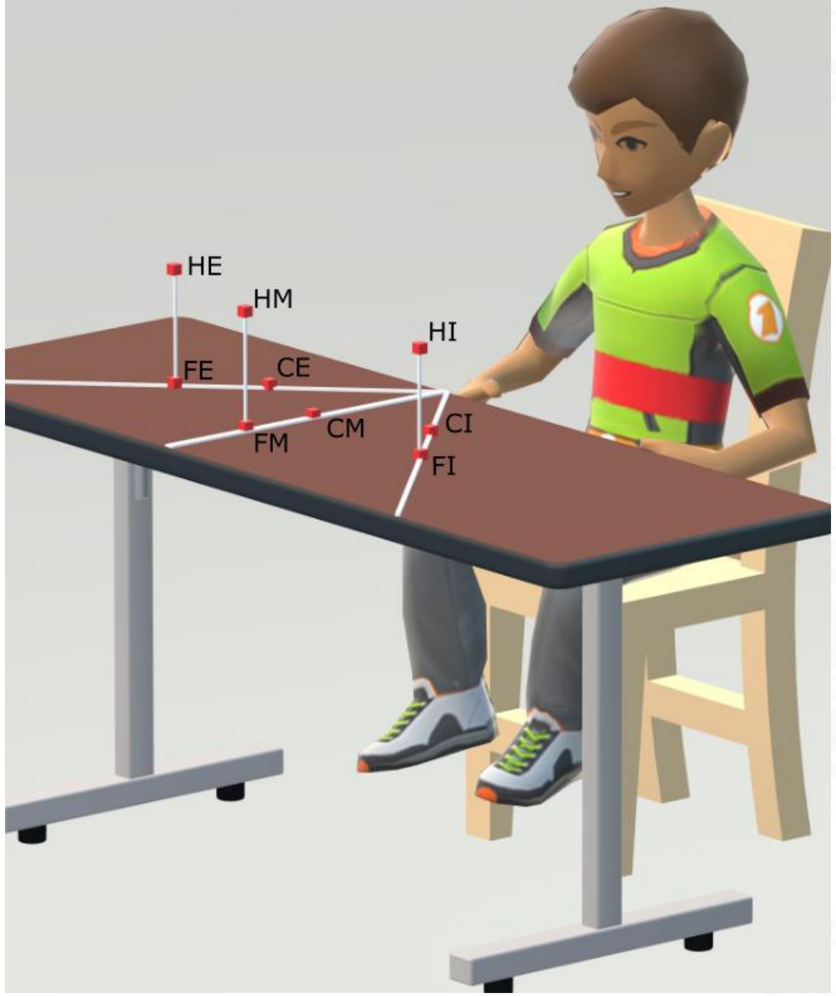
Materials - Experimental Setup

- Subject sitting on a chair
- Table at navel level
- Subject trunk fixed to the chair
- Subject wearing a wrist splint with a pointer



Materials - Experimental Setup

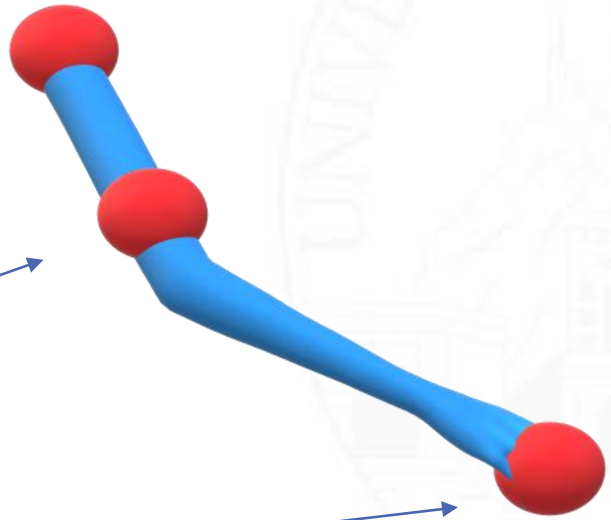
- 6 targets to reach at 7 cm above the table: 3 **directions** (internal, middle, external), 2 **distances** (far: 90% of arm length, close: 65% of arm length)
- 3 targets to reach at acromion level: 3 directions only far distance



Materials - Acquisition System

- Polhemus FASTRAK electromagnetic tracking device:
  - 1 transmitter
  - 4 receivers-sensors
  - Sampling frequency: 30 Hz

- Sensors position:
  - Manubrium
  - Acromion process
  - Upper third of humerus
  - Dorsum of the wrist splint

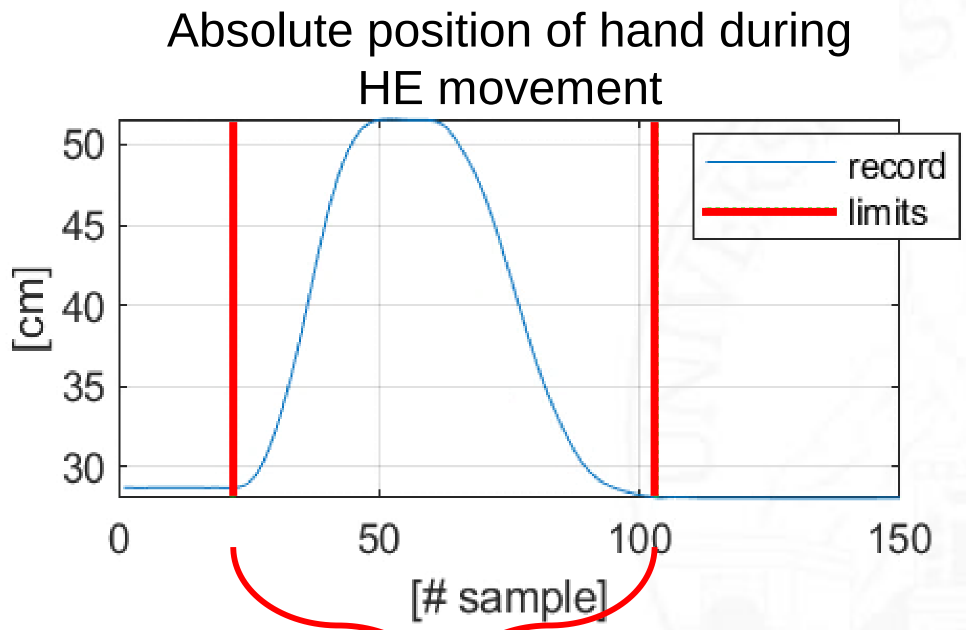


Materials - Acquisition Protocol

- For each hand: 3 recorded repetitions for each target;
- Touch the target and come back;
- Comfortable speed;
- No feedback;
- Standardized order: close-middle (CM), far-internal (FI), high-external (HE), far-middle (FM), close-external (CE), high-internal (HI), close-internal (CI), far-external (FE), high-middle (HM)

Methods - Data Elaboration

- **Motion edges identification**
- Data normalization
- Feature extraction
- Feature scaling



