

Tagless indoor human localization and identification using capacitive sensors



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- ▶ Rationale for long-range capacitive sensing
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Why long-range indoor capacitive sensing?

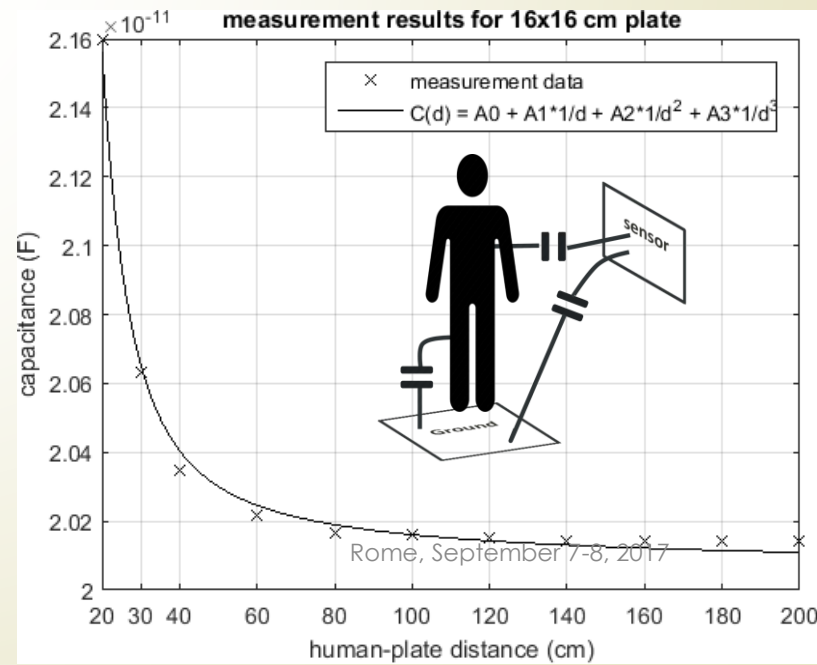
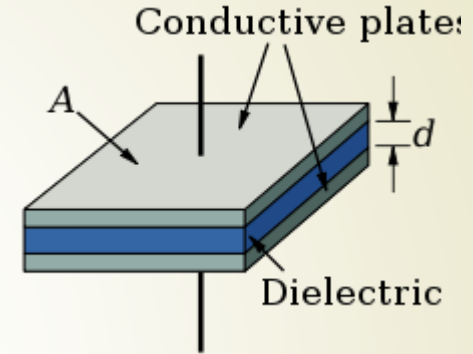


- ▶ Indoor human localization and identification can enable many automation and monitoring apps
- ▶ Long-range load-mode capacitive sensors are small, inexpensive, easy to install and operate
- ▶ Generally low accuracy and low range
- ▶ Low noise measurement techniques ($C \sim A / d^{2+3}$)
- ▶ Sensor data post-processing:
 - ▶ Improve SNR ($\Delta C < 0.01\%$)
 - ▶ Infer human location and behavior

