Computer Vision, Speech Communication & Signal Processing Group,
Intelligent Robotics and Automation Laboratory
Institute of Communication and Computer Systems (ICCS)
National Technical University of Athens, Greece (NTUA)

Part 3 & Part 4: Audio-Visual HRI: Methodology and Applications in Assistive Robotics

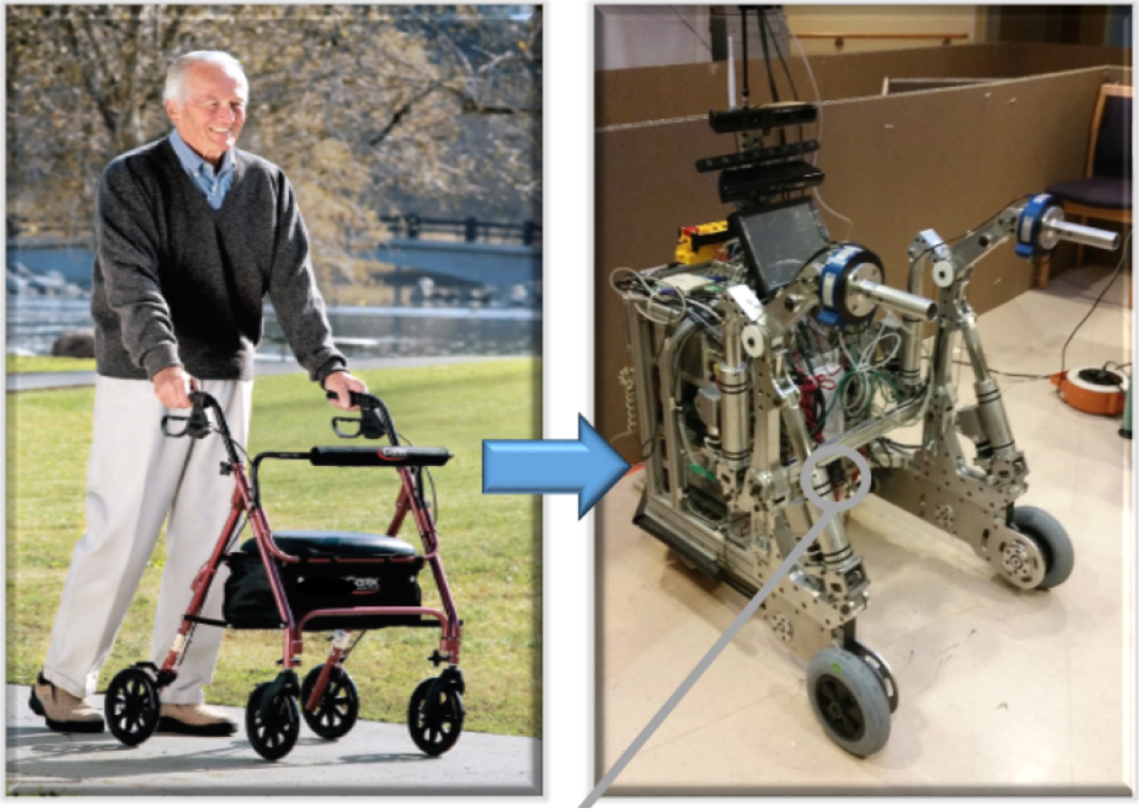
Petros Maragos and Petros Koutras

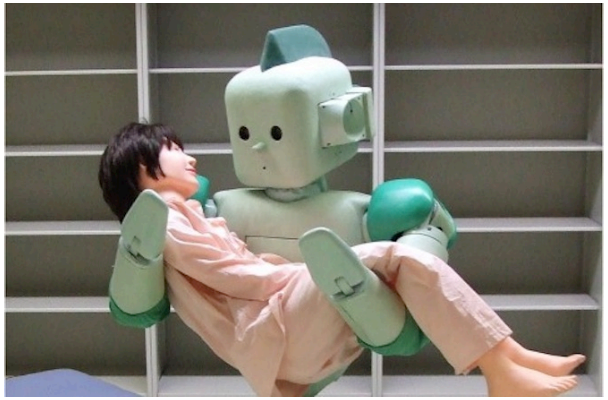
Tutorial at IEEE International Conference on Image Processing 2019,
Taipei, Taiwan, September 22, 2019

3.
Audio-Visual HRI: General Methodology

Multimodal HRI: Applications and Challenges

assistive robotics





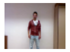
education, entertainment

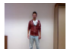
- Challenges
  - ❑ Speech: distance from microphones, noisy acoustic scenes, variabilities
  - ❑ Visual recognition: noisy backgrounds, motion, variabilities
  - ❑ Multimodal fusion: incorporation of multiple sensors, integration issues
  - ❑ Elderly users, Children

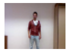
Database of Multimodal Gesture Challenge

(in conjunction with *ACM ICMI 2013*)

- 20 cultural/anthropological signs of Italian language


- ‘vattene’ (get out)


- ‘vieni qui’ (come here)


- ‘perfetto’ (perfect)

- ‘furbo’ (clever)

- ‘che due palle’ (what a nuisance!)

- ‘che vuoi’ (what do you want?)

- ‘d’accordo’ (together)

- ‘sei pazzo’ (you are crazy)

- ‘combinato’ (combined)

- ‘freganiente’ (damn)

- ‘ok’ (ok)

- ‘cosa ti farei’ (what would I make to you!)

- ‘basta’ (that’s enough)

- ‘prendere’ (to take)

- ‘non ce ne piu’ (there is none more)

- ‘fame’ (hunger)

- ‘tanto tempo’ (a long time ago)

- ‘buonissimo’ (very good)

- ‘messi d’accordo’ (agreed)

- ‘sono stufo’ (I am sick)

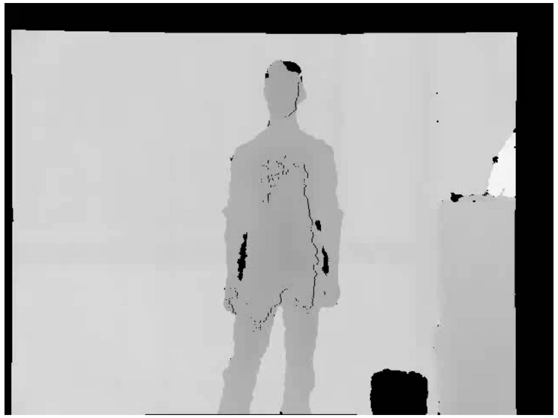
- 22 different users
- 20 repeats per user approximately
(~1 minute for each gesture video)

Multimodal Gesture Signals from Kinect-0 Sensor

RGB Video & Audio

Depth

(vieniqui - *come here*)

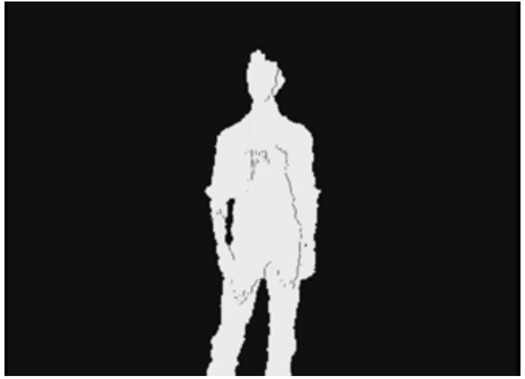


Skeleton

(vieniqui - *come here*)

User Mask

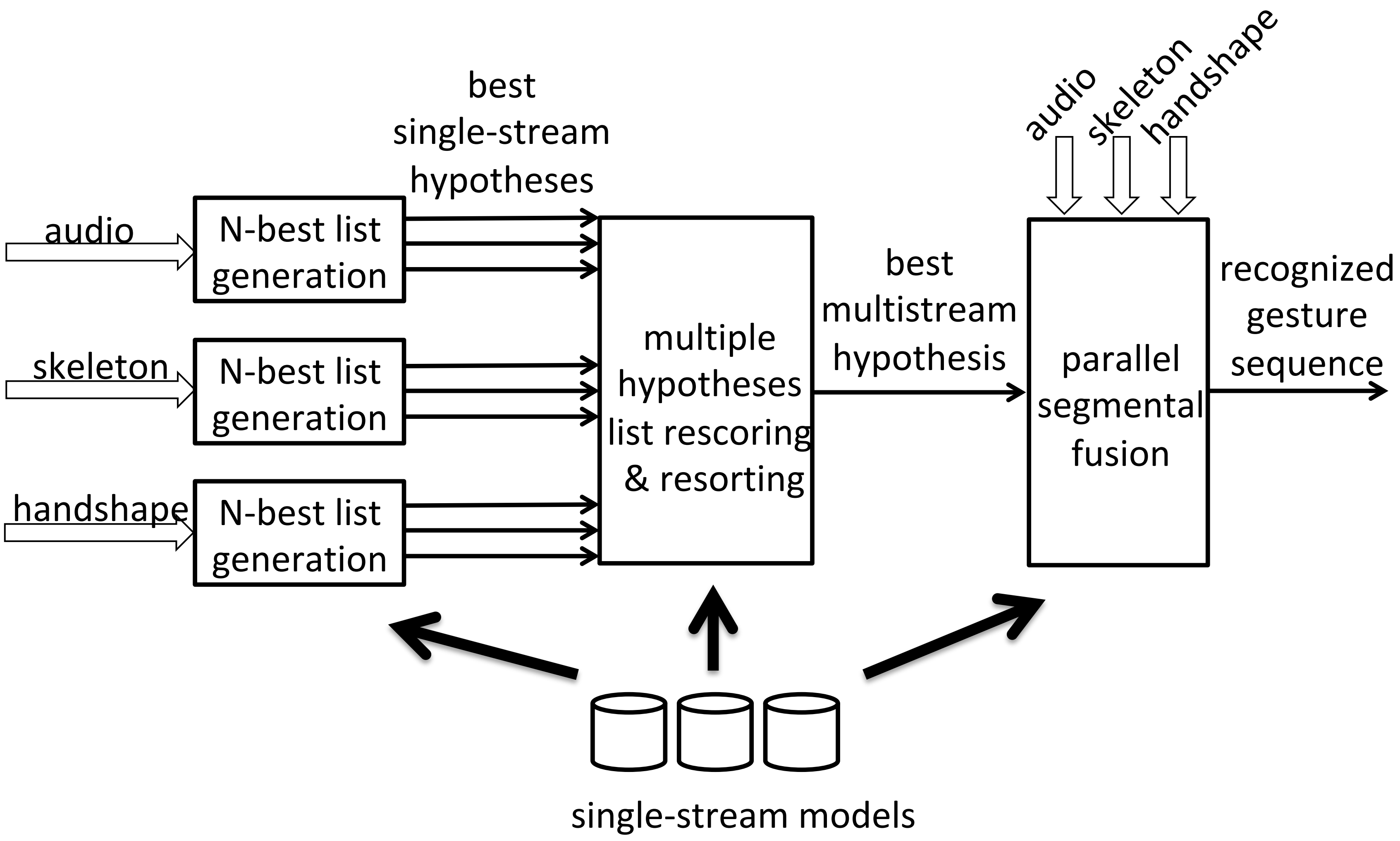
(vieniqui - *come here*)



ChaLearn corpus

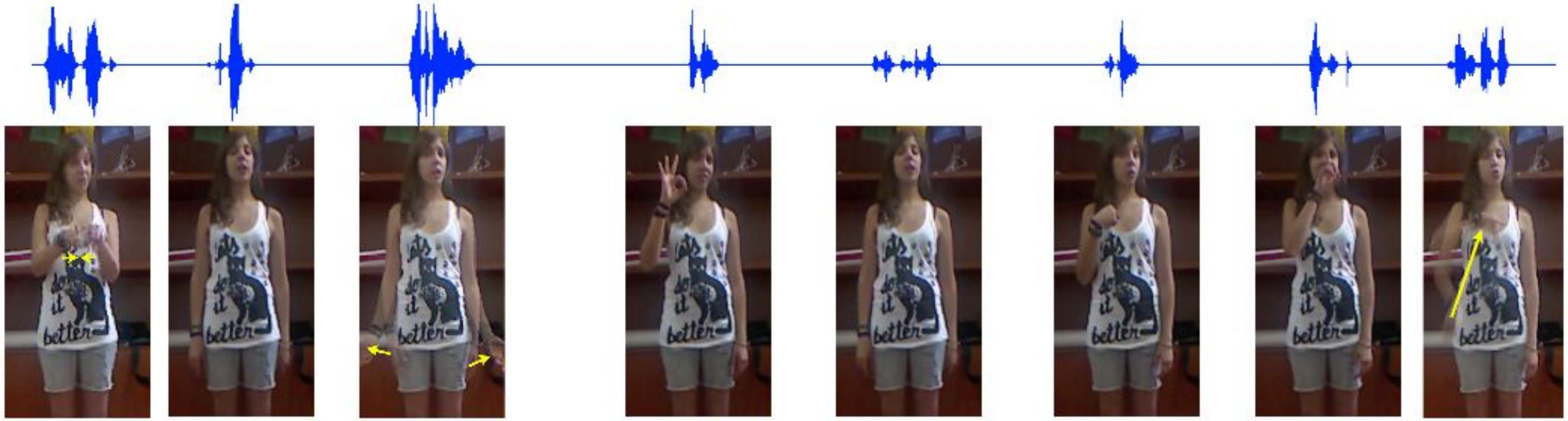
[S. Escalera, J. Gonzalez, X. Baro, M. Reyes, O. Lopes, I. Guyon, V. Athitsos, and H. Escalante, "*Multi-modal gesture recognition challenge 2013: Dataset and results*", Proc. 15th ACM Int'l Conf. Multimodal Interaction, 2013.]

Multimodal Hypothesis Rescoring + Segmental Parallel Fusion



[V. Pitsikalis, A. Katsamanis, S. Theodorakis & P. Maragos, "*Multimodal Gesture Recognition via Multiple Hypotheses Rescoring*", JMLR 2015]

Audio-Visual Fusion & Recognition



REF	DACCORDO	OOV	OOV	OK	OOV	OOV	OOV	SONOSTUFO
AUDIO	DACCORDO	BM	PREDERE	OK	BM	FAME	BM	SONOSTUFO
P1	DACCORDO	BM	BM	OK	BM	BM	OK	SONOSTUFO
P2	DACCORDO	BM	BM	BM	BM	BM	BM	SONOSTUFO
P1+P2	DACCORDO	BM	BM	OK	BM	BM	BM	SONOSTUFO

- Audio and visual modalities for A-V gesture word sequence.
- Ground truth transcriptions (“REF”) and decoding results for audio and 3 different A-V fusion schemes.
- Results in top rank of ChaLearn (ACM 2013 Gesture Challenge – 50 teams - 22 users x 20 gesture phrases x 20 repeats).