First derivative of sensors position

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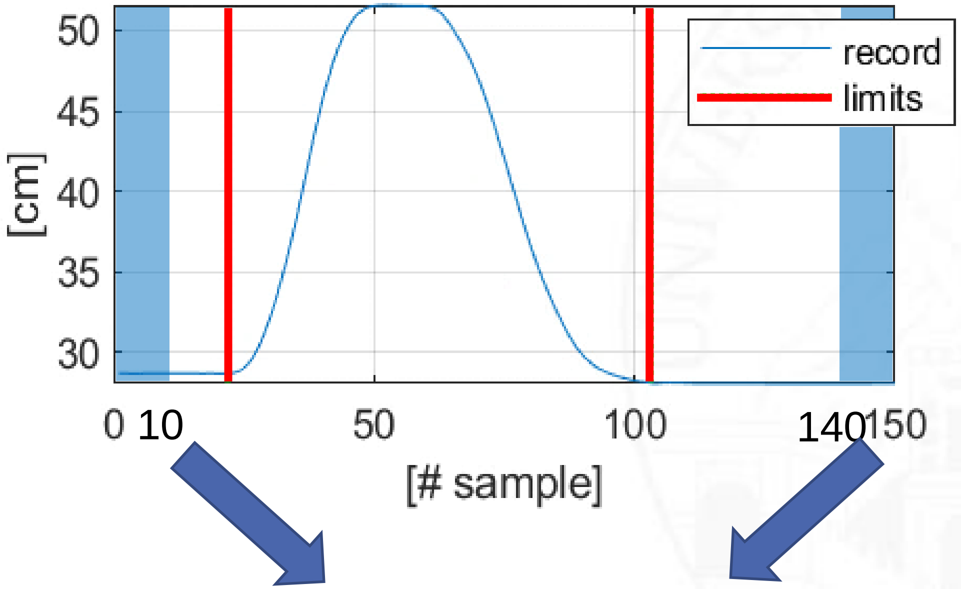
Threshold

Methods - Data Elaboration

- Motion edges identification
- Data normalization
- Feature extraction
- Feature scaling

Absolute position of hand during HE movement



Data from the first and last 10 samples (subjects in starting position) are used to compute subjects anthropometrical data used as normalization parameters

Methods - Data Elaboration

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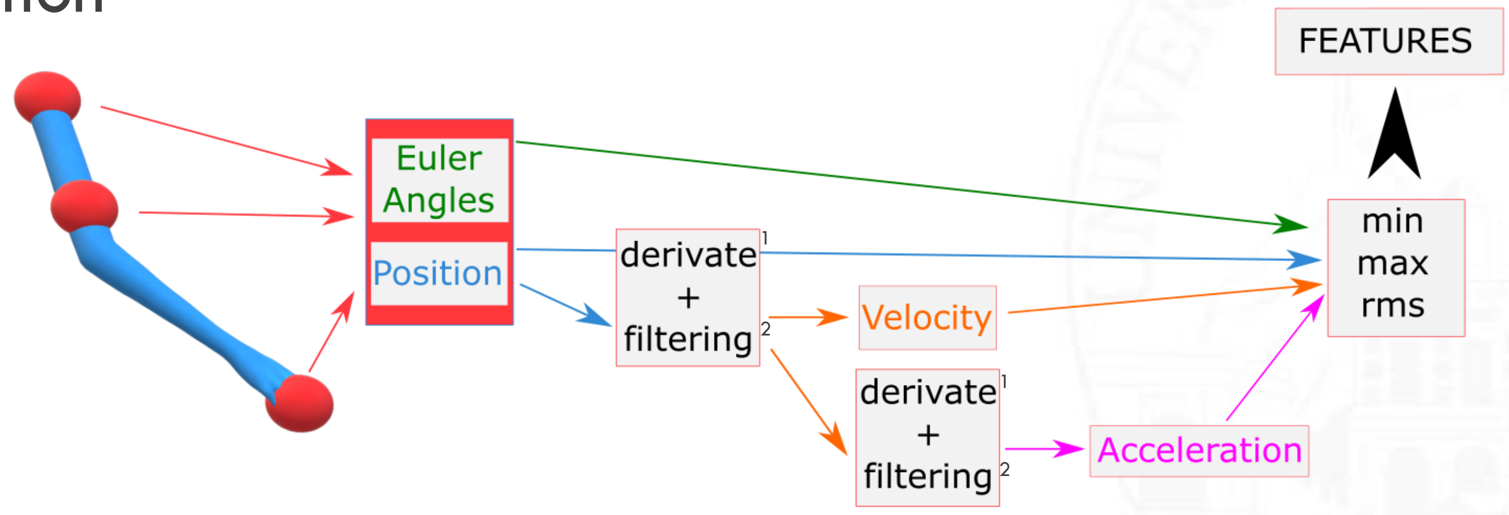

[1]two-point numerical derivation

[2]fourth order zero-phase low-pass Butterworth filter

Methods - Data Elaboration

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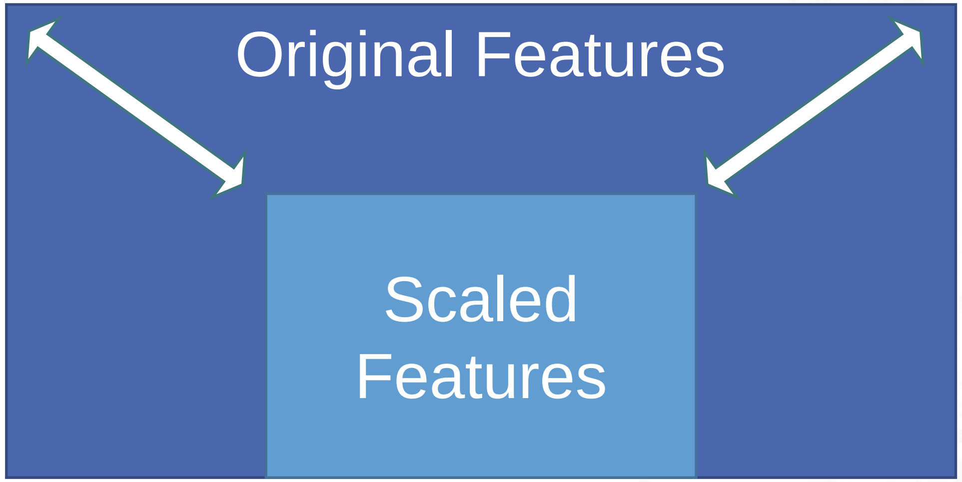


Computed features were rescaled from their actual values to [-0.80, +0.80]

