Efficient Object Detection through Grasp Intention

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Presentation of the Master Thesis

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Agenda

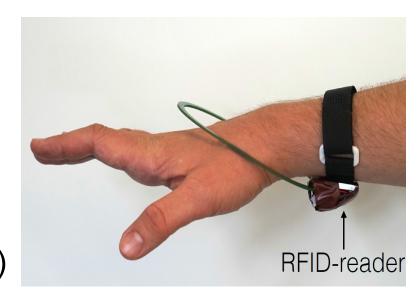
- Motivation
- Overview
- Sensors
- Grasp Analysis
- Feature Extraction
- Energy Efficiency
- Grasp Detection

Motivation

Detect handled objects

Applications:

- Stocktaking [1]
- Reason about activity [2] (activities of daily living, ...)
- Guidance [3]



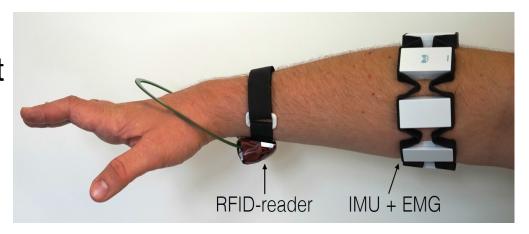
Drawback

- High energy consuming object detectors [4]
- ~ 2 h battery lifetime

Overview

Idea:

 Only activate object detector when a grasp is performed



Implementation:

- Additional grasp detection
- Additional sensors
- Prototype split into three subsystems:
 - Object detector
 - Forearm sensor (grasp detection sensing)
 - Assisting standard computer (grasp detection)

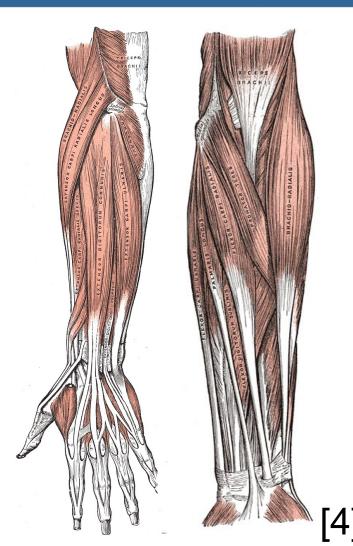
Sensors Object Detection

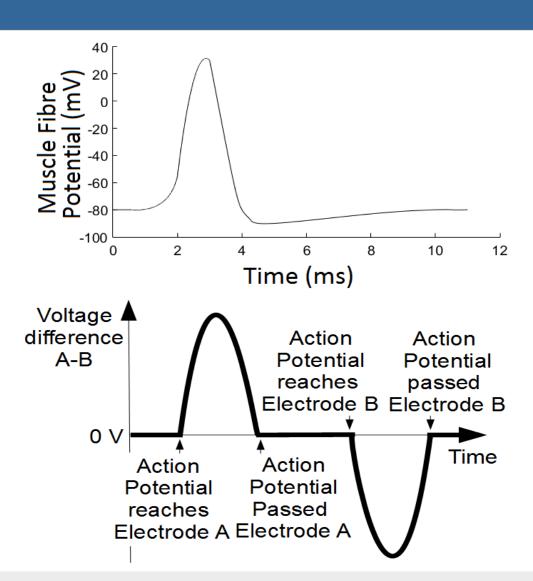
- Multiple sensors available
 - RFID (used)
 - Camera based
 - Microphone
 - Capacitive and electromagnetic sensing

Sensors Forearm Sensor

- Commercial device: Thalmic Labs Myo
- IMU (InvenSense MPU9150)
 - Three axis accelerometer (50 Hz, ±16 g)
 - Three axis gyroscope (50 Hz, ±2000 °/s)
- Electromyographie sensor
 - 8 channel
 - 200 Hz

Sensors Electromyography



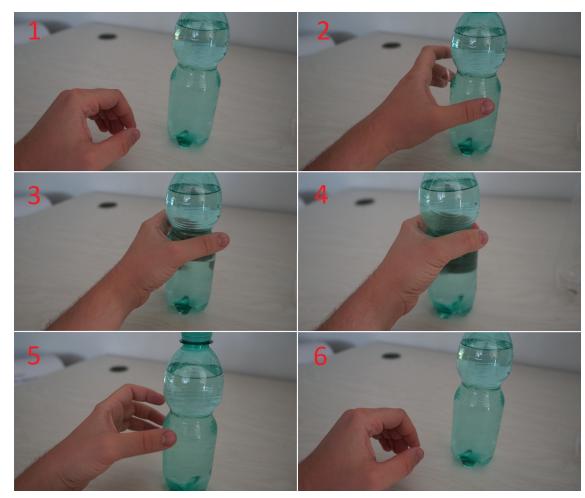


Grasp Analysis Taxonomy

- Found in Literature [5,6]
- Two different main grasp classes
 - Power grasps (easy to detect)
 - Precision grasps (difficult to detect)
- Object geometry
- Thumb position (adducted / abducted)
- Finger opposition (palm / pad / side)
- Virtual fingers

Grasp Analysis Steps

- Right image: sequence of a grasp
- Grasp divided into five steps (1 and 6: null)
- Similar features per step in different grasps



Grasp Analysis Three Layer Model - Overview

Layer 1: base activity detection

Layer 2: grasp segment recognition

Layer 3: final grasp evaluation

Grasp Analysis Three Layer Model – Layer 1

- Detection of the base activity
- Find activities where no grasp is possible
- Implemented activities
 - Rest (no detection)
 - Walk (no detection)
 - Work (detection possible)
- Implemented only on IMU features
- Can disable further processing and sensors