Measurement challenges



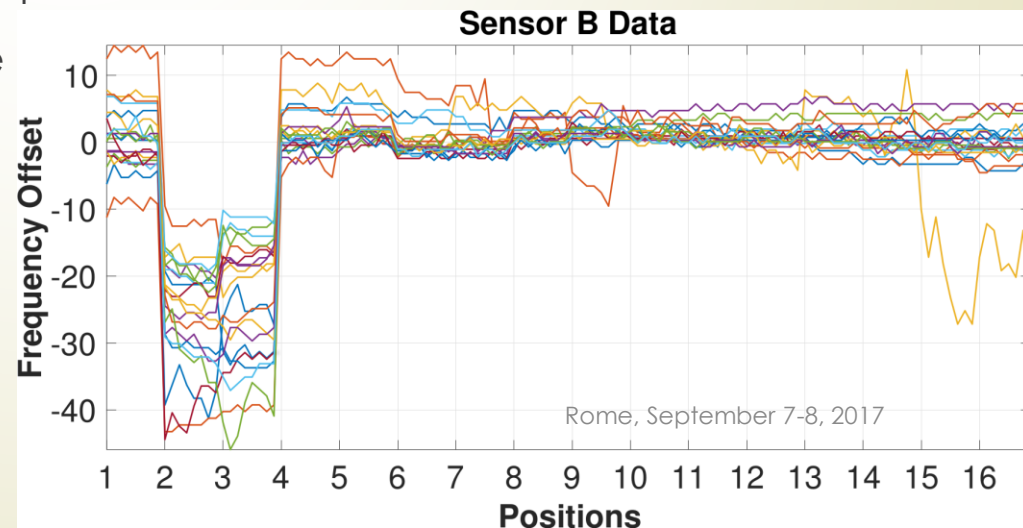
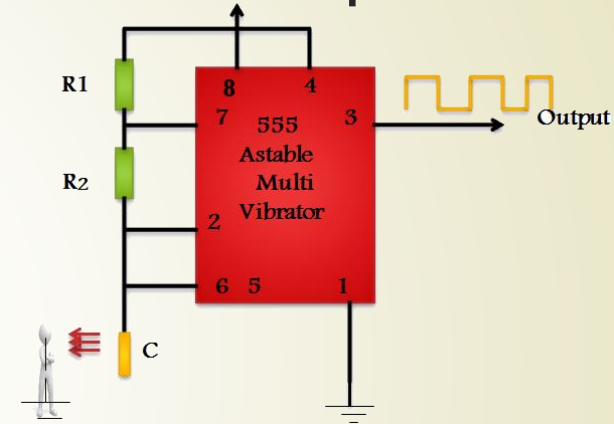
- ▶ Planar capacitors with $\sqrt{A} \gg d$
 - ▶ $C = \varepsilon A / d$
- ▶ Load-mode capacitors with $d \gg \sqrt{A}$
 - ▶ $C \sim A / d^{2+3}$
- ▶ d (meters) $\gg \sqrt{A}$ (tenths of cm):
 - ▶ Very low ΔC ($< 0.01\%$)
 - ▶ Very high measurement sensitivity
 - ▶ Low noise sensitivity
 - ▶ Good noise rejection



Base band measurement: charge-to-voltage => freq.



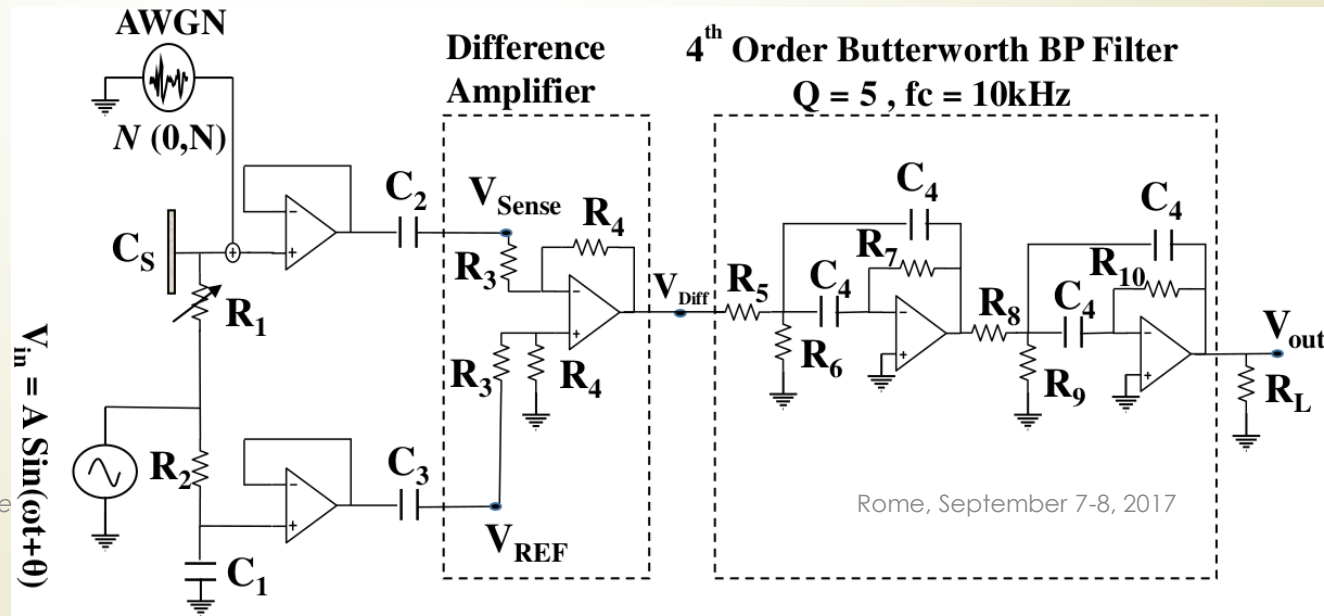
- ▶ $C = Q / V$
 - ▶ Control Q flow, set V thresholds
 - ▶ Measure $f \sim 1 / \text{time-to-V threshold}$
- ▶ Simple, cheap, low-power
- ▶ Low C, low I for kHz-range f (lower quantization noise)
 - ▶ Very high impedance input
 - ▶ Susceptible to EM noise (V noise => f jitter)
 - ▶ Difficult noise filtering
- ▶ Low SNR overall