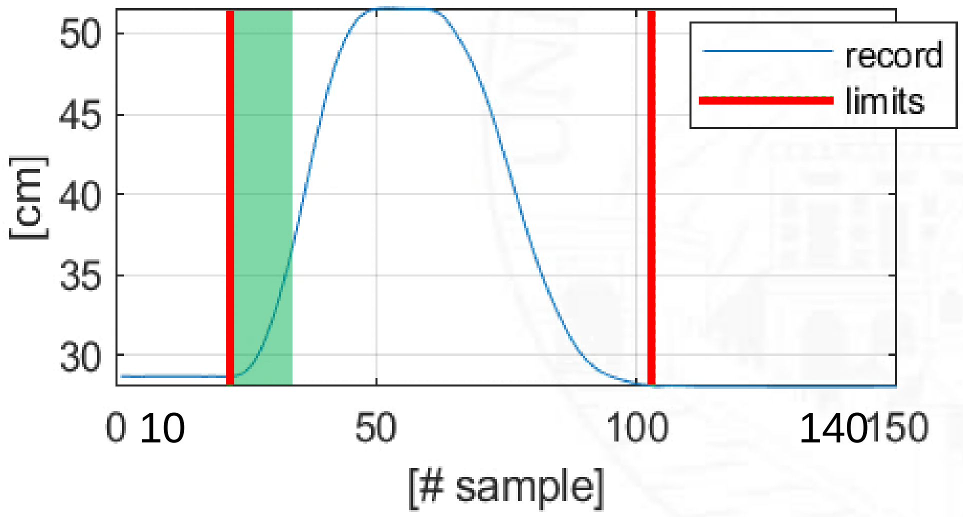
Methods - Observation Window

Only the first part of the motion must be considered:

- 1/10 and 1/7 of the overall motion length

Average 1/10	Average 1/7
8 samples – 0.27 [s]	11 samples – 0.37 [s]

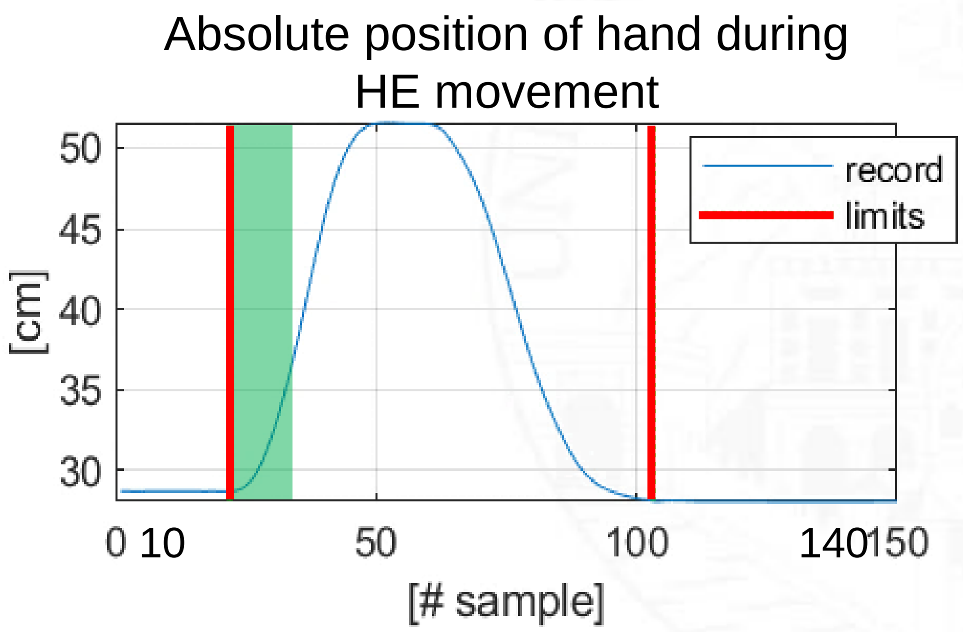
Absolute position of hand during HE movement



Methods - Observation Window

Window size strategies:

- **Custom window approach**: a value is computed *a posteriori* for each trial;
- **Average window approach**: the average motion length of all the trials and subjects is used to compute the observation window size;



Results - Intention Prediction

Test parameters:

- Considered features
- Observation window size
- Observation window approach

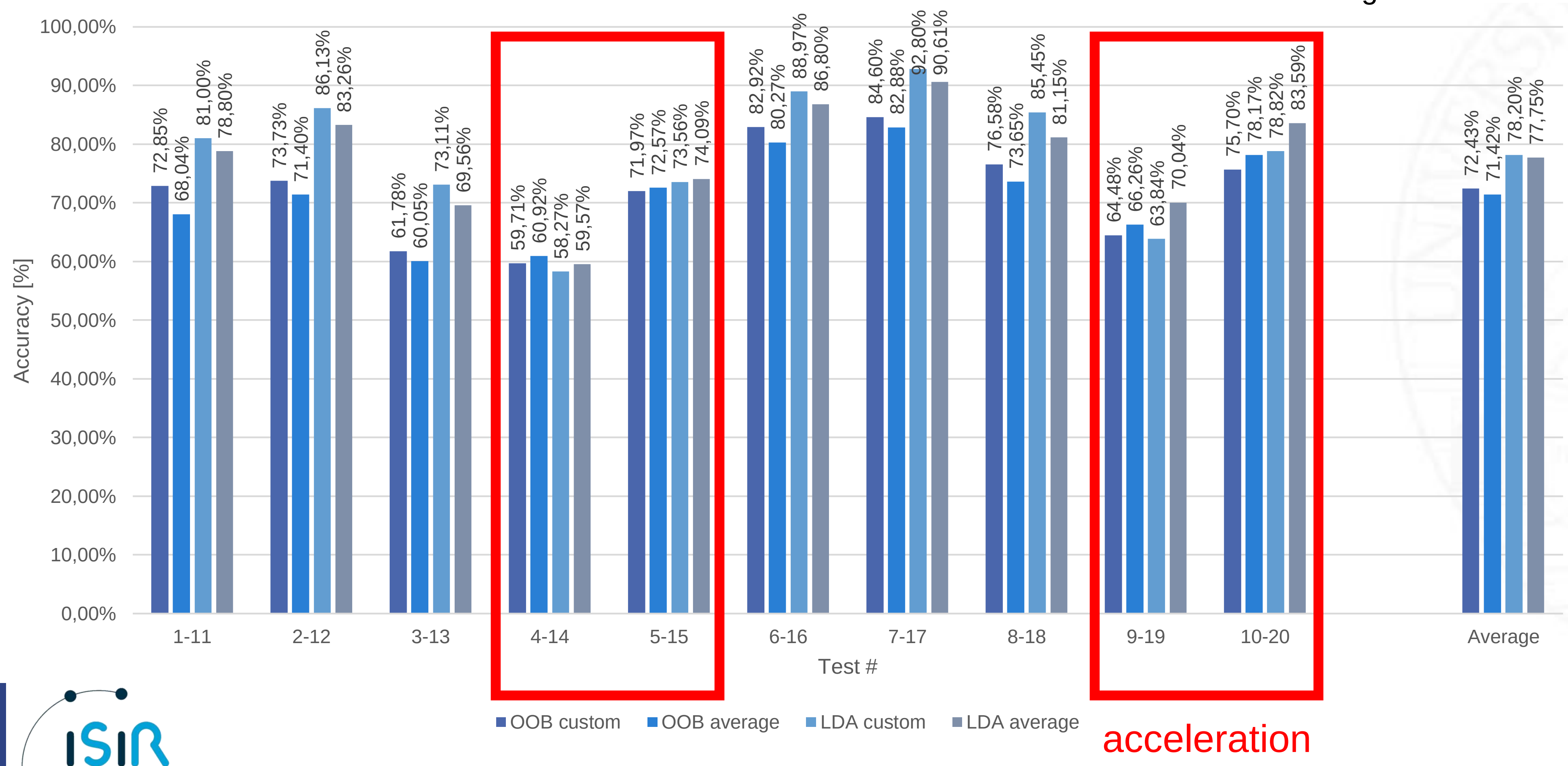
A multiclass Machine Learning problem is addressed. Used labels are the targets positions.