[V. Pitsikalis, A. Katsamanis, S. Theodorakis & P. Maragos, JMLR 2015]

Visual Activity Recognition

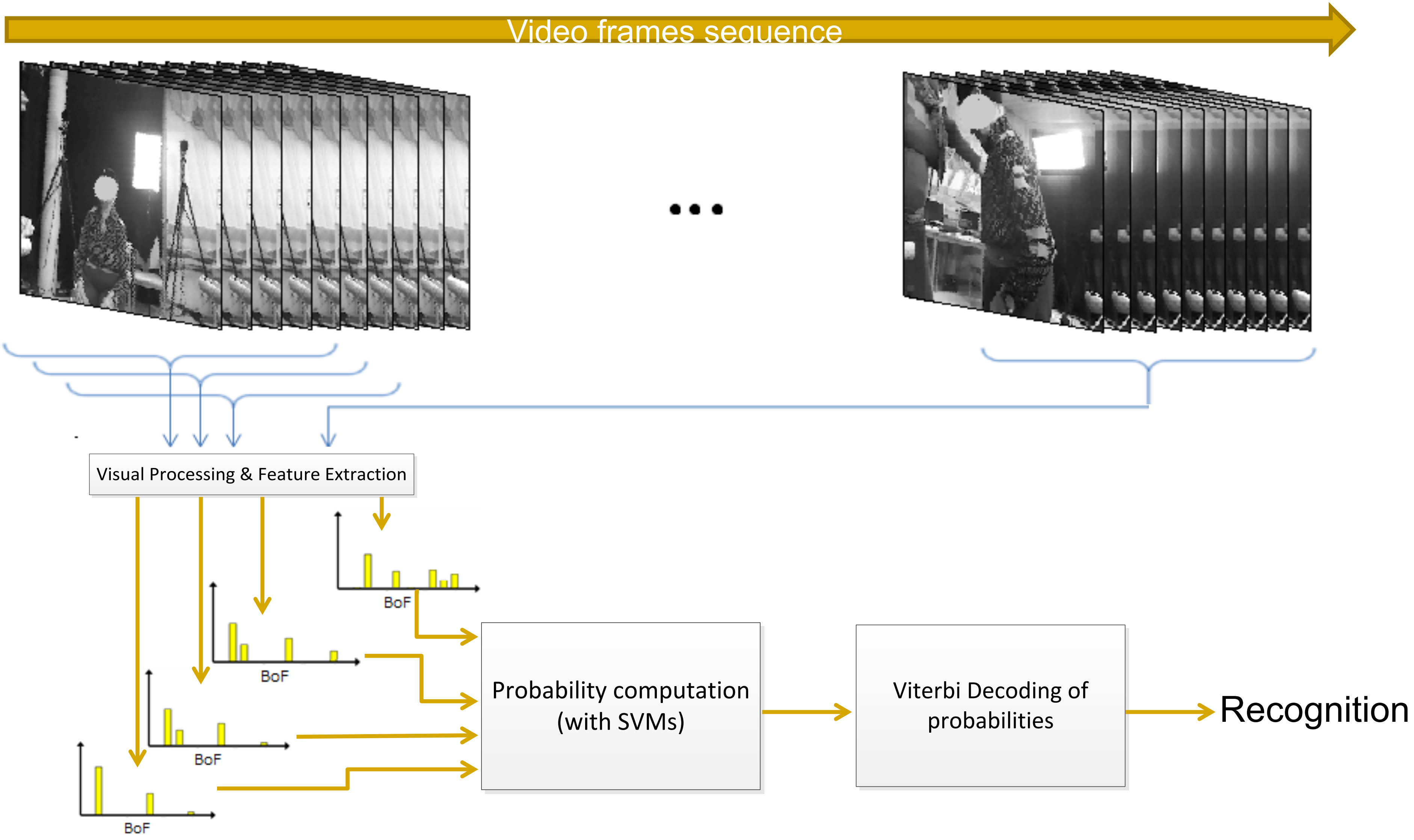
action
gesture
sign

Action: sit to stand

Gestures: come here, come near

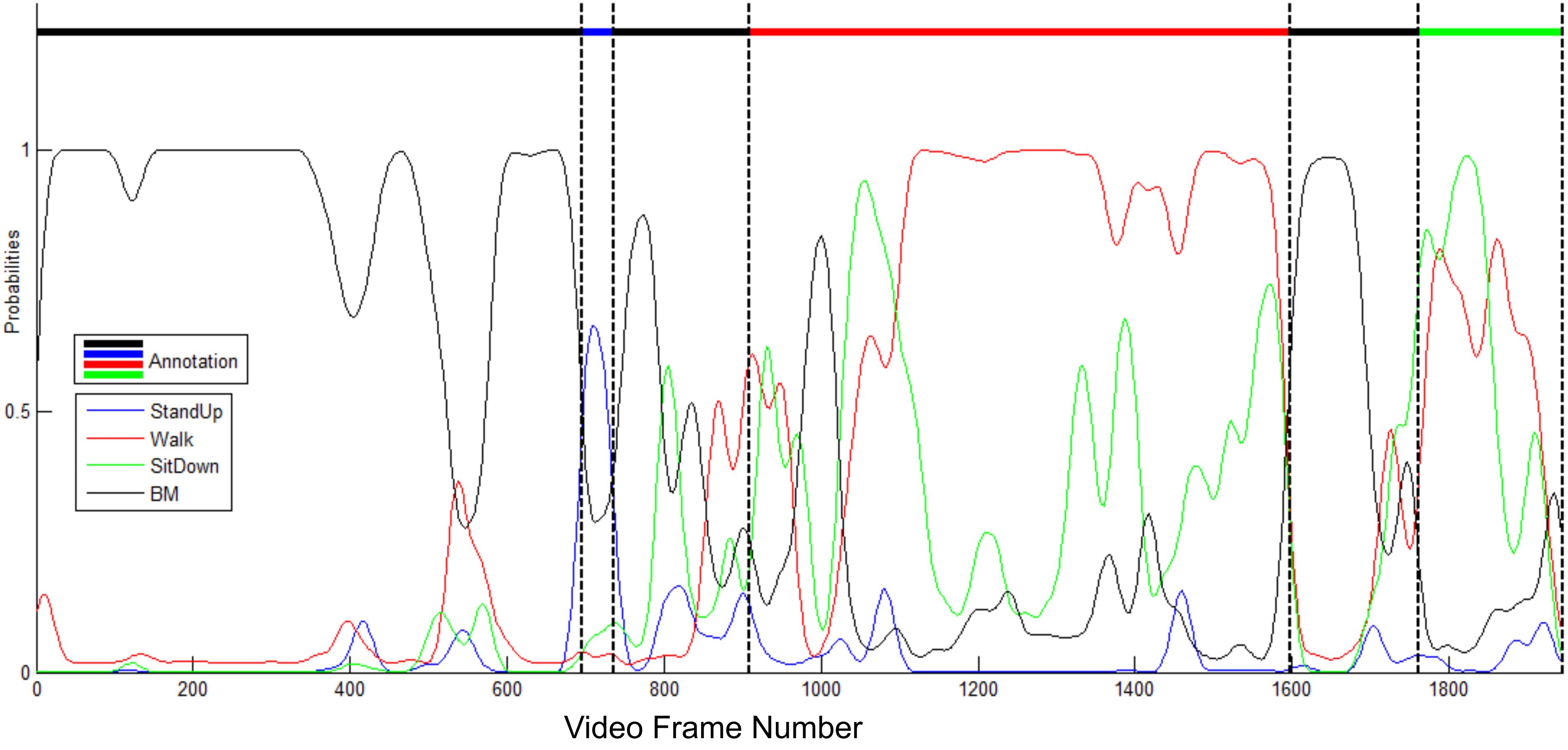
Sign:
(GSL) Europe

Action Recognition framework

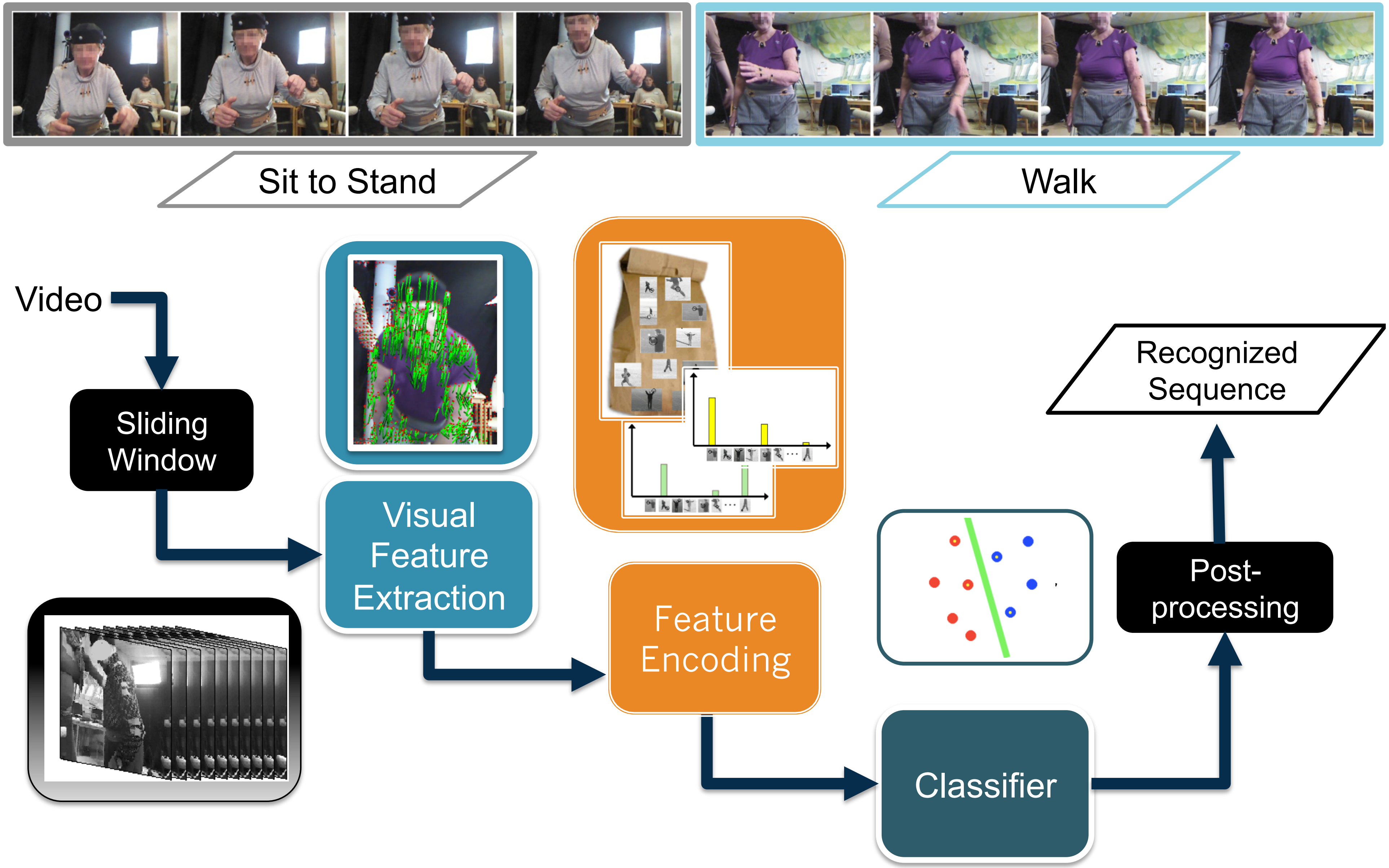

Video frames sequence
• • •
Visual Processing & Feature Extraction
BoF
BoF
BoF
BoF
Probability computation (with SVMs)
Viterbi Decoding of probabilities
Recognition

Action Probabilities from SVMs

Smoothed probabilities of actions for each frame based on Gabor3D STIP.
Probabilities are obtained with SVMs.