Carrier modulation: phase and amplitude



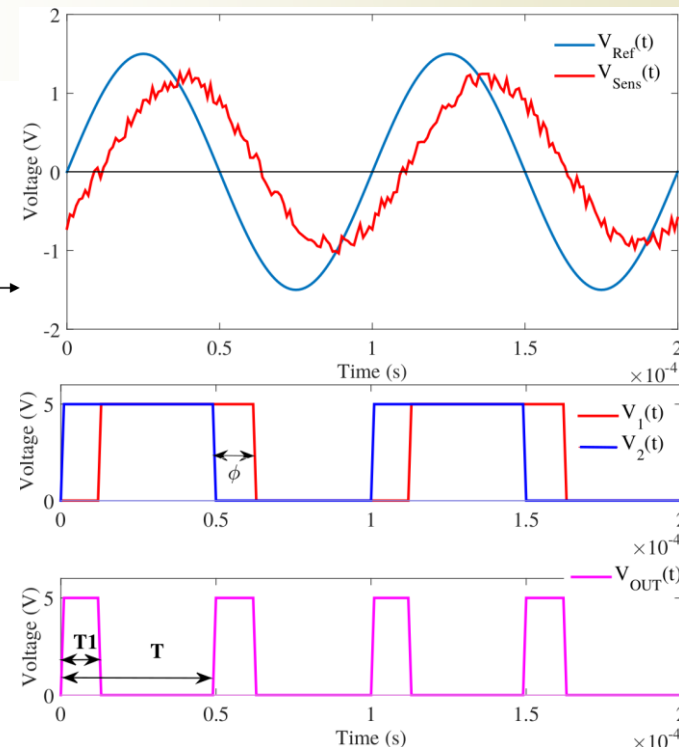
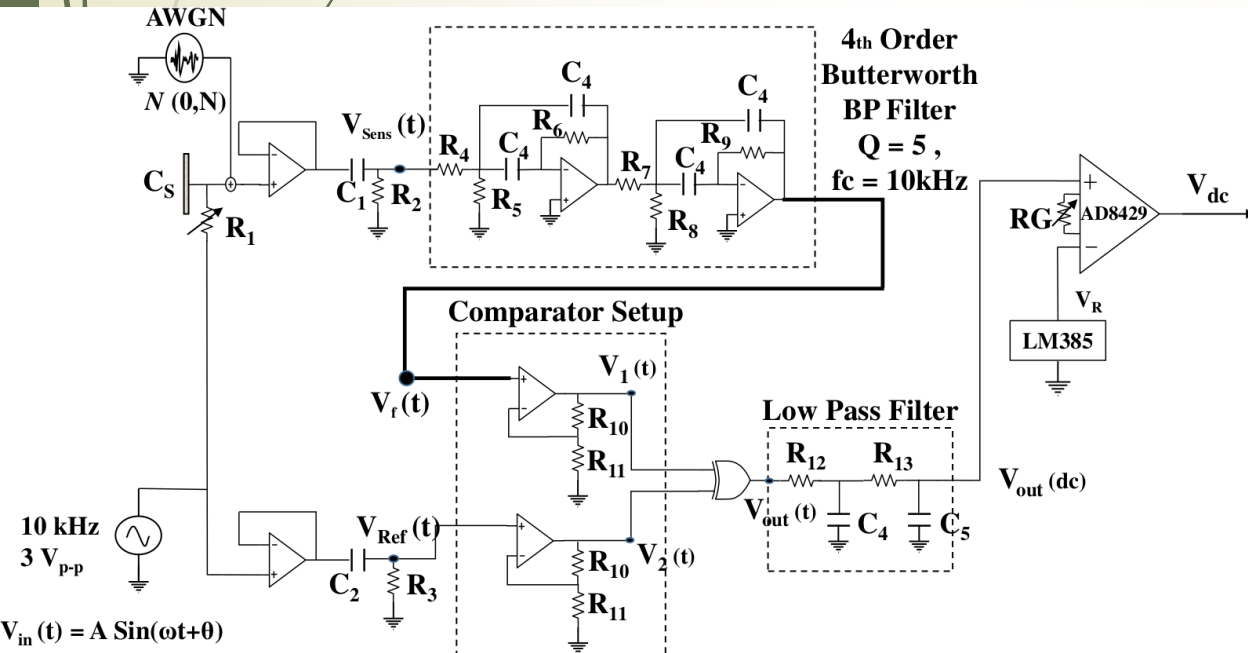
- V_{diff} correlated to carrier amplitude and phase shifts due to X_{Cs} changes
- Effective carrier noise filtering (stable known frequency)
- Output signal can be amplified before measurement (lower quantization noise)
- Overall improved SNR and sensitivity