For RF the Out-of-Bag (OOB) error is computed.

Results - Observation Window Approaches - Accuracy

Training dataset: RF 90% LDA 85%

Results Averaged over 200 tests



Results - Observation Window Approaches - Accuracy

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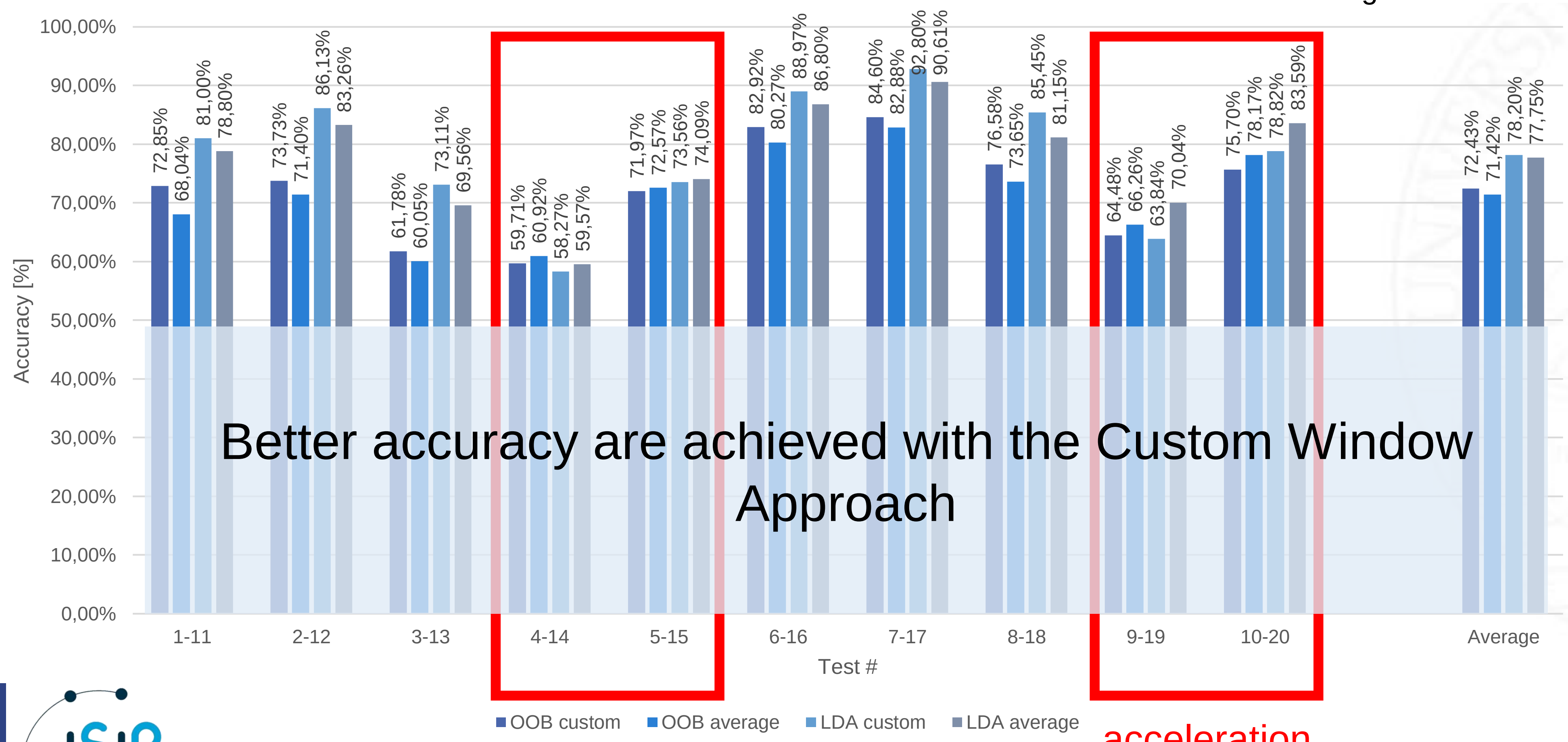


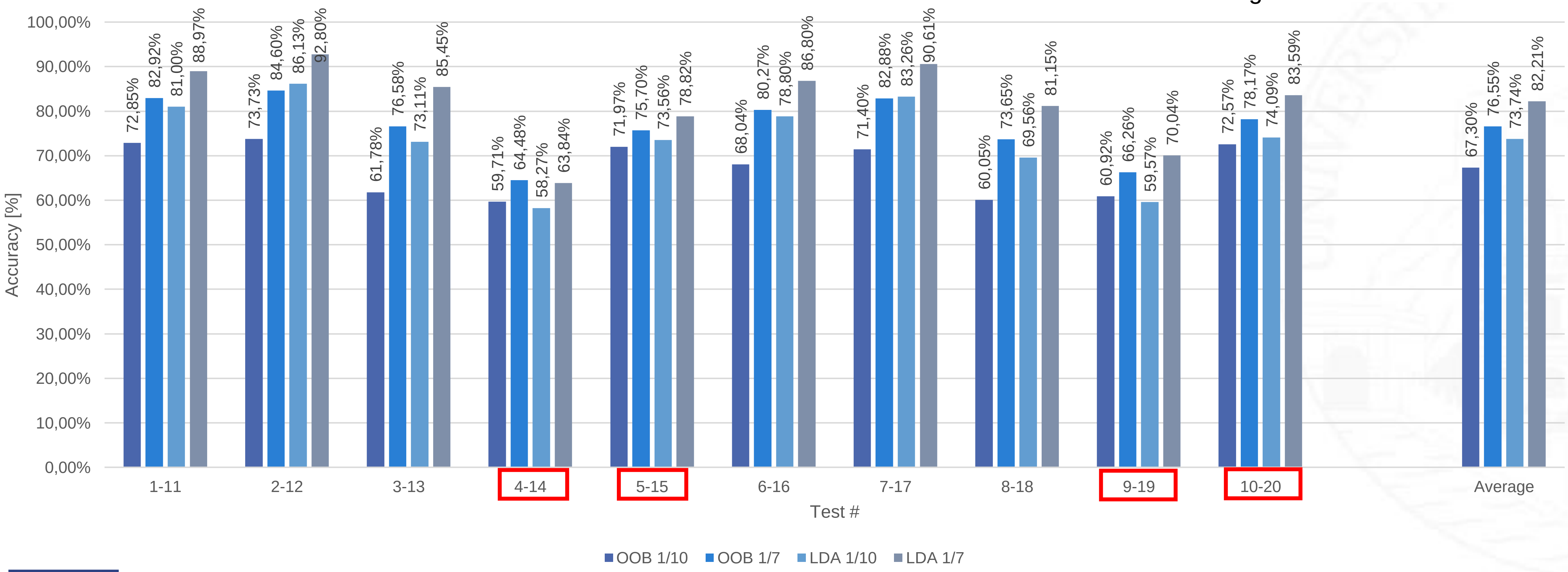
Better accuracy are achieved with the Custom Window Approach