Visual action recognition pipeline



Sit to Stand

Walk

Video

Sliding Window

Visual Feature Extraction

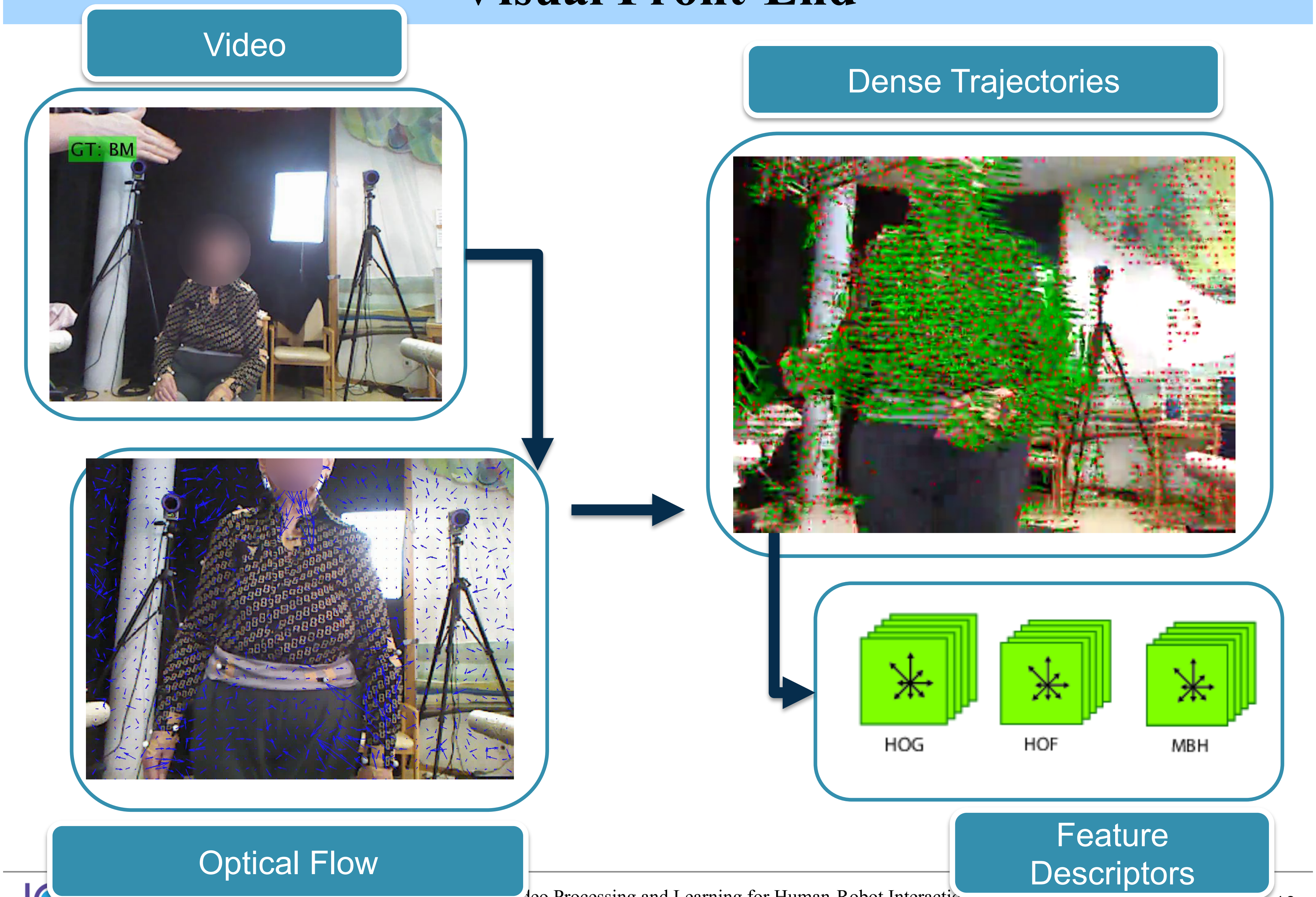
Feature Encoding

Classifier

Post-processing

Recognized Sequence

Visual Front-End



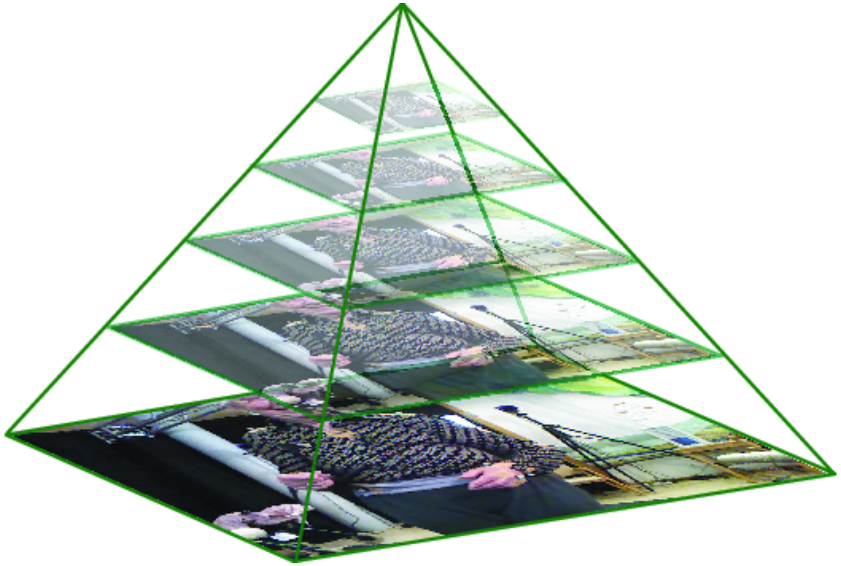
Video

Optical Flow

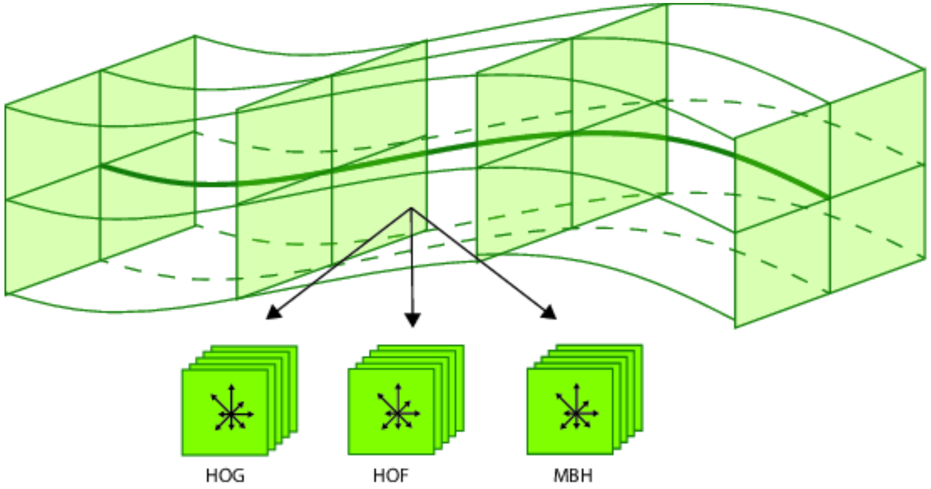
Dense Trajectories

Feature Descriptors

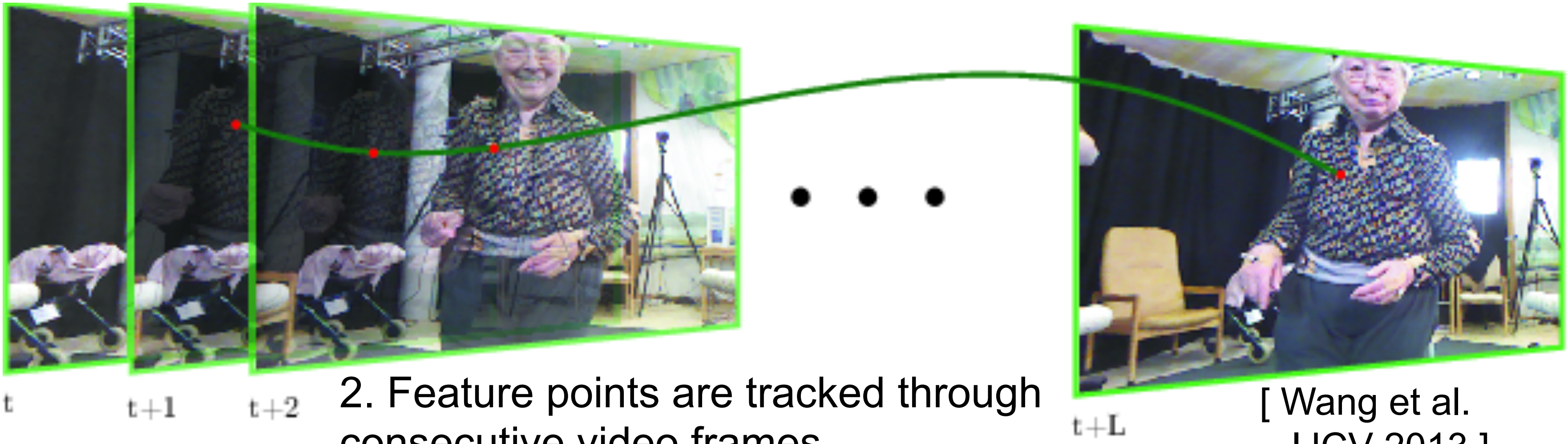
Features: Dense Trajectories



1. Feature points are sampled on a regular grid in multiple scales



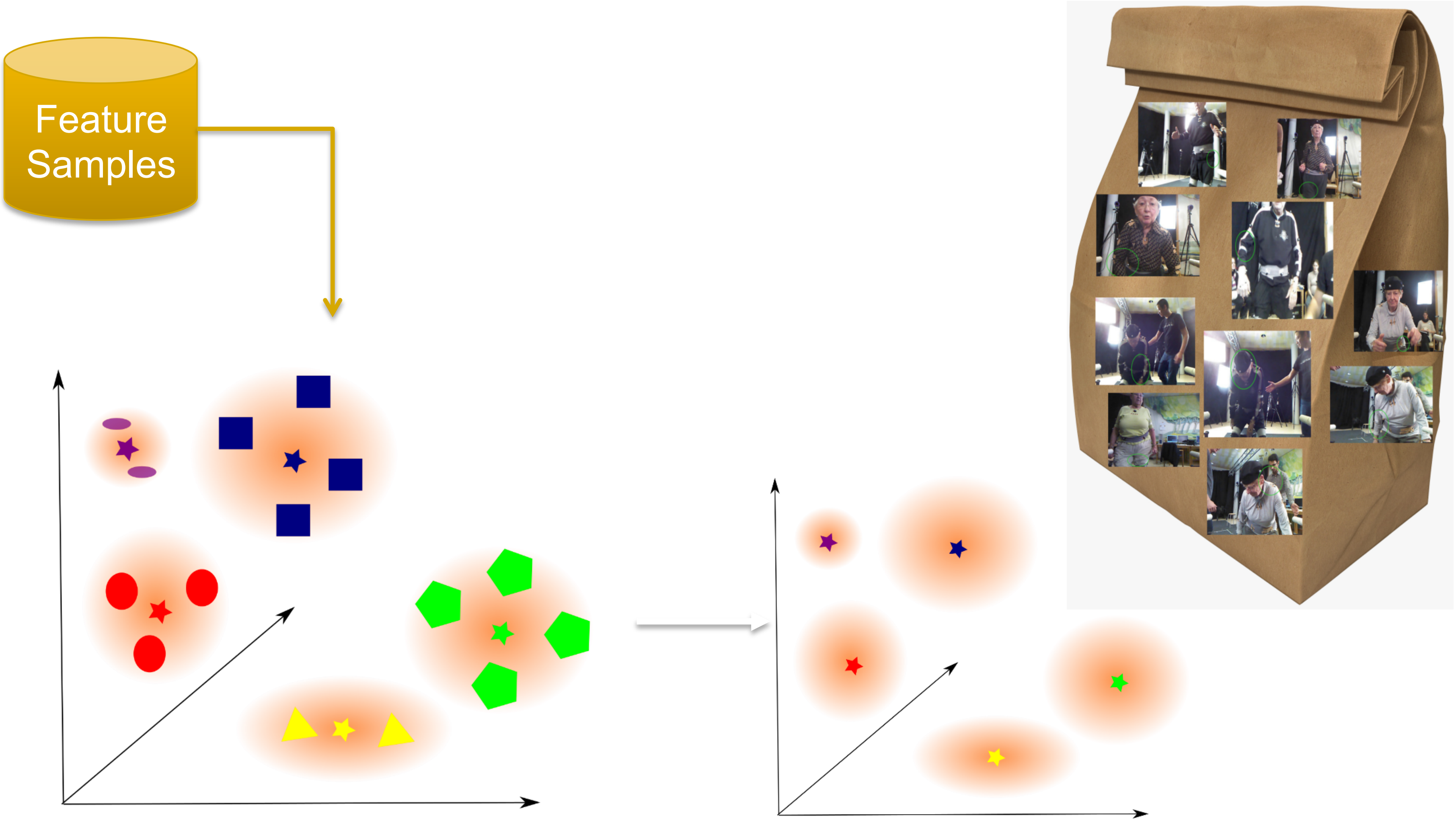
3. Descriptors are computed in space-time volumes along trajectories



2. Feature points are tracked through consecutive video frames

[Wang et al. IJCV 2013]