Grasp Analysis Three Layer Model – Layer 2

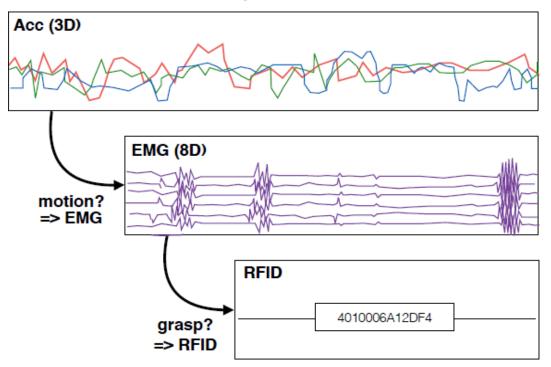
- Grasp segment recognition
- Check for grasp related features

Based on IMU and EMG features

- Adaptive thresholding
 - Is a muscle activity found?
 - No setup normalization necessary

Grasp Analysis Three Layer Model – Layer 3

- Final grasp evaluation
- Sequencing of the found Layer 2 features
- Controlls starts of object scans



Feature Extraction Methods

- Inspection of data
 - Visualize sensor data
 - Statistical values
 - Principal component analysis
- Knowledge
 - Muscle positions and functions
 - Taxonomy
 - Step sequence
 - Typical grasping behaviours

Energy Efficiency Sensors

Grasp detection

- Accelerometer < 0.2 mA
- Gyroscope ~ 3 mA
- 8 channel EMG ~ 8 mA
- Processing ~ 7.7 mA

Object detection

- RFID (full duty cycle) > 60 mA
- RFID (1 Hz) > 18.2 mA (former study [7]: 65 % of tags detected towards full duty cycle)

Energy Efficiency Three Layer Model Implementation

- Processing: 7.7 mA
- Layer 1 (accelerometer only): 0.2 mA
- Layer 2 (additional EMG sensor): 8 mA

 Assuming half time resting and walking activity: total overhead of 11.9 mA

Grasp Detection Boxtest

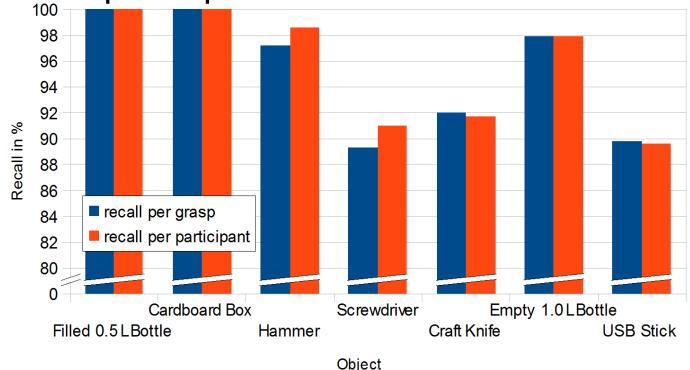
- Comparison with former study [7]
- Grasps are free to choose
- Less information to participants
 - No active feedback of grasp detection
 - No information about purpose of the test
 - Participants told tests
 have been about how
 they perform tasks



Grasp Detection Boxtest Results

- 95.5 % recall at start of grasp
- Better results with power grasps

5 of 12 participants: 100 % recall



Grasp Detection Realtime Analysis

- Test with detection feedback to participants
- Active plotting of sensor data
- No test script
- Participants informed about test purpose
- Performed with random participants
 - 20 years celebration faculty of engineering
 - Wearables sensor laboratory presentation
- Results:
 - Untypical behaviour
 - Feedback used by participants

Grasp Detection False Positive Grading

- Used to get a number of false positives
- Similar to grasp gestures for false positives:
 - Scratch head
 - Use light switch
 - ...

- Crosscheck recall on boxtest's objects
- False positive rate 78.5 %, recall 82.3 %

Grasp Detection Object Detection

- Same setup as boxtest
- Many misses (RFID range too short)
- 32 of 94 objects missed completely
- 1 of 94 objects missed by grasp detection
- Tight set with less pauses
 - 0.94 detections per second
 - 0.02 not task script related detections per second, also including grasps

References

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- [2] A. Hein, T. Kirste. A Hybrid Approach for Recognizing ADLs and Care Activities Using Inertial Sensors and RFID. In Universal Access in Human-Computer Interaction. Intelligent and Ubiquitous Interaction Environments, volume 5615. Springer Berlin Heidelberg, 2009
- [3] P.M. Scholl, M. Wille K. Van Laerhoven. Wearables in the Wet Lab: A Laboratory System for Capturing and Guiding Experiments. In Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 2015
- [4] Images by Dr. Henry Vandyke Carter
- [5] M. Cutkosky. On Grasp Choice, Grasp Models, and the Design of Hands for Manufacturing Tasks. IEEE Transactions on Robotics and Automation, 5(3), 1989
- [6] T. Feix, R. Pawlik, H. Schmiedmayer, J. Romero, D. Kragic. The GRASP Taxonomy of Human Grasp Types. In IEEE Transactions on Human-Machine Systems, 2015
- [7] E. Berlin, J. Liu, K. Van Laerhoven, B. Schiele. Coming to Grips with the Objects We Grasp: Detecting Interactions with Efficient Wrist-Worn Sensors. In International Conference on Tangible and Embedded Interaction, 2010

End

Thanks for listening.

Questions?