acceleration

Results - Observation Window Size - Accuracy

Training dataset: RF 90% LDA 85%

Results Averaged over 200 tests



Acceleration

Results - Observation Window Size - Accuracy

Training dataset: RF 90% LDA 85%

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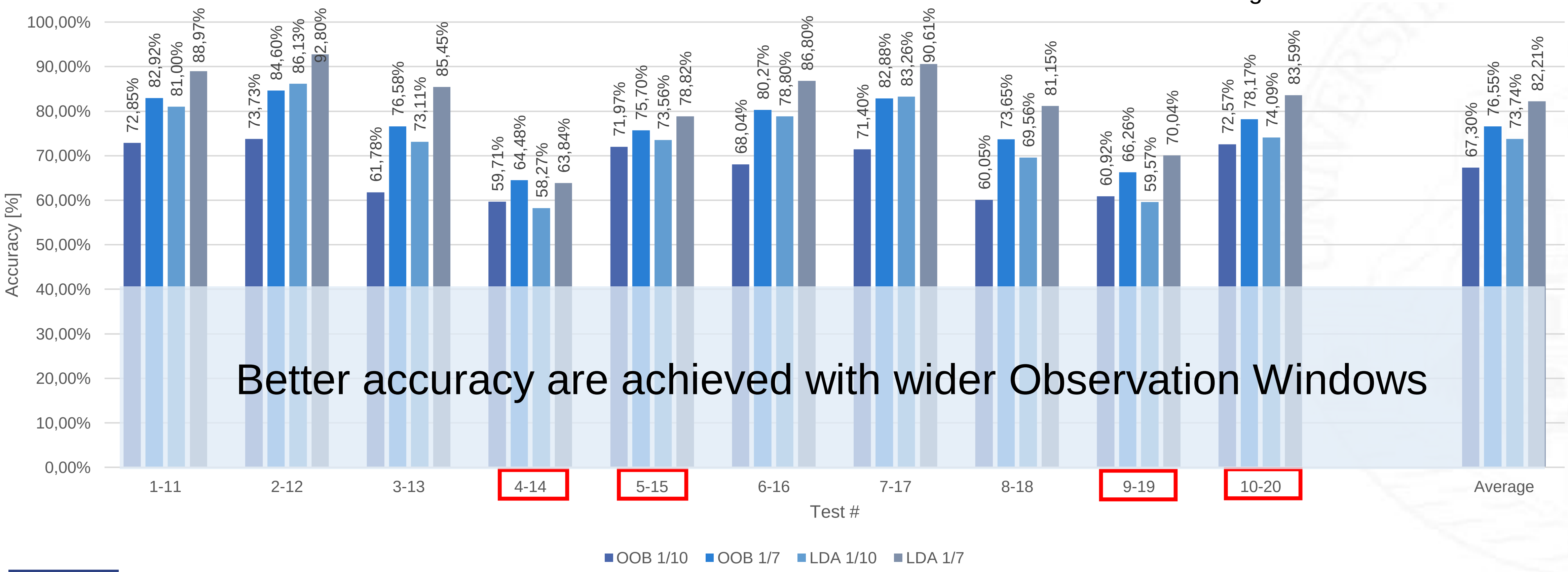