K-means Clustering and Dictionary

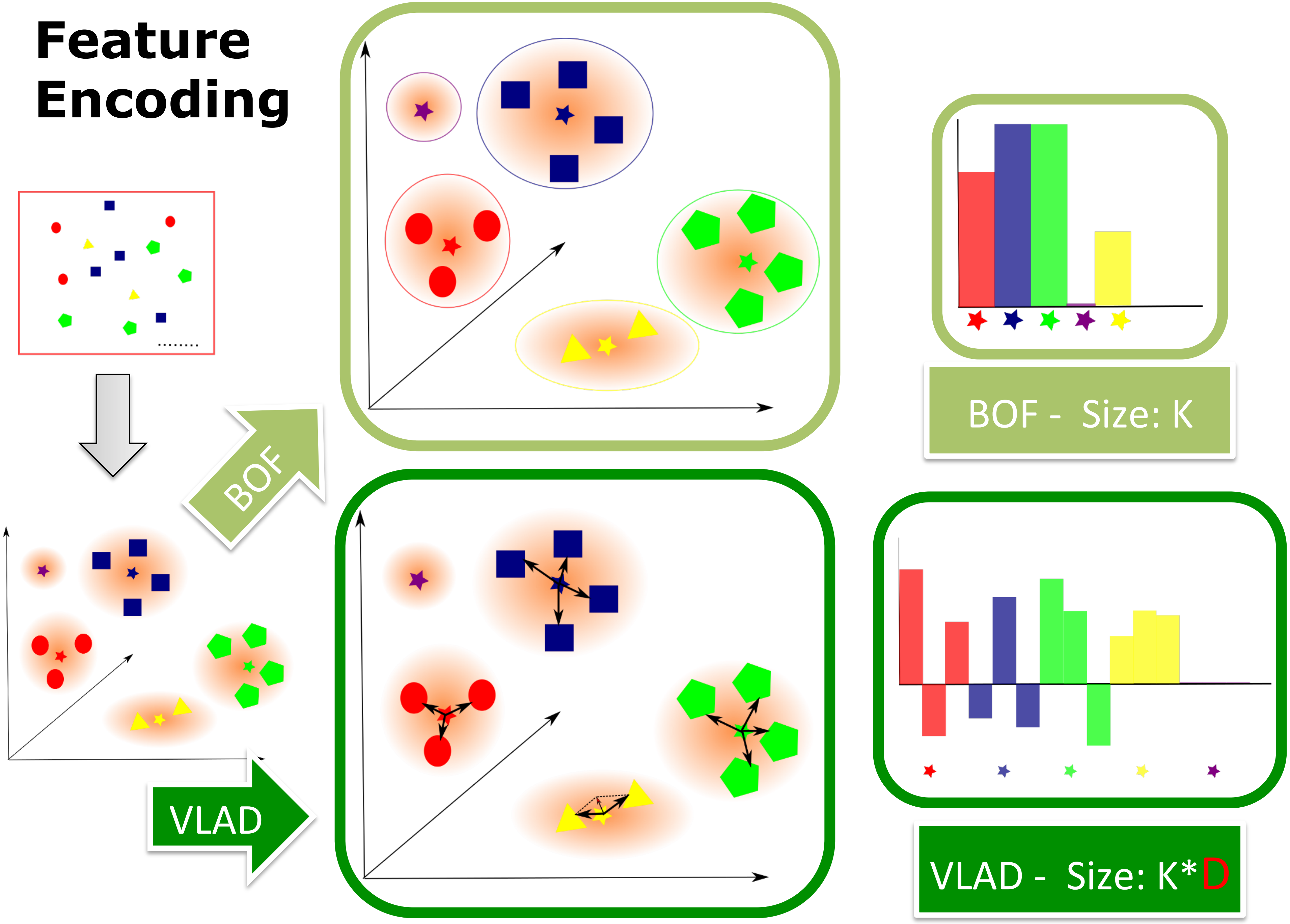


Feature Samples

K-means

Dictionary

Feature Encoding



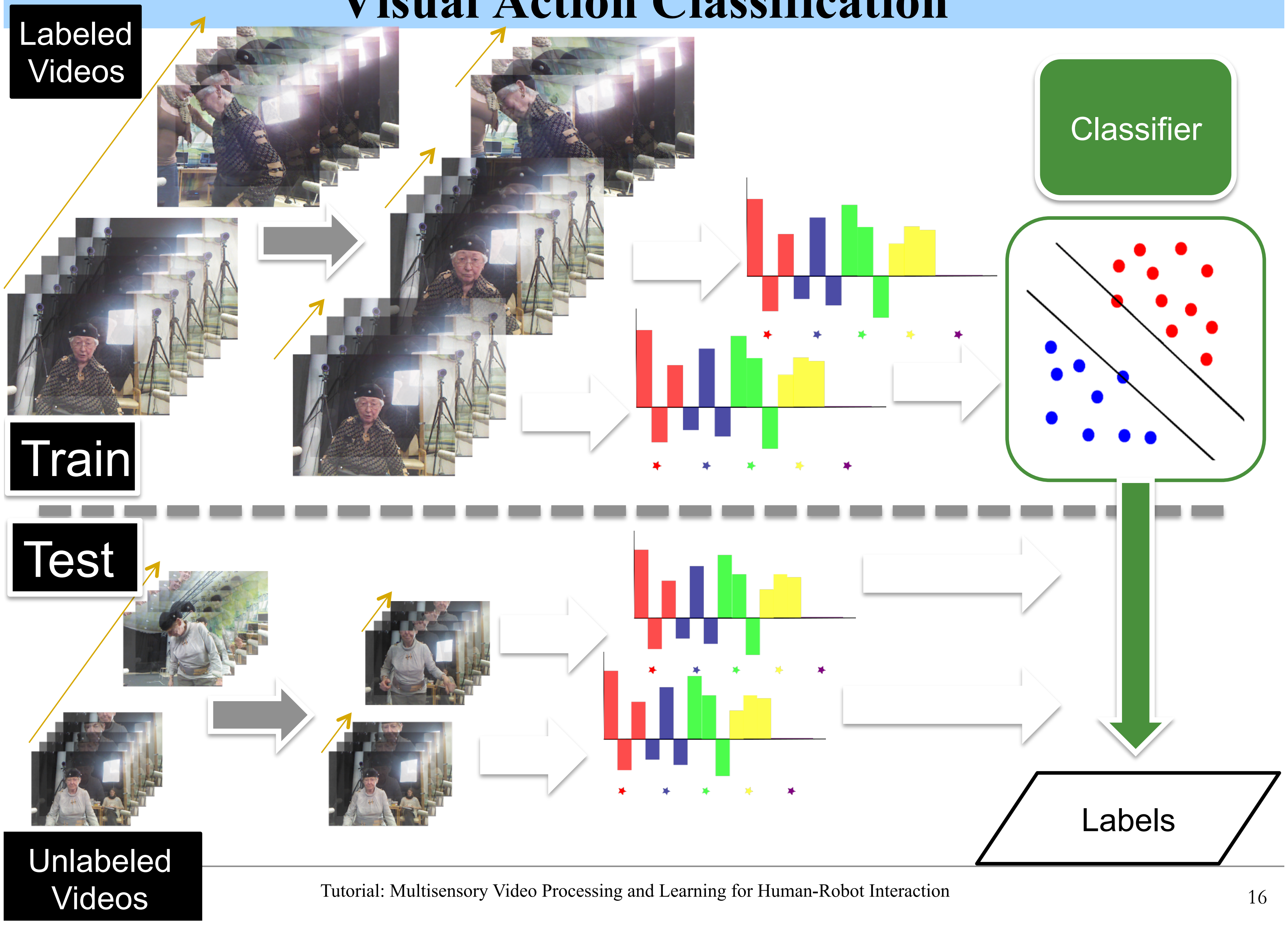
BOF

VLAD

BOF - Size: K

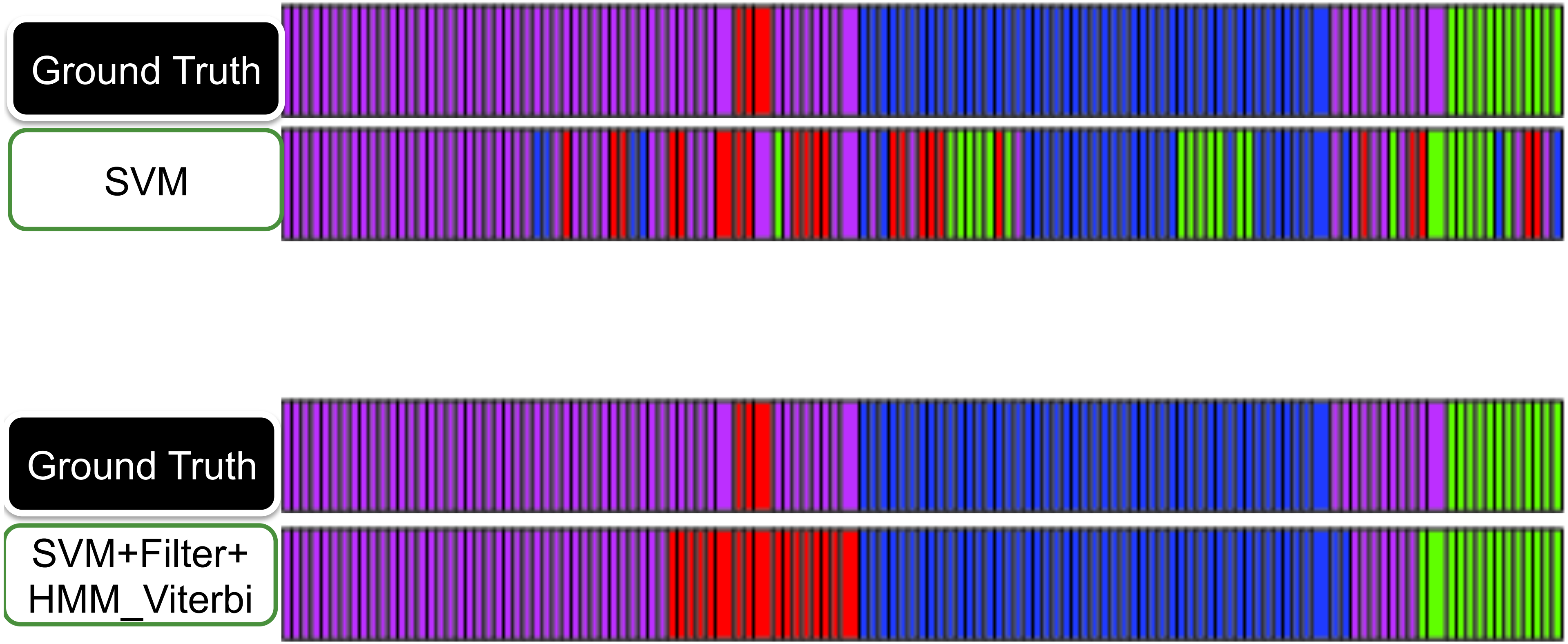
VLAD - Size: K*D

Visual Action Classification



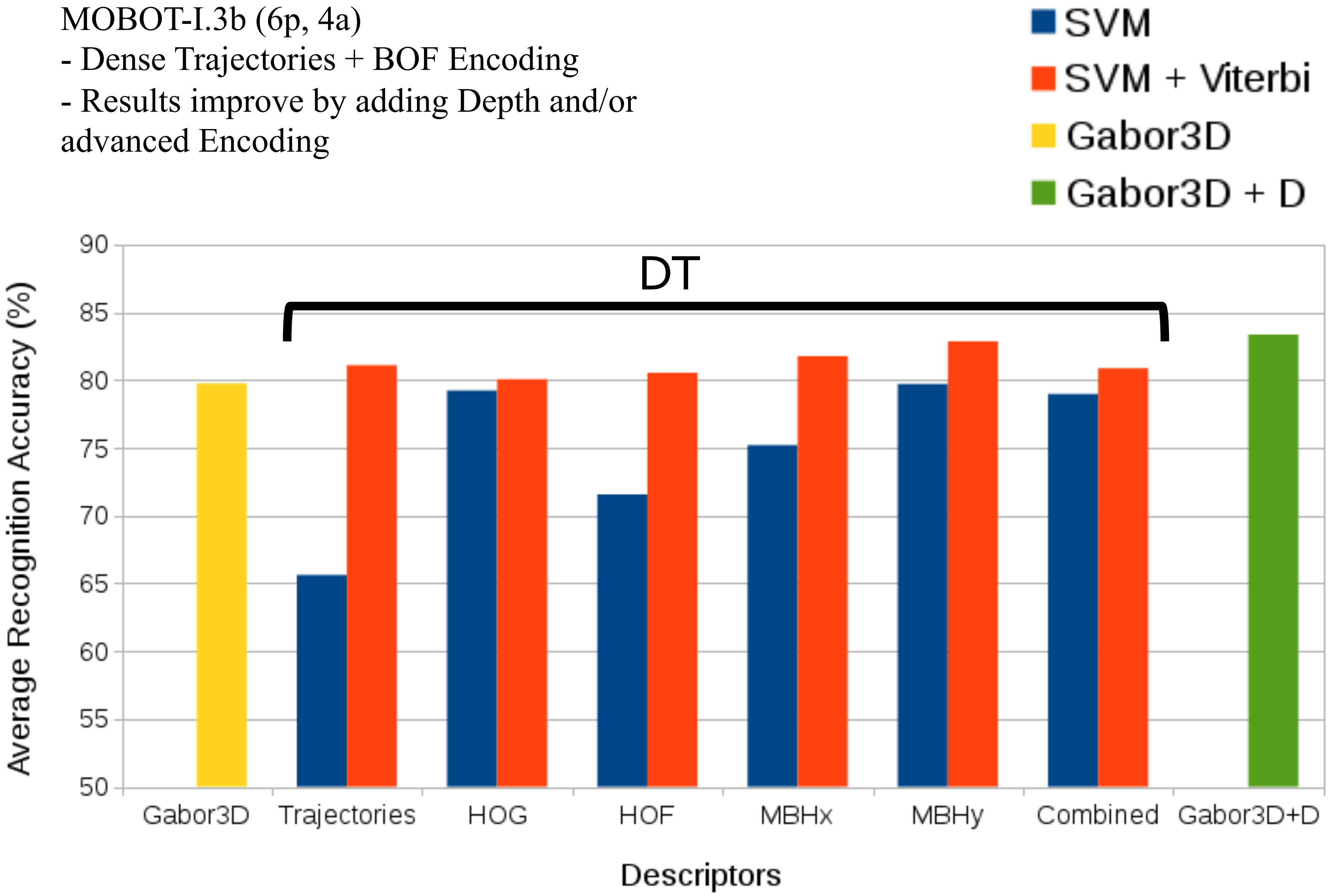
Temporal Segmentation Results

Sit	🟩
Walk	🟦
Stand	🟥
- B.M.	🟪



Action Recognition Results (4a, 6p)

MOBOT-I.3b (6p, 4a)
- Dense Trajectories + BOF Encoding
- Results improve by adding Depth and/or advanced Encoding



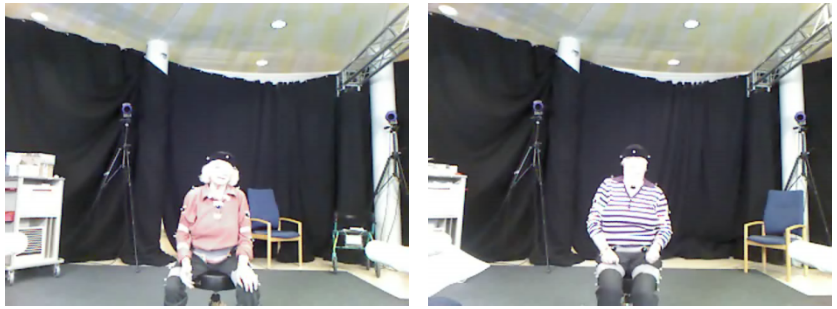
Gesture Recognition

Gesture Recognition Challenges

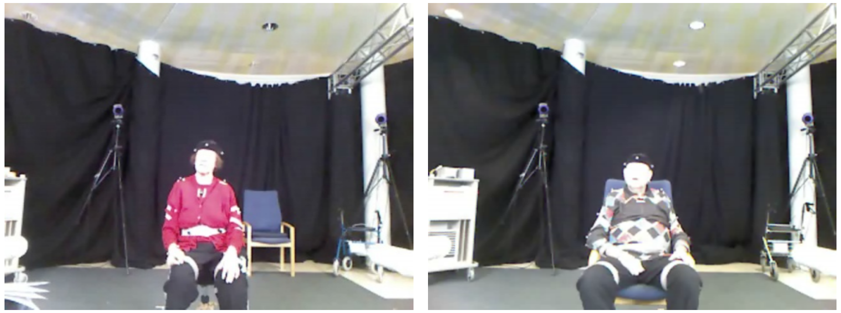
Challenging task of recognizing human gestural movements:

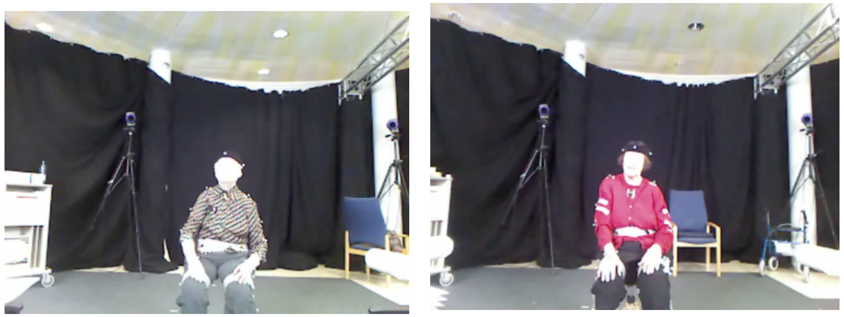
- Large variability in gesture performance.
- Some gestures can be performed with left or right hand.