Carrier modulation: phase



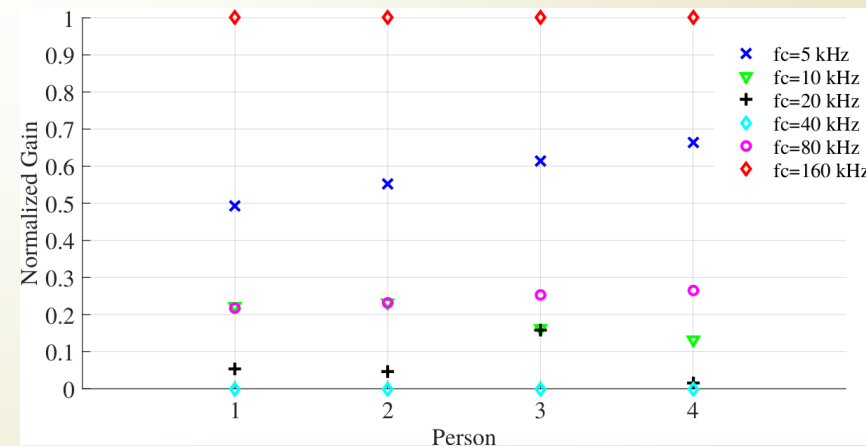
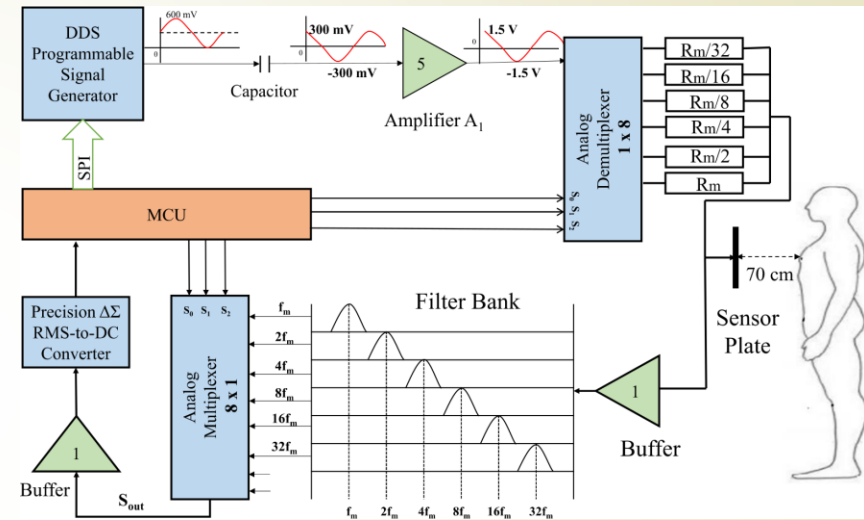
- V_{dc} correlated to carrier phase shifts due to X_{C_s} changes
- Carrier noise can be filtered well
- Output can be amplified
- Improved SNR and sensitivity