Acceleration

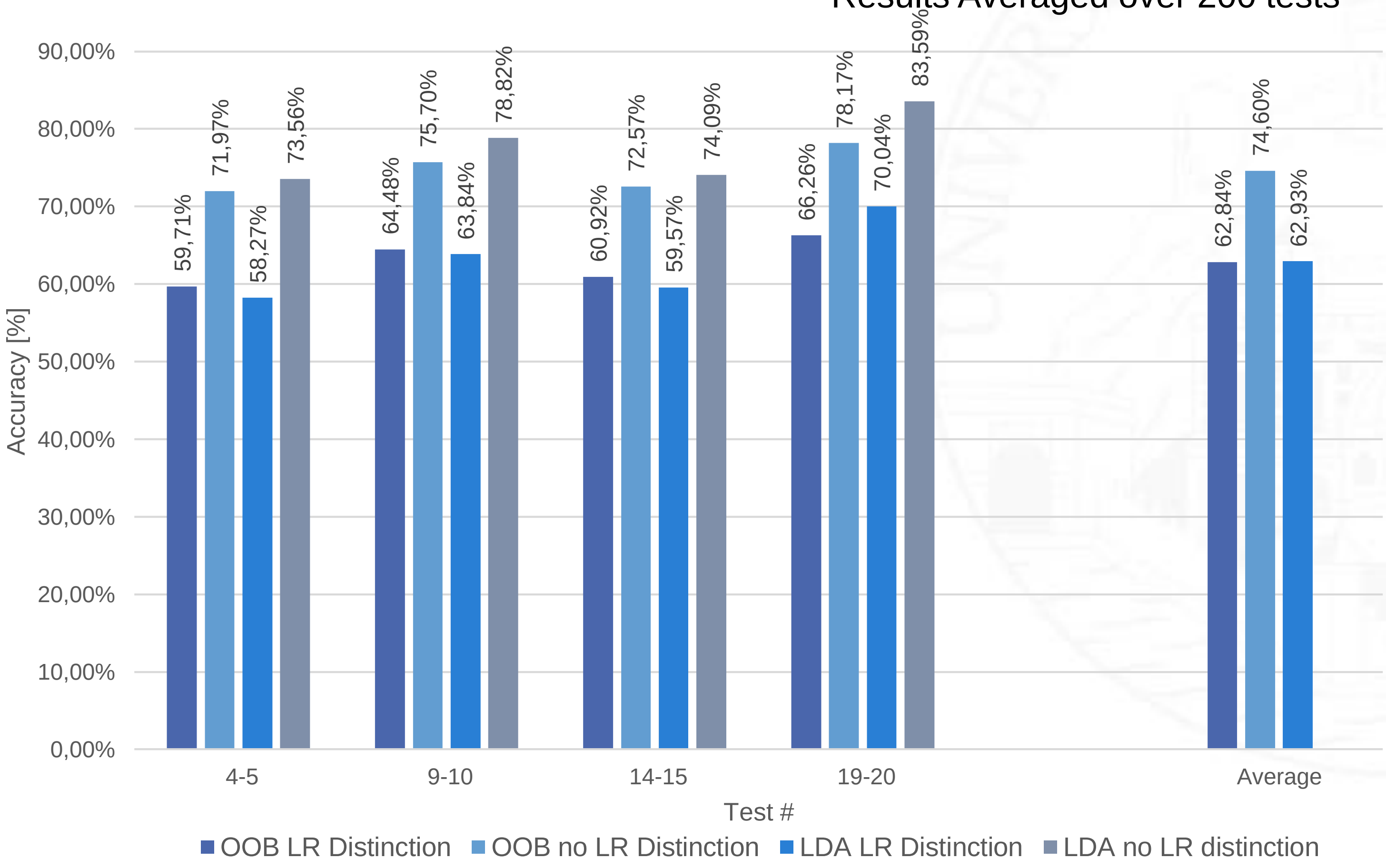
Results - Acceleration - Accuracy

Acceleration is obtained with a double derivation and consequently it contains noise;

Better accuracy is achieved without the distinction of which hand is performing the motion;

Training dataset: RF 90% LDA 85%

Results Averaged over 200 tests



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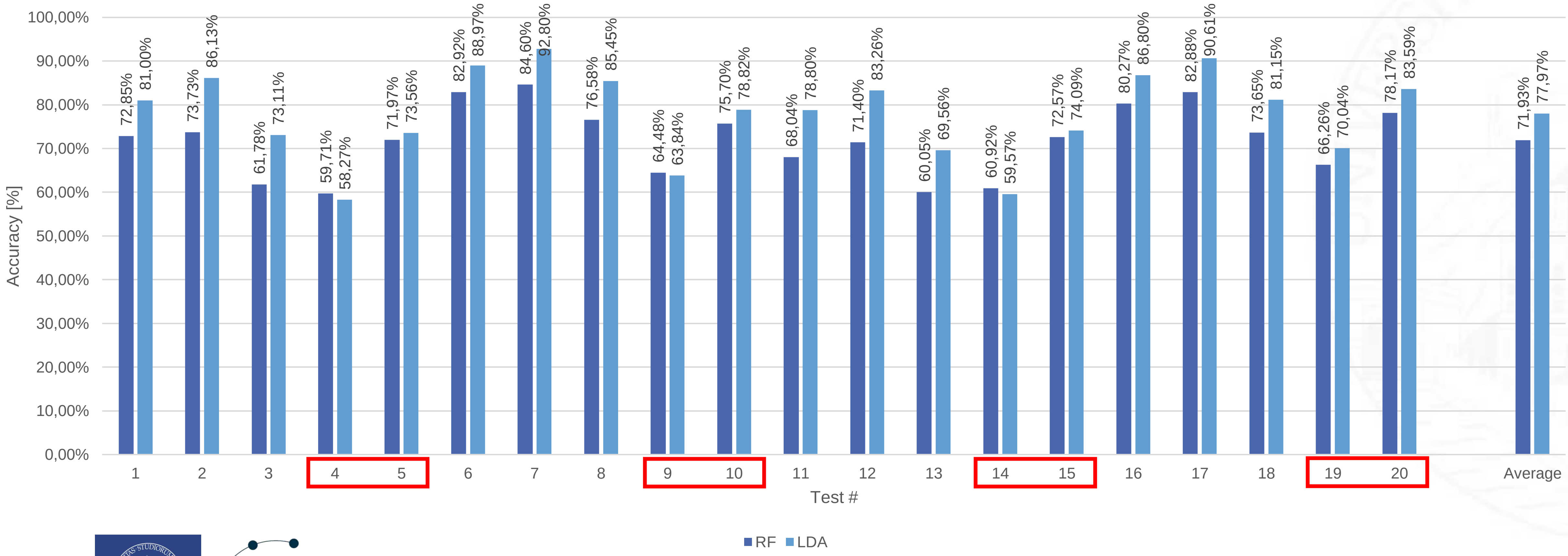
Results - RF vs LDA - Accuracy

Training dataset: 90% for RF and 85% for LDA;

Results Averaged over 200 tests

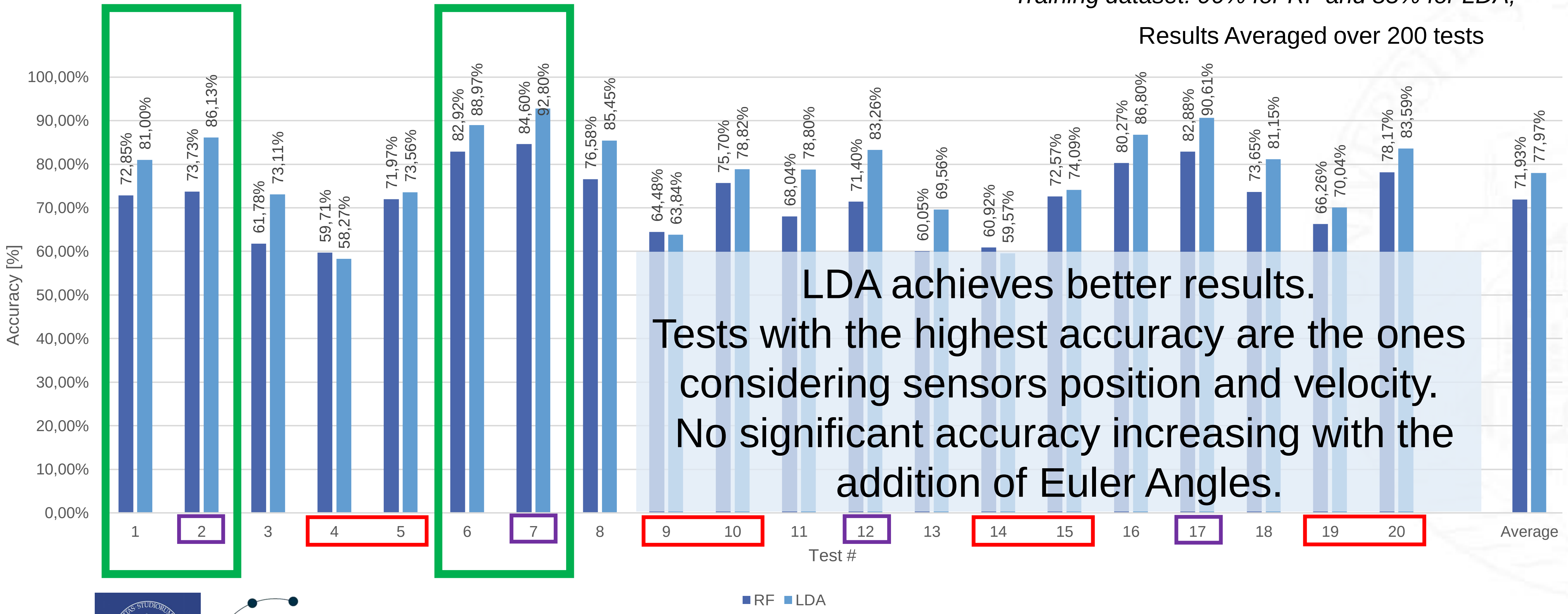


Acceleration

Results - RF vs LDA - Accuracy

Training dataset: 90% for RF and 85% for LDA;