Come Closer

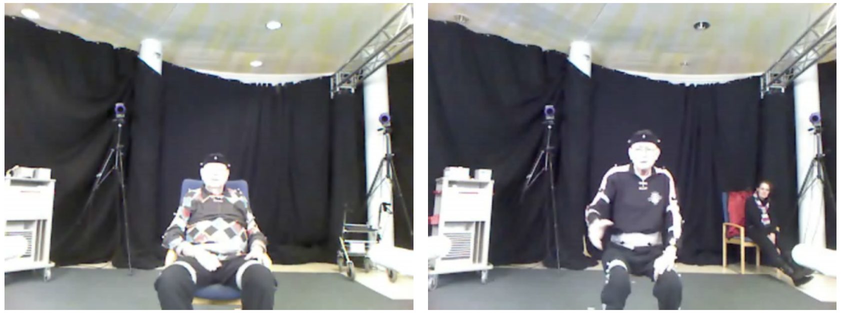


I want to Sit Down



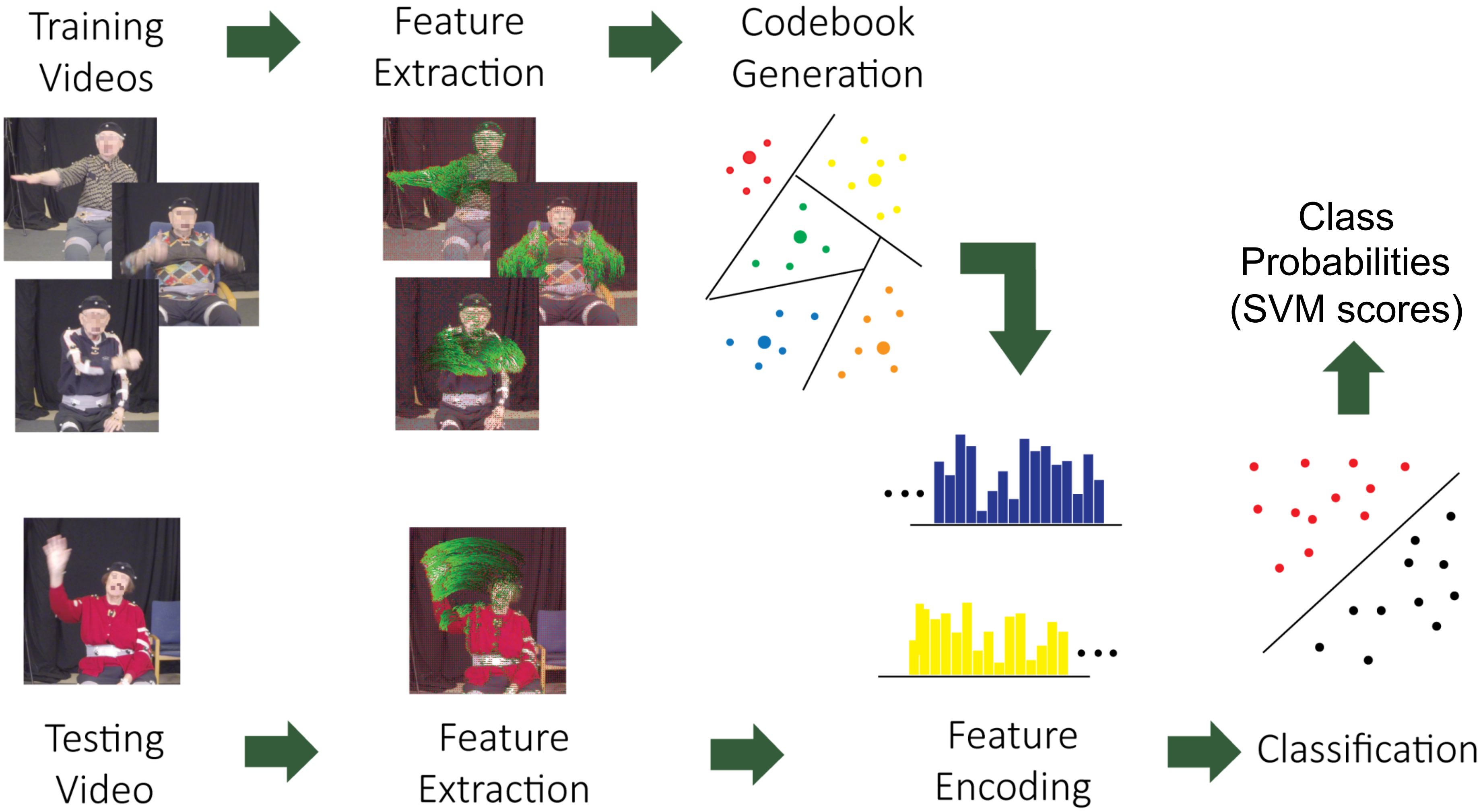


Park



I want to Perform a Task

Visual Gesture Classification Pipeline



Training Videos

Feature Extraction

Codebook Generation

Class Probabilities (SVM scores)

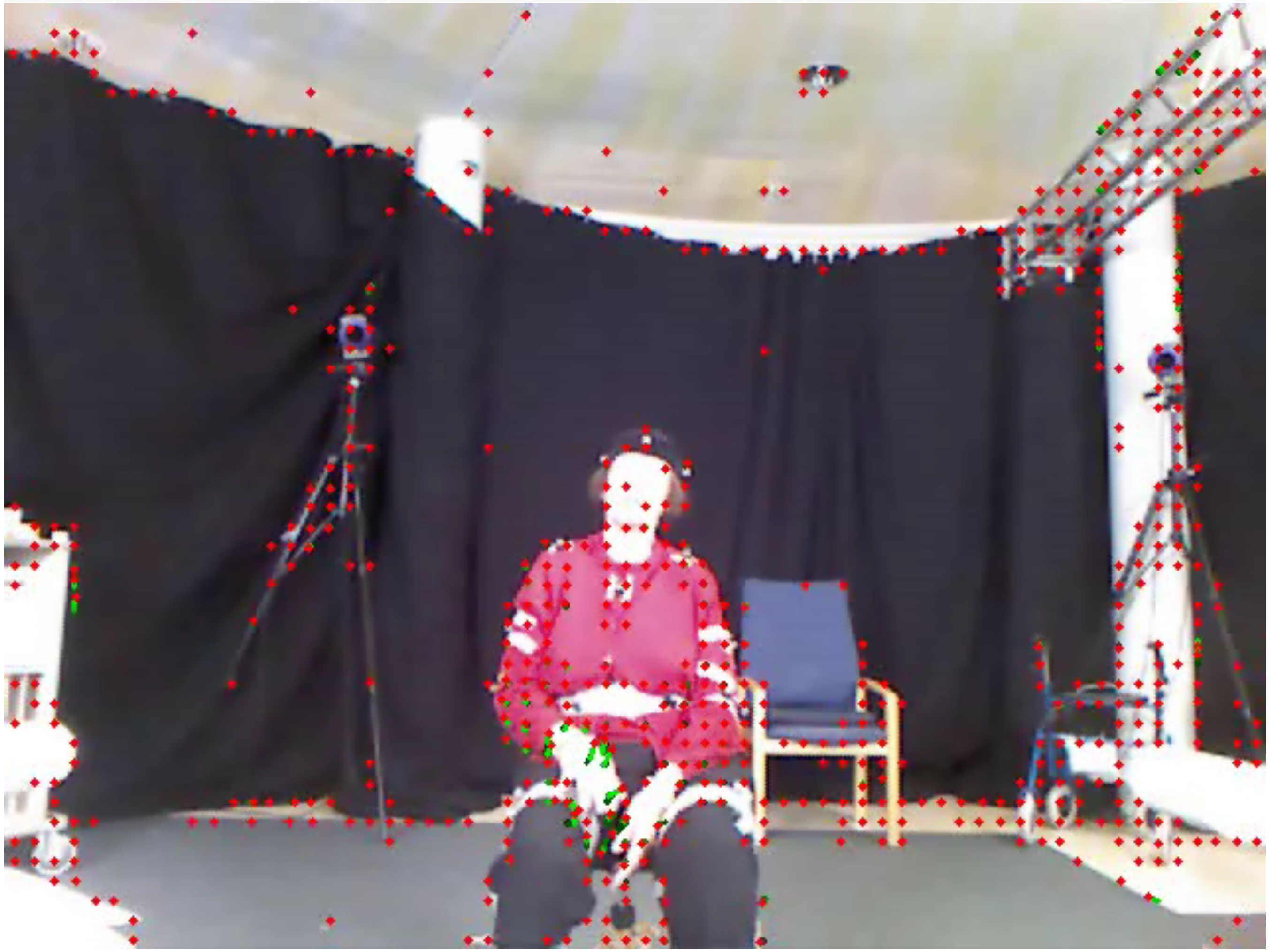
Testing Video

Feature Extraction

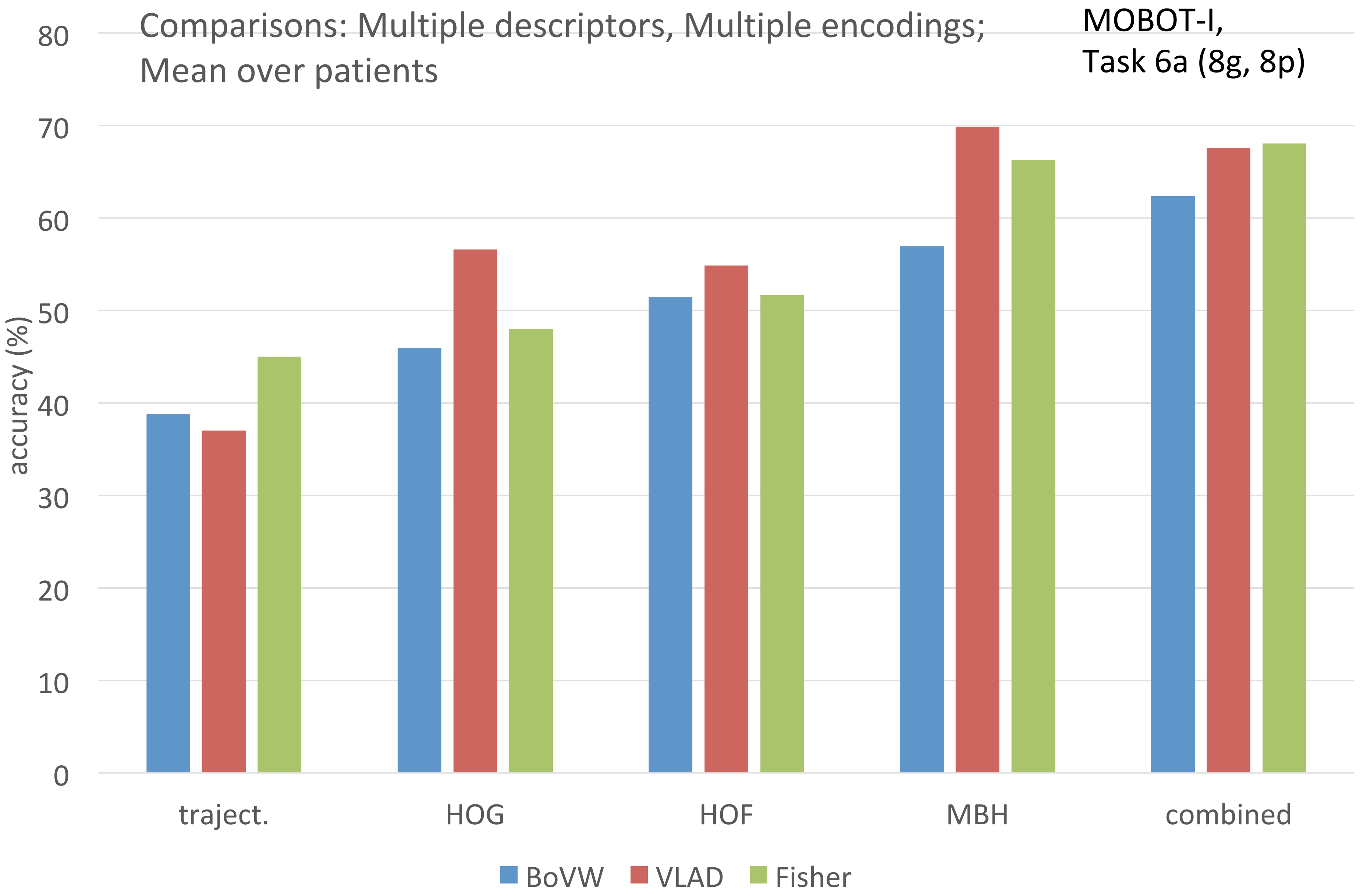
Feature Encoding

Classification

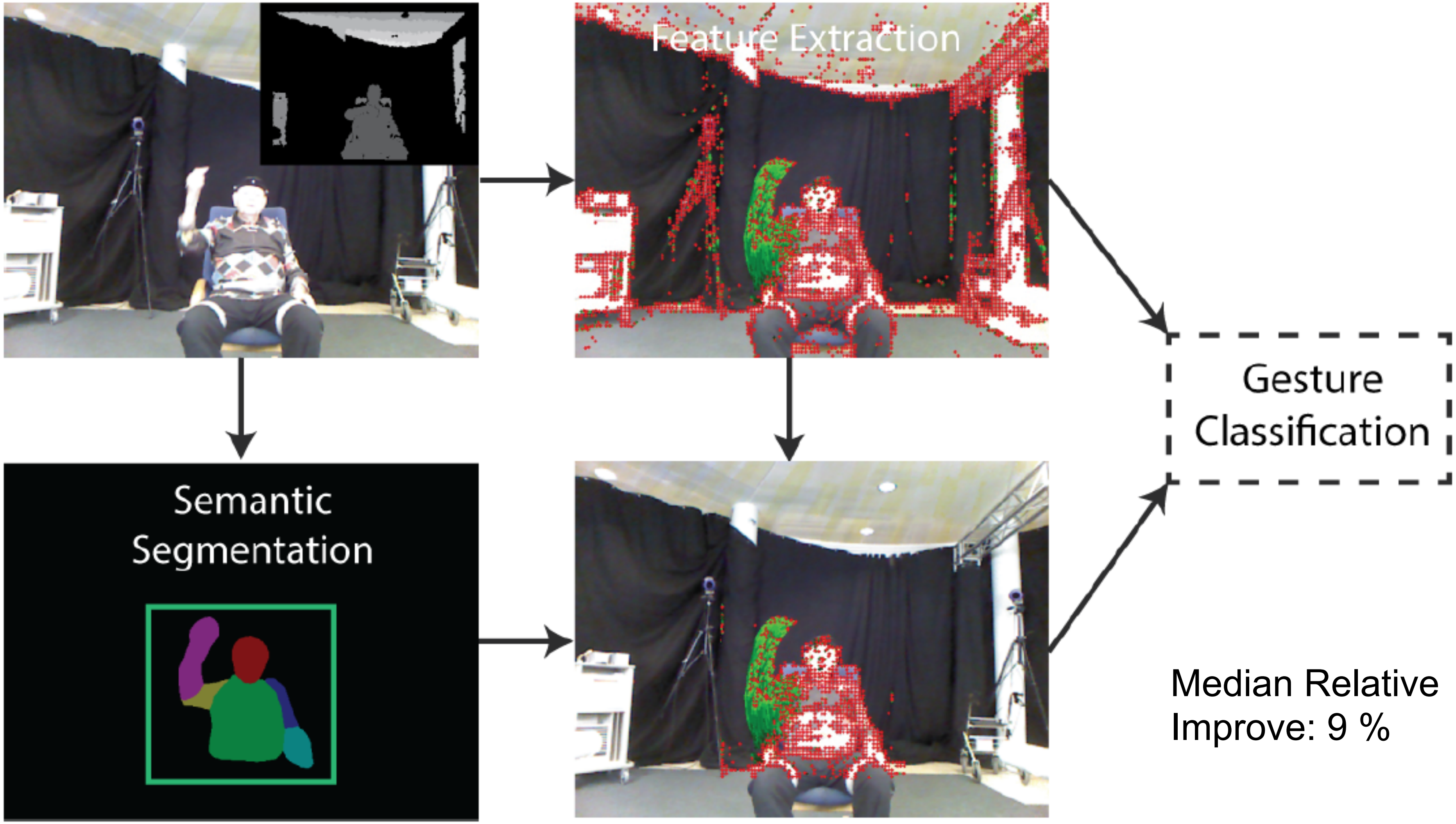
Applying Dense Trajectories on Gesture Data