Human identification



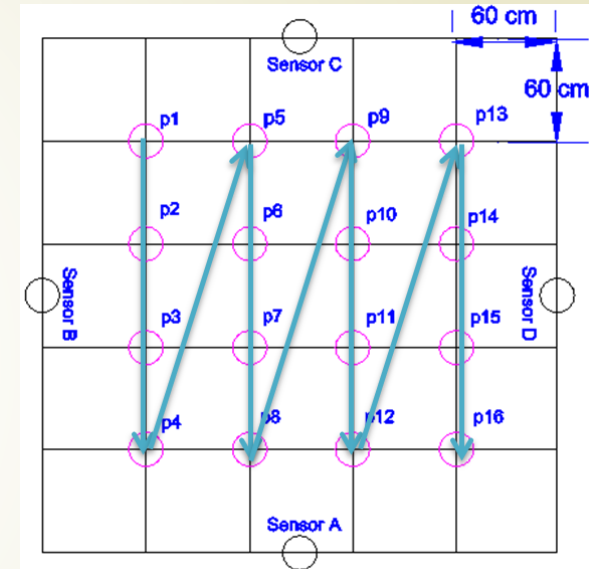
- Measure the body-sensor capacity at several frequencies at (almost) the same time
- Capacity-frequency dependency pattern depends on body properties (tissue ratios, shape, ...)
- Distinct patterns can identify persons from limited pool
- Monitor passage through doors



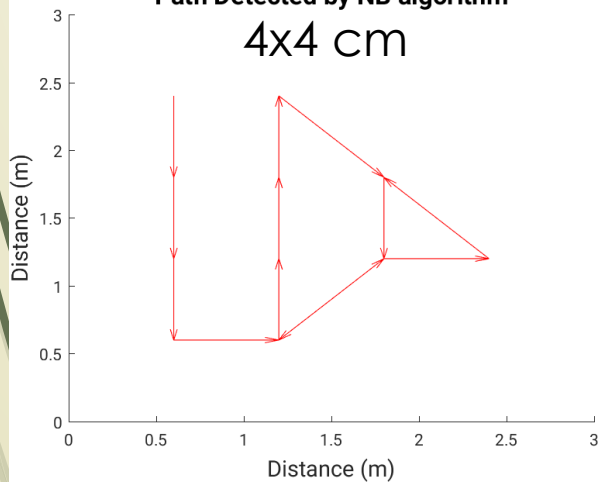
Localization using machine learning classification



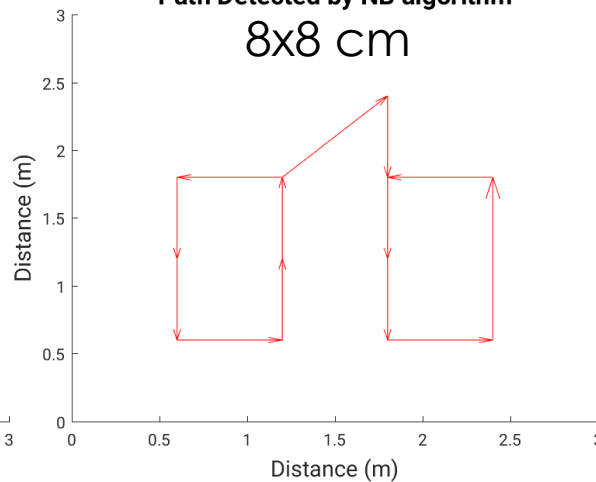
- Room localization experiment using ML classification and the “noisy” sensors
 - Train k-NN, Naïve Bayes, SVN to classify 16 room locations using sensors of different sizes
 - Test algorithms classification accuracy
- Naïve Bayes performed best, especially for the largest sensor size (16 x 16 cm)