Results Averaged over 200 tests



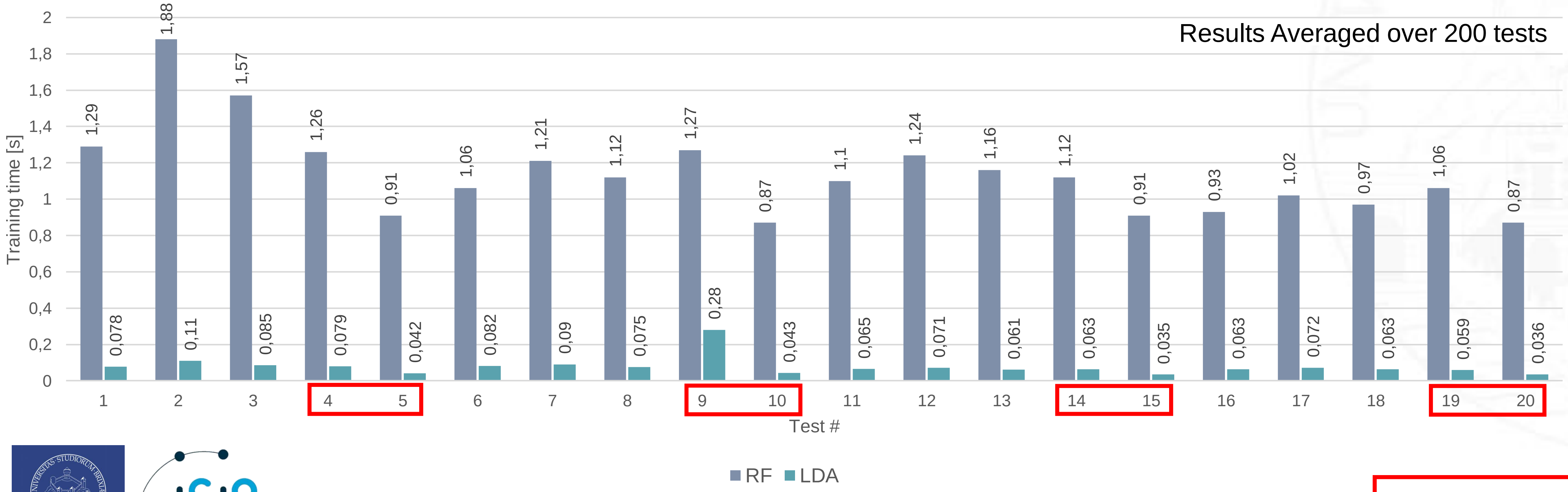
LDA achieves better results.
Tests with the highest accuracy are the ones considering sensors position and velocity.
No significant accuracy increasing with the addition of Euler Angles.

+Euler Angles

Acceleration

Results - Training Time

LDA requires shorter training times.



Acceleration

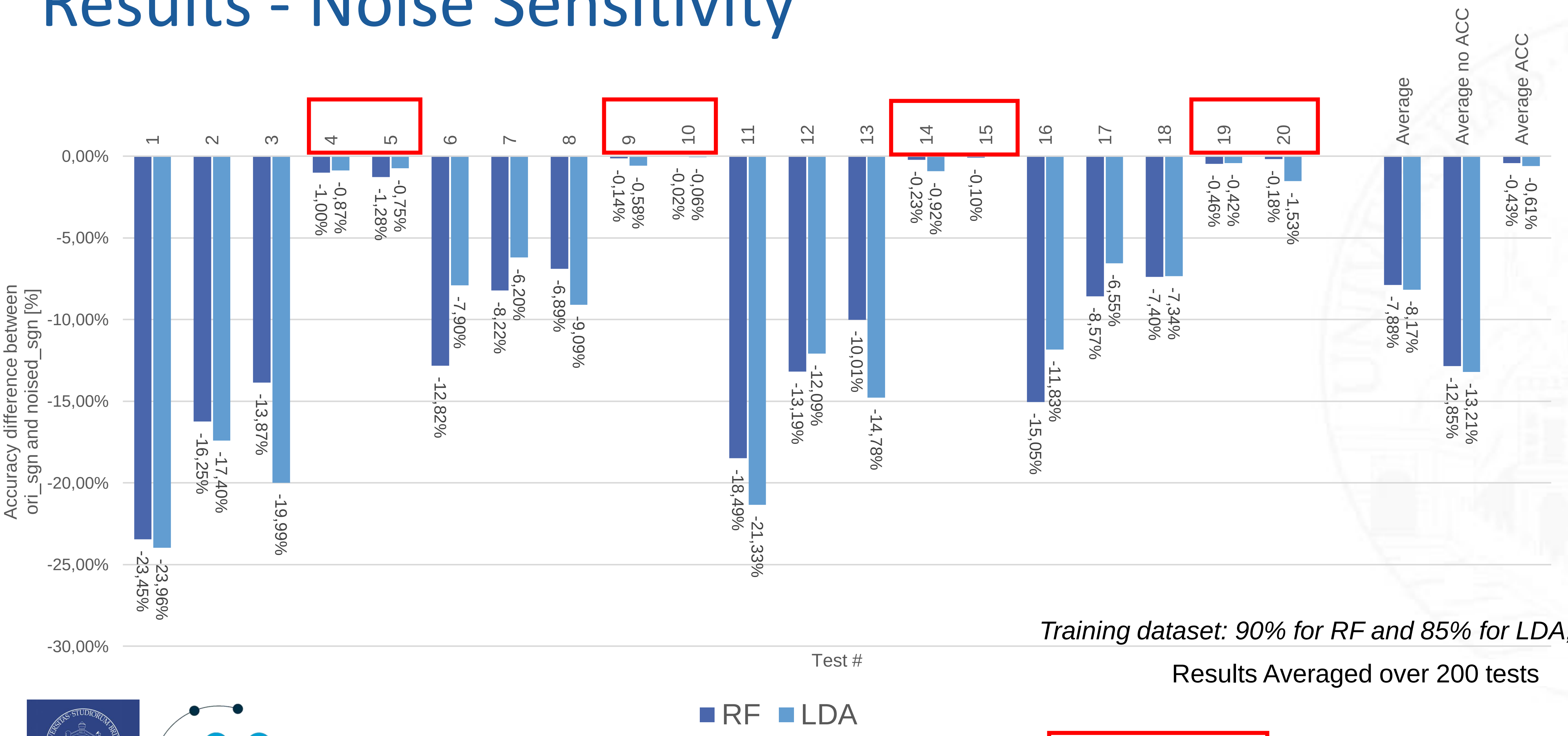
Results - Prediction Time

LDA presents faster prediction times.