Extended Results on Gesture Recognition



Visual Synergy: Semantic Segmentation + Gesture Recognition



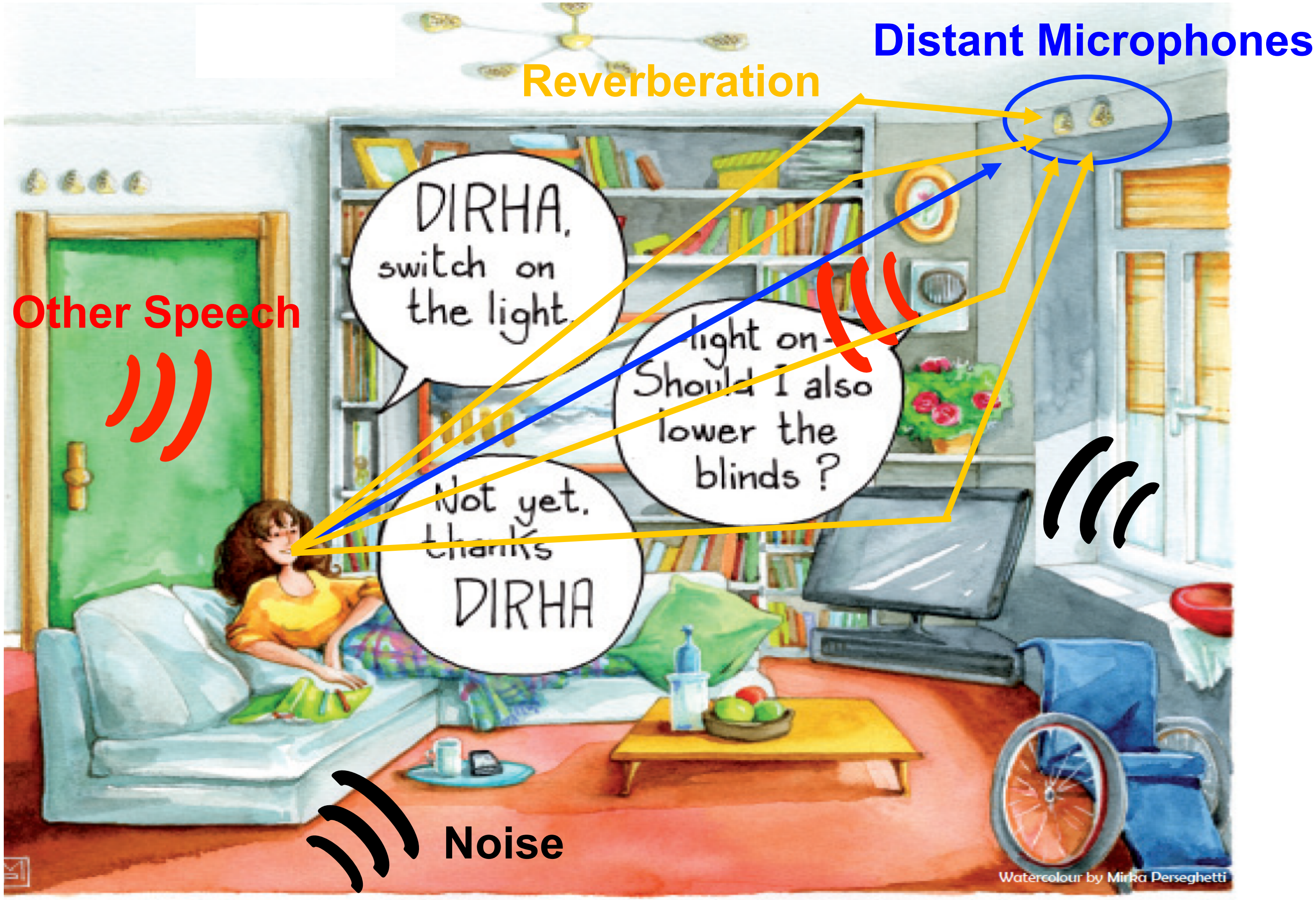
Median Relative Improve: 9 %

foreground/background+gesture recognition

A. Guler, N. Kardaris, S. Chandra, V. Pitsikalis, C. Werner, K. Hauer, C. Tzafestas, P. Maragos and I. Kokkinos, “*Human Joint Angle Estimation and Gesture Recognition for Assistive Robotic Vision*” ECCV Workshop on Assistive Computer Vision and Robotics, 2016.

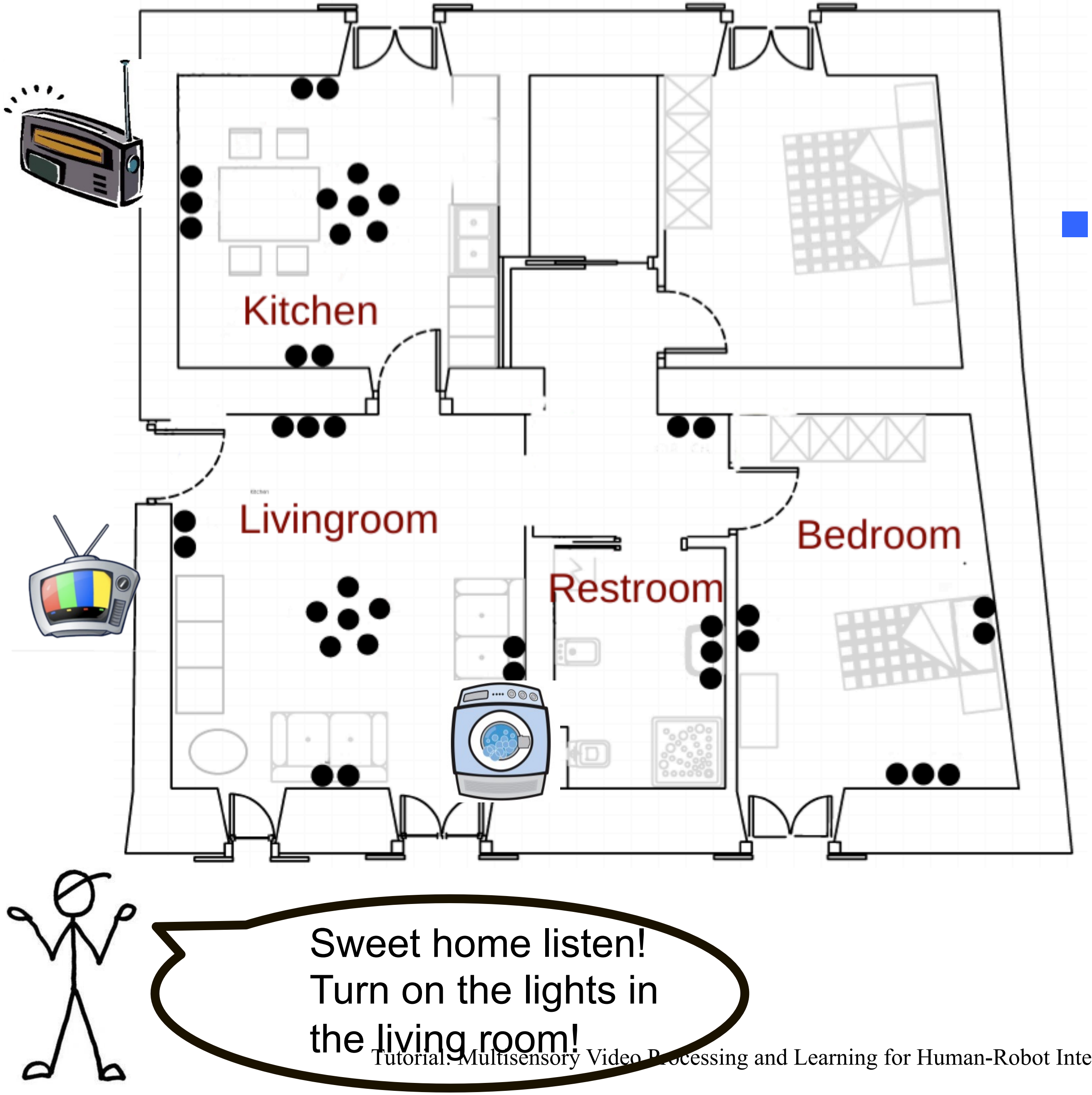
Spoken Command Recognition

Distant Speech Recognition inVoice-enabled Interfaces


Distant Microphones
Reverberation
Other Speech
DIRHA, switch on the light.
light on- Should I also lower the blinds ?
Not yet, thanks DIRHA
Noise
Watercolour by Mirka Perseghetti

https://dirha.fbk.eu/

Smart Home Voice Interface



- Main technologies:
  - ❑ Voice Activity Detection
  - ❑ Acoustic Event Detection
  - ❑ Speaker Localization
  - ❑ Speech Enhancement
  - ❑ Keyword Spotting
  - ❑ Far-field command recognition

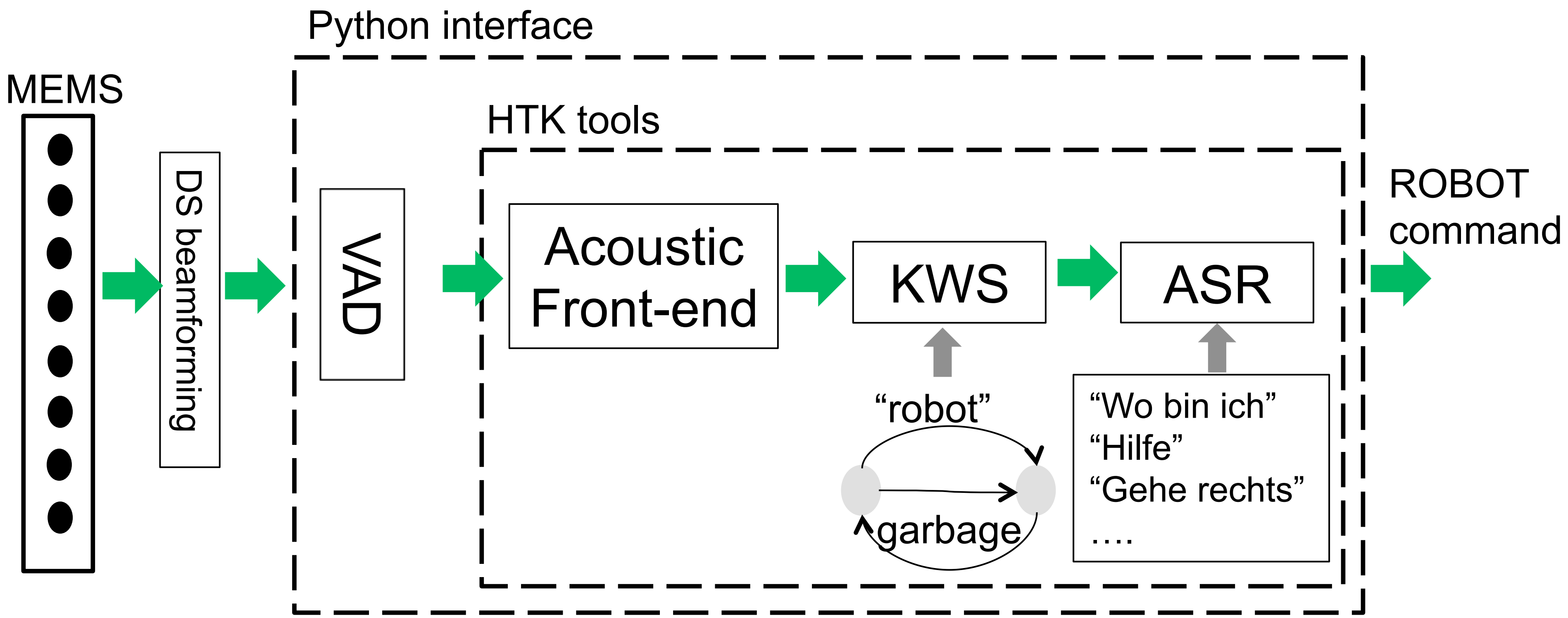
DIRHA demo ("spitaki mou")

https://www.youtube.com/watch?v=zf5wSKv9wKs

- I. Rodomagoulakis, A. Katsamanis, G. Potamianos, P. Giannoulis, A. Tsiami, P. Maragos, "Room-localized spoken command recognition in multi-room, multi-microphone environments", *Computer Speech & Language*, 2017.
- A. Tsiami, I. Rodomagoulakis, P. Giannoulis, A. Katsamanis, G. Potamianos and P. Maragos, "ATHENA: A Greek Multi-Sensory Database for Home Automation Control", INTERSPEECH 2014.