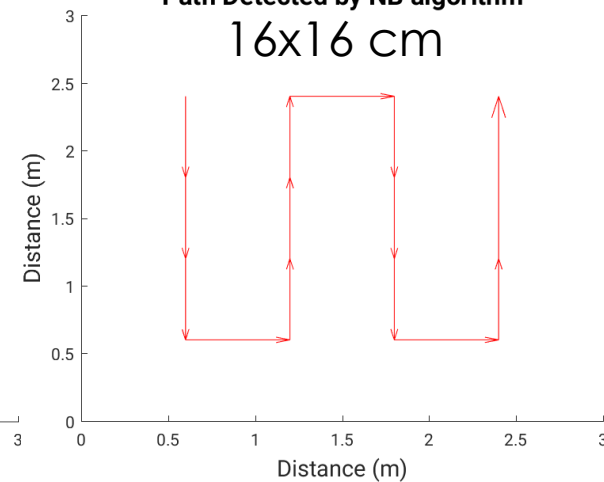
Path Detected by NB algorithm
4x4 cm



Path Detected by NB algorithm
8x8 cm



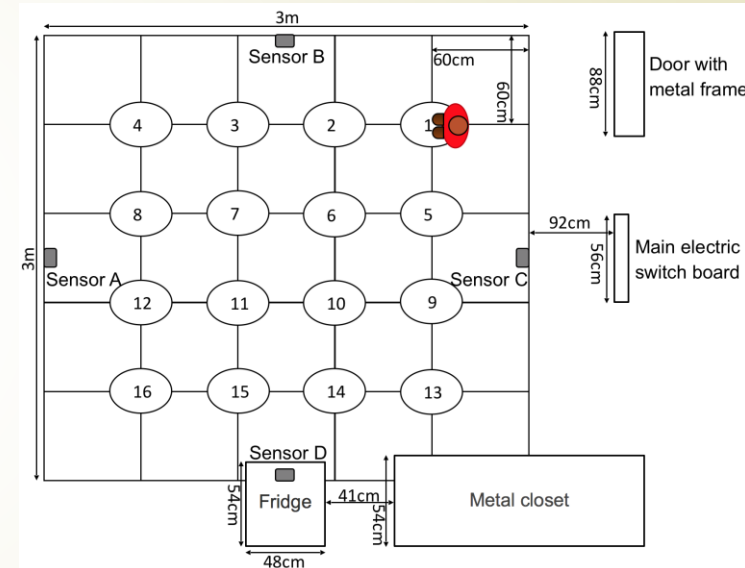
Path Detected by NB algorithm
16x16 cm



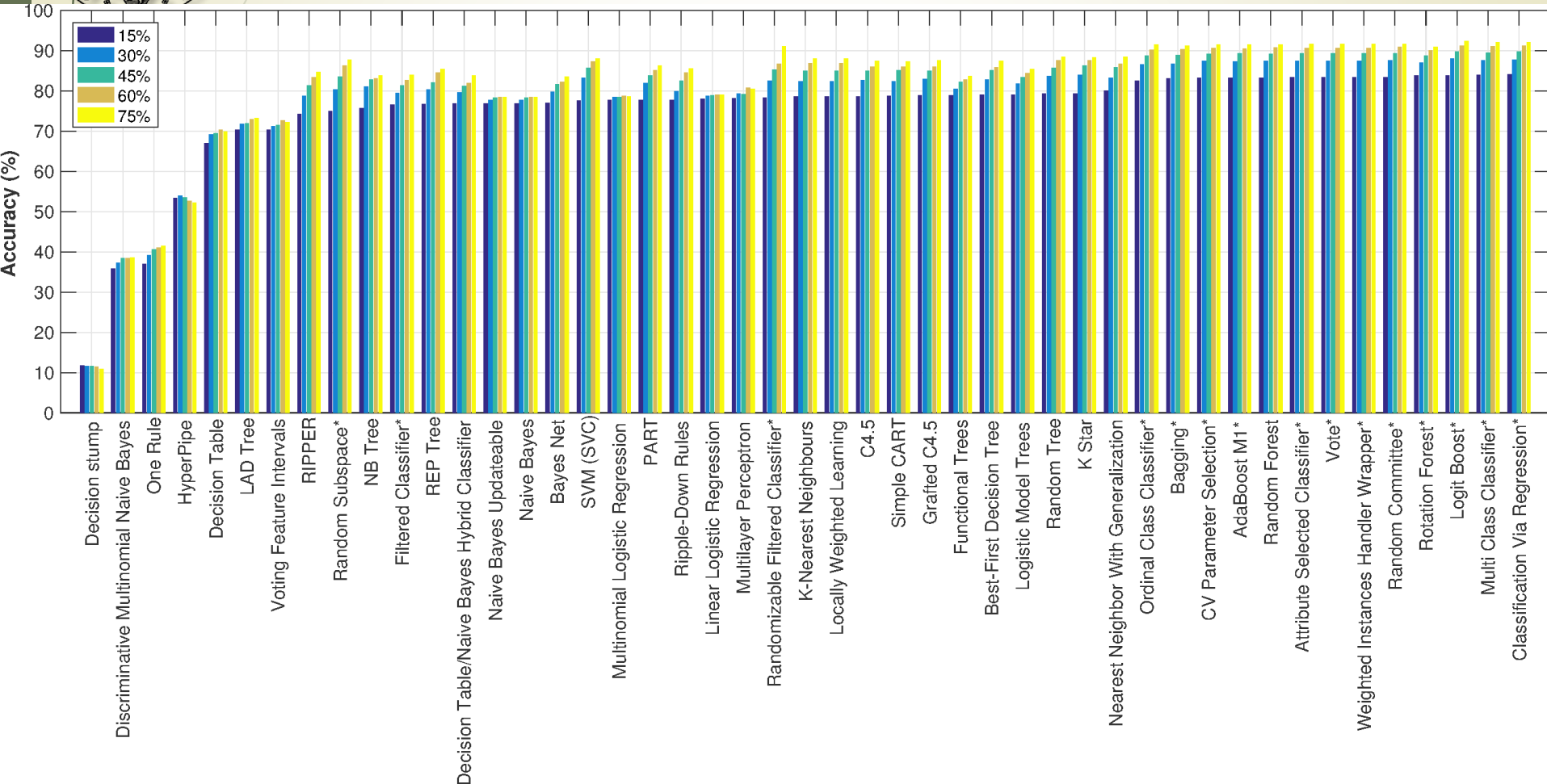
Performance of machine learning localization (1)



- Same room, same sensors, but:
 - Data acquired using different body angles
 - Acquisitions weeks or months apart
- Tested performance of most (48) Weka collection algorithms
 - Training using with different set sizes
 - Testing with unseen data sets
- Performance measurement
 - Accuracy, error, precision, recall, train effort, classification effort, memory requirements



Performance of machine learning localization (2)



Using advanced machine learning algorithms



- ▶ Classification (1 out of 16 locations) has a significant quantization error (15cm on average with 60cm grid) and may not be suitable for all applications
- ▶ Can use neural networks to directly convert sensor outputs to (x,y) location within room, with improved precision
- ▶ Recurrent neural networks (with feedback) can also reduce the need for filtering (the network “learns” the expected speed range of the person moving around the room)
- ▶ However, NNs and RNNs have much higher computational complexity: 100K neurons are required to achieve a mean distance error of 10cm

Energy requirements of machine learning algorithms



- ▶ The computational load of a neural network evaluation for human localization can easily be 1MFLOP
- ▶ The requirements to track millions of people exceed 1 ExaFLOP
- ▶ Energy requirements are becoming the bottleneck for large data centers, hence FPGAs are being used to accelerate computationally intensive workloads
- ▶ The ECOSCALE H2020 project n. 671632 is aimed at enabling the use of FPGAs in data centers
- ▶ The machine learning algorithms for human localization using capacitive sensors will be used as a design driver in ECOSCALE

Conclusions



- ▶ Capacitive sensing may provide the low cost indoor sensing needed to enable many smart applications
- ▶ Combined with other sensing techniques, it may contribute to define a platform that enables to *install apps on the home*
- ▶ Needs effective techniques to reject and reduce noise
- ▶ Intensive data processing may improve performance
 - ▶ Low power analog and digital processors (μ P, FPGA) and communication essential for low exploitation costs



Thank you.



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