RF	LDA
3.1×10^{-3} [s]	1.1×10^{-4} [s]

Averaged over all the tests

Results - Noise Sensitivity

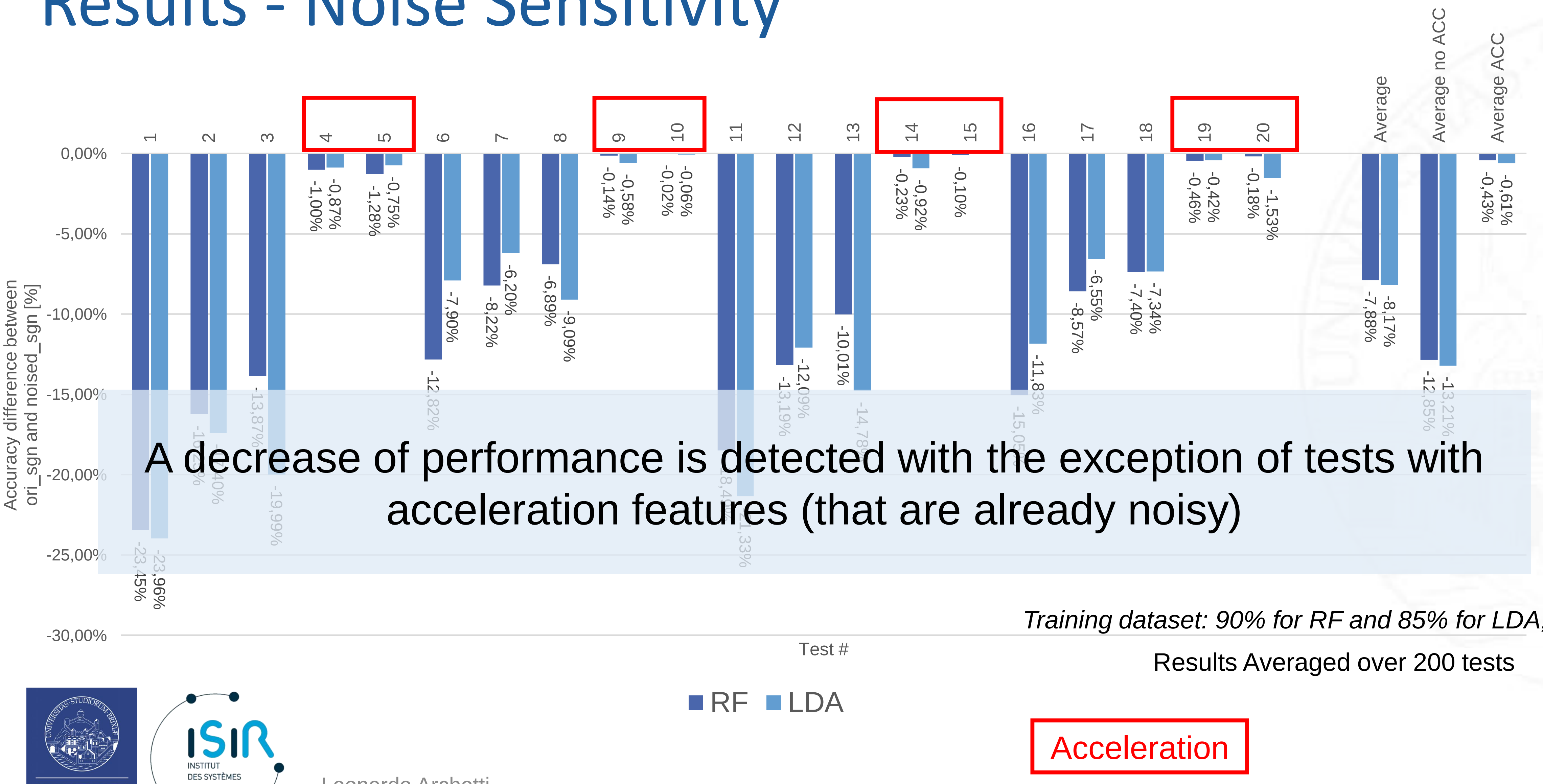


Training dataset: 90% for RF and 85% for LDA;

Results Averaged over 200 tests

Acceleration

Results - Noise Sensitivity



A decrease of performance is detected with the exception of tests with acceleration features (that are already noisy)

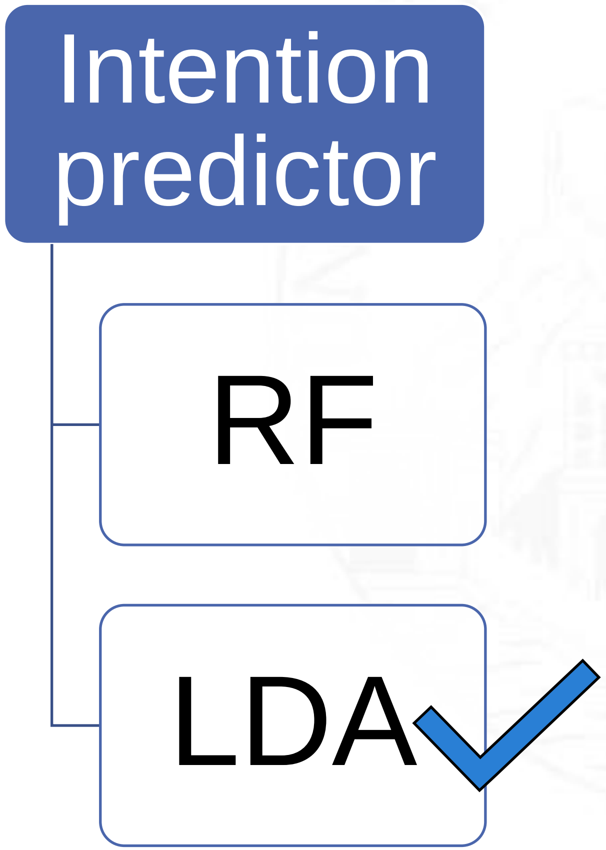
Training dataset: 90% for RF and 85% for LDA;

Results Averaged over 200 tests

Conclusions

LDA is the more promising algorithm as it presents

- ✓ Higher accuracy
- ✓ Shorter training time
- ✓ Faster prediction time



Future Developments

- Inclusion of pathological subject to the population
- Addition of new sensors (e.g. IMU, accelerometers …)
- Real life applications:
    - Human-Robot collaboration

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