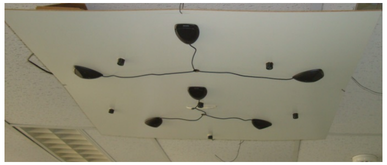
Spoken-Command Recognition Module for HRI

- integrated in ROS, always-listening mode, real time performance

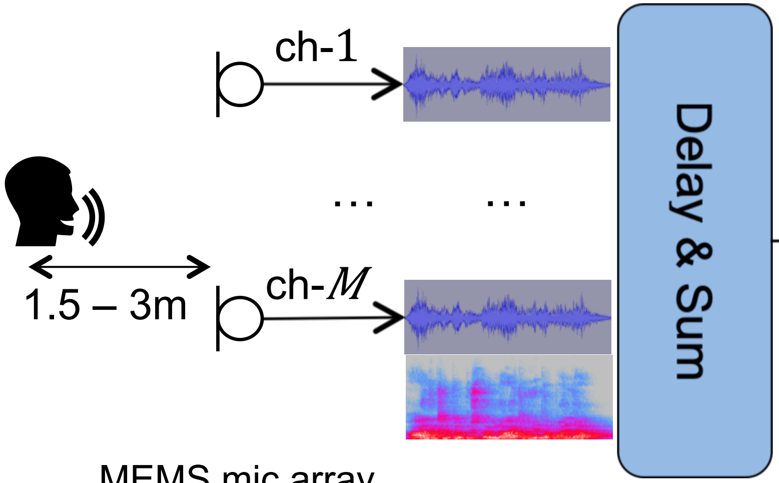


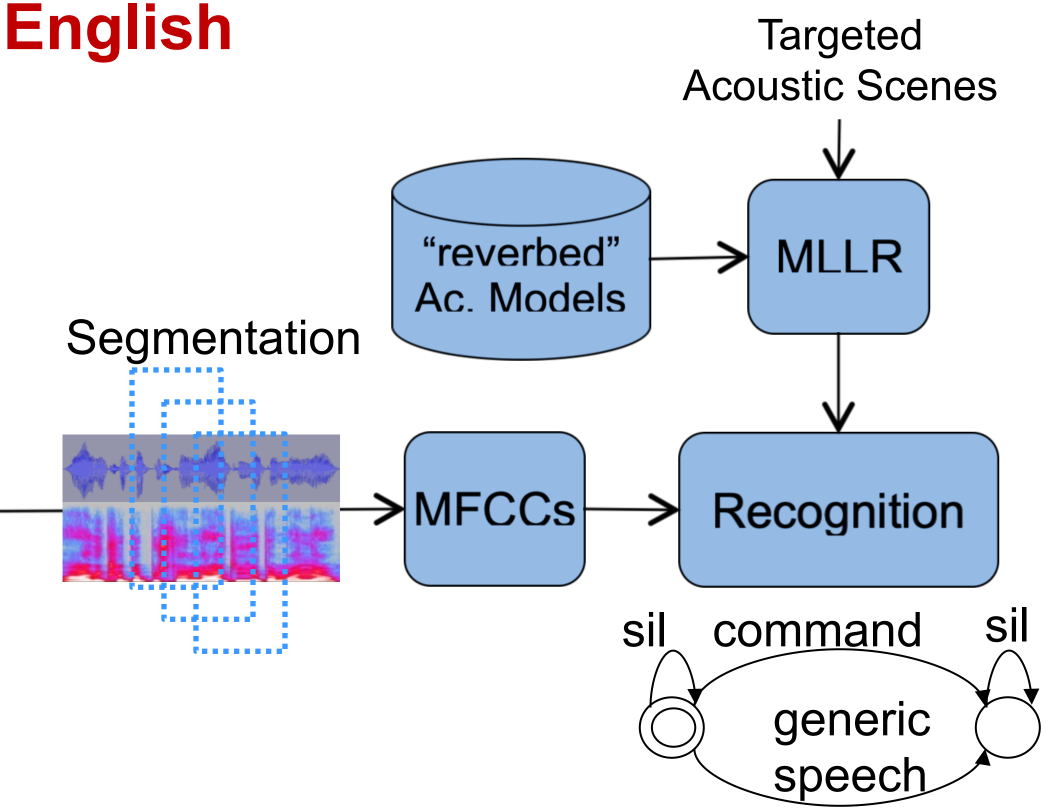
Online Spoken Command Recognition

- **Greek, German, Italian, English**

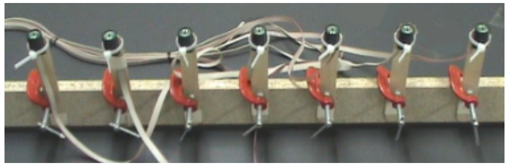


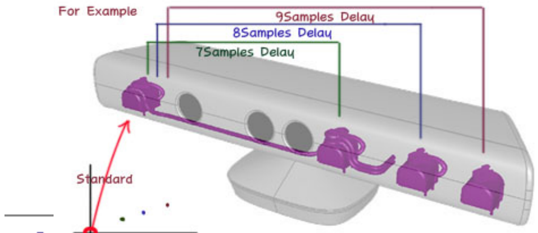
Pentagon ceiling array (Shure)



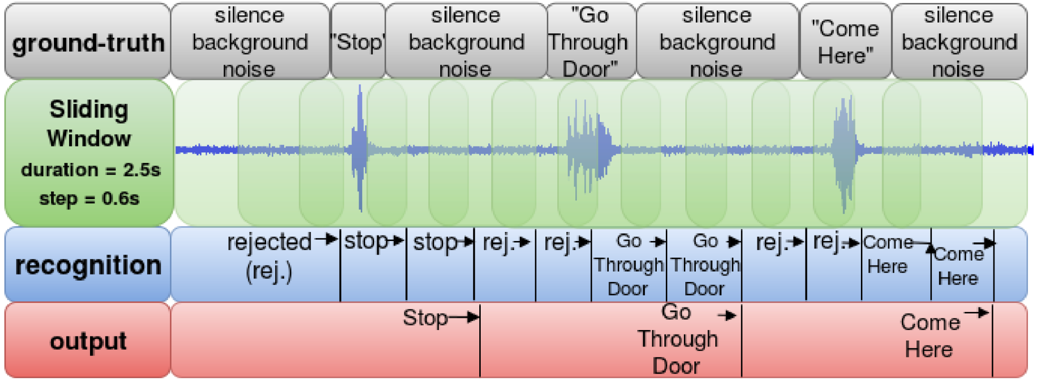


MEMS mic array





Kinect mic array



ground-truth: silence background noise | "Stop" | silence background noise | "Go Through Door" | silence background noise | "Come Here" | silence background noise

Sliding Window duration = 2.5s step = 0.6s

recognition: rejected (rej.) → | stop → | stop → | rej. → | rej. → | Go Through Door → | Go Through Door → | rej. → | rej. → | Come Here → | Come Here →

output: Stop → | Go Through Door → | Come Here →

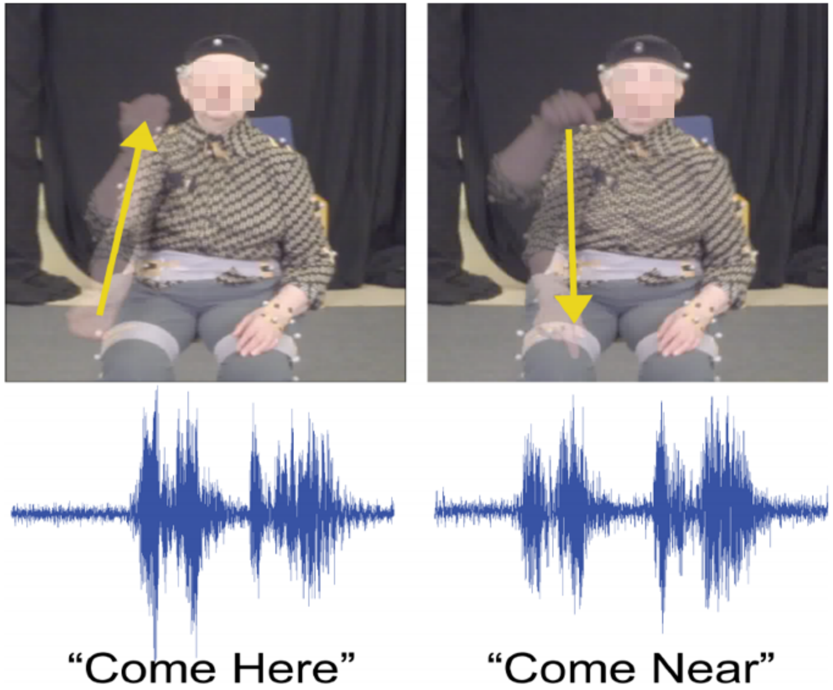
Audio-Visual Fusion

for

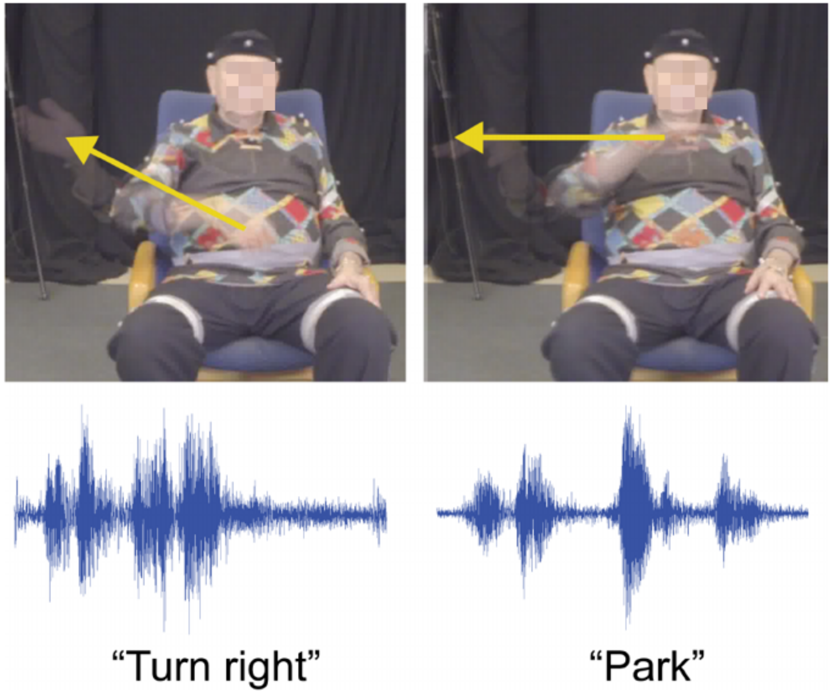
Multimodal Gesture Recognition

Multimodal Fusion:
Complementarity of Visual and Audio Modalities

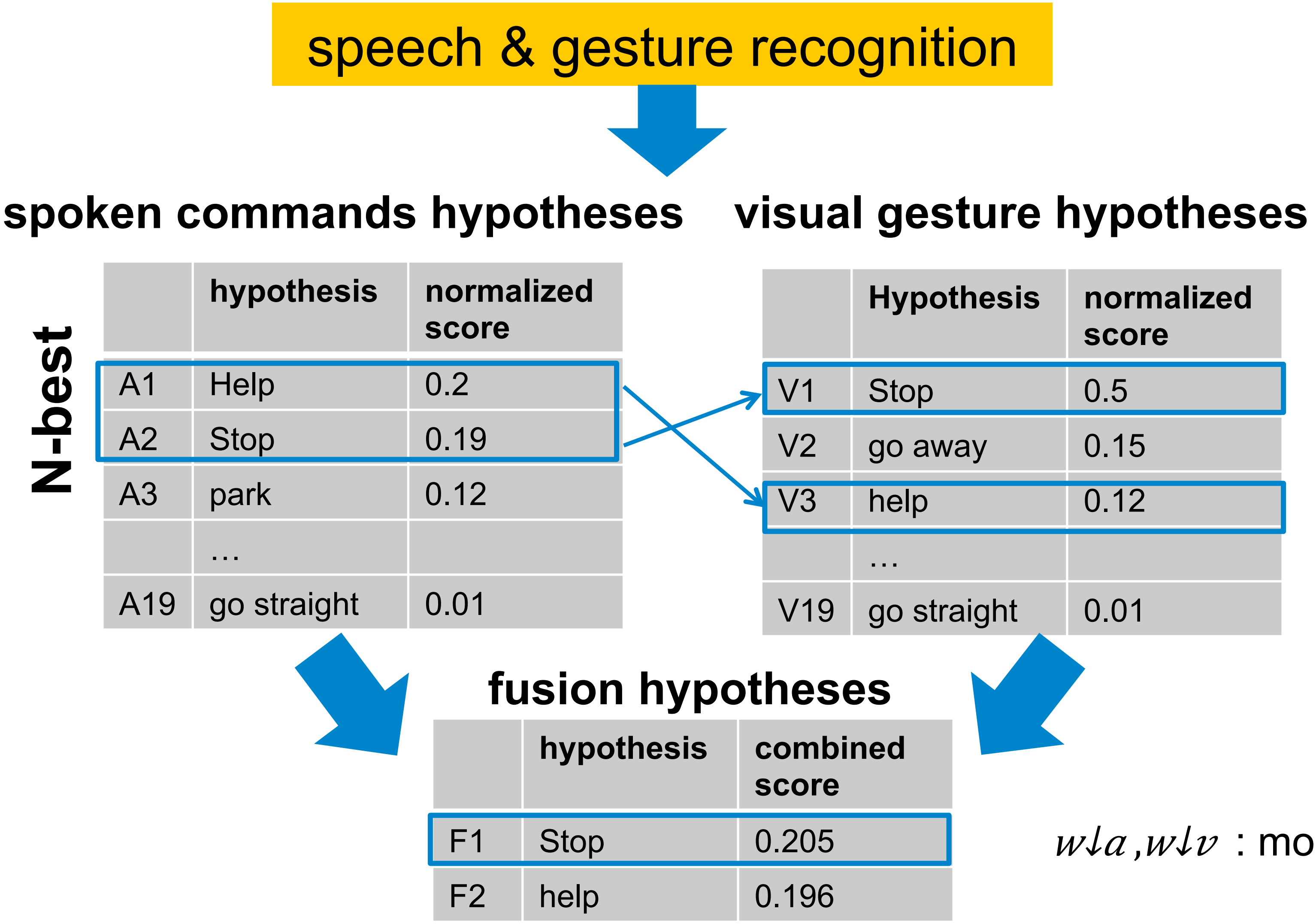
Similar audio,
distinguishable gesture



Distinguishable audio,
similar gesture



Audio-Visual Fusion: Hypotheses Rescoring



speech & gesture recognition

spoken commands hypotheses

N-best

	hypothesis	**normalized score**
A1	Help	0.2
A2	Stop	0.19
A3	park	0.12
	…	
A19	go straight	0.01

visual gesture hypotheses

	Hypothesis	**normalized score**
V1	Stop	0.5
V2	go away	0.15
V3	help	0.12
	…	
V19	go straight	0.01

fusion hypotheses

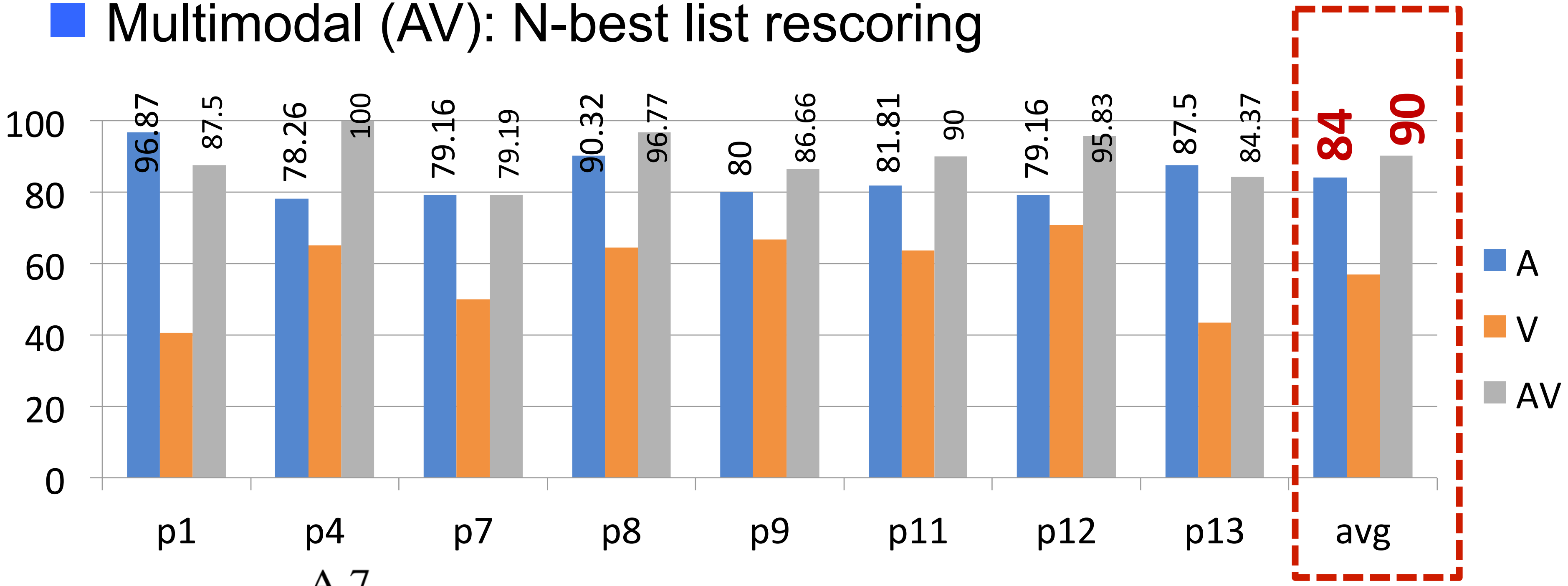
	hypothesis	**combined score**
F1	Stop	0.205
F2	help	0.196

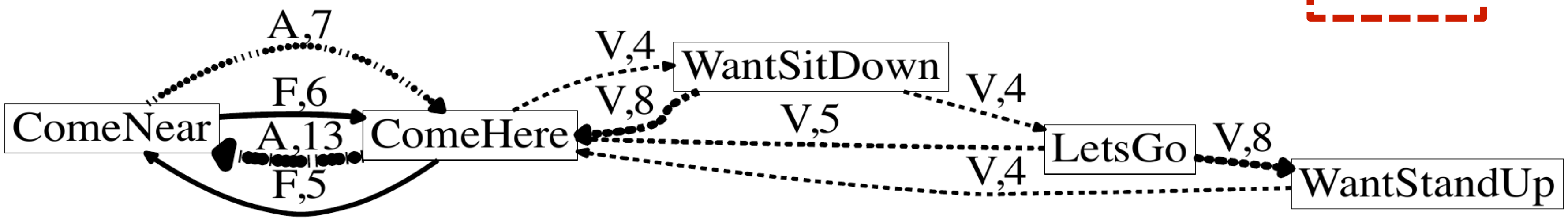
w_a, w_v : modality weigh

$$\mathrm{MAX}(w_a \times score(A_1) + w_v \times score(V_3),\ w_a \times score(A_2) + w_v \times score(V_1))$$

Offline Multimodal Command Classification

- Leave-one-out experiments (Mobot-I.6a data: 8p,8g)
- Unimodal: audio (A) and visual (V)
- Multimodal (AV): N-best list rescoring

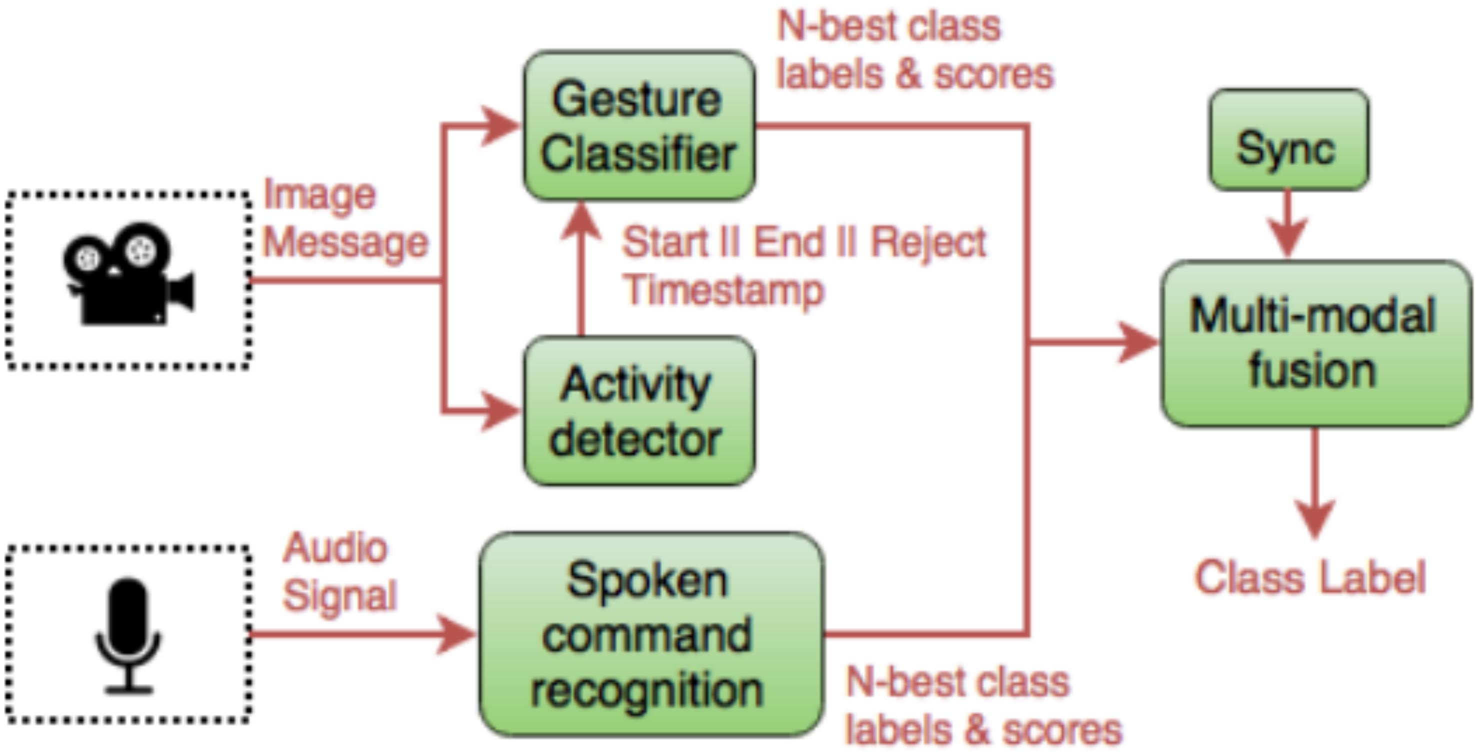




Multimodal confusability graph

HRI Online Multimodal System Architecture

- ROS based integration
  - ❑ Spoken command recognition node
  - ❑ Activity detection node
  - ❑ Gesture classifier node
  - ❑ Multimodal fusion node
- Communication using ROS messages

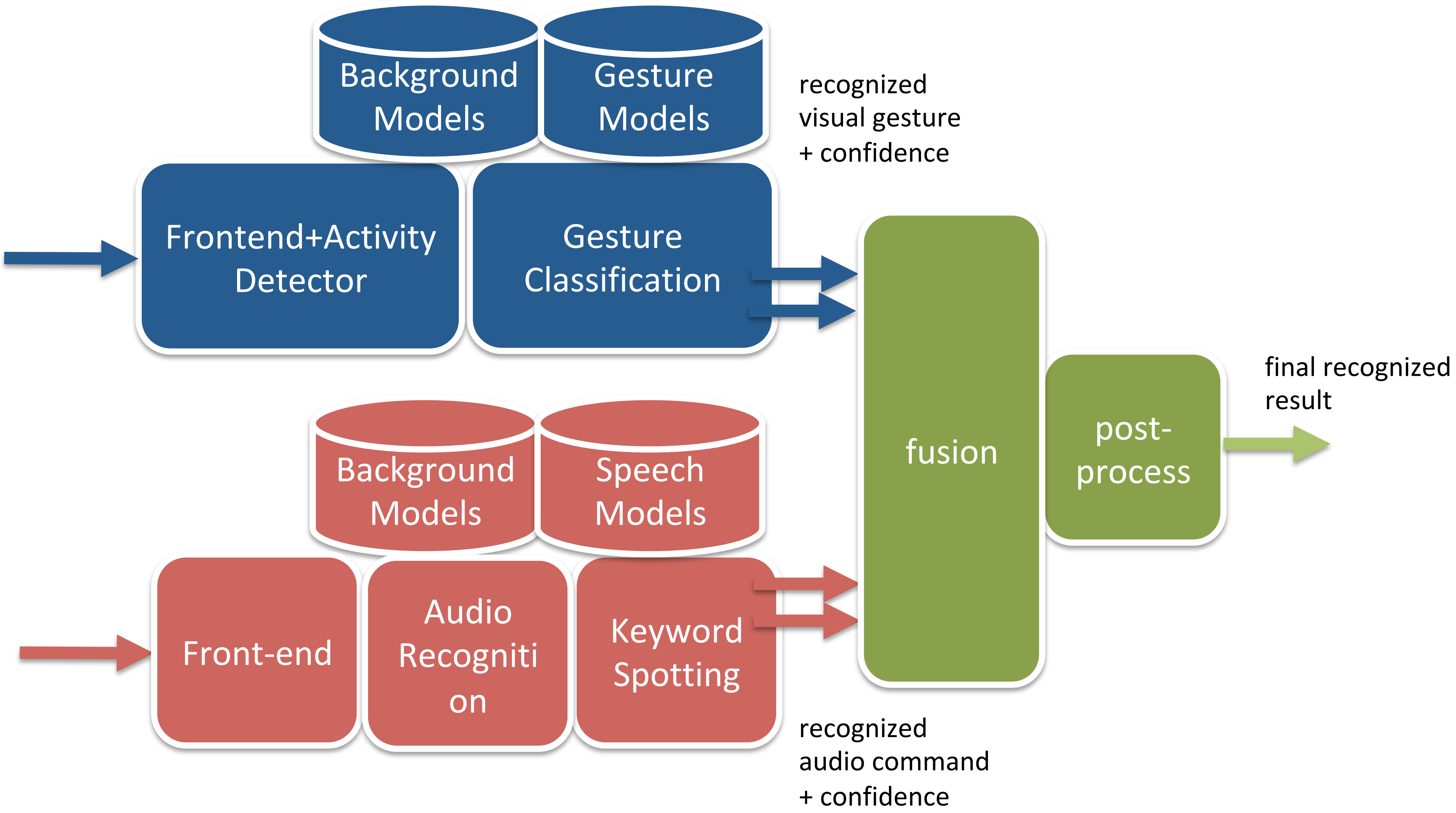


Gesture Classifier
N-best class labels & scores
Sync
Image Message
Start II End II Reject Timestamp
Multi-modal fusion
Activity detector
Class Label
Audio Signal
Spoken command recognition
N-best class labels & scores

Audio-Gestural Command Recognition

Online processing system – Open Source Software

http://robotics.ntua.gr/projects/building-multimodal-interfaces

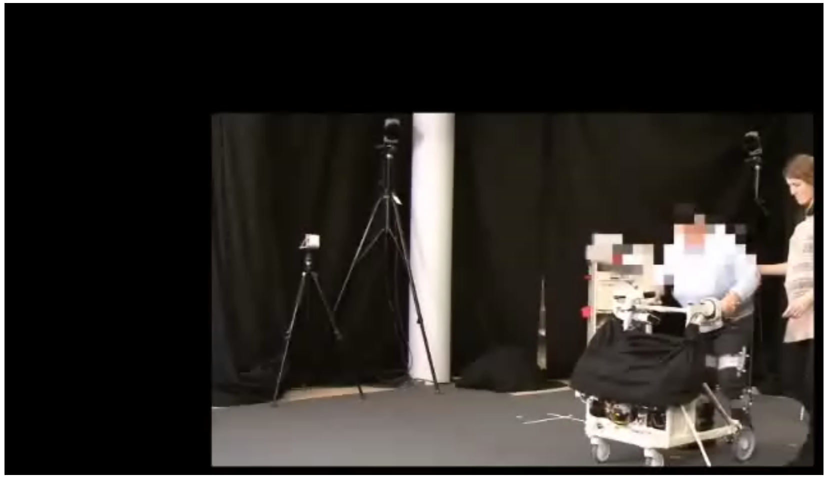


N. Kardaris, I. Rodomagoulakis, V. Pitsikalis, A. Arvanitakis and P. Maragos, *A platform for building new human-computer interface systems that support online automatic recognition of audio-gestural commands*, Proc. ACM Multimedia 2016.

4.
Audio-Visual HRI: Applications in Assistive Robotics

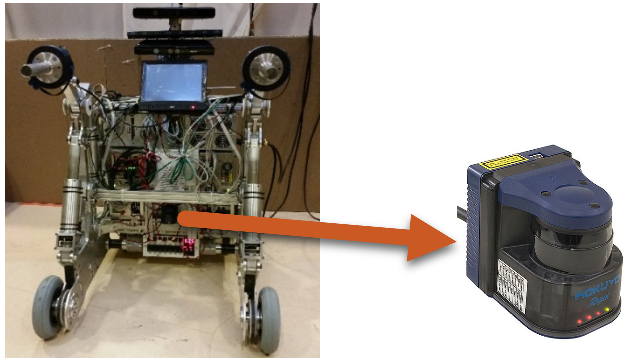
EU Project MOBOT: Motivation

Experiments conducted at
Bethanien Geriatric Center Heidelberg



Mobility & **Cognitive** impairments, prevalent in **elderly** population, limiting factors for ***Activities of Daily Living* (ADLs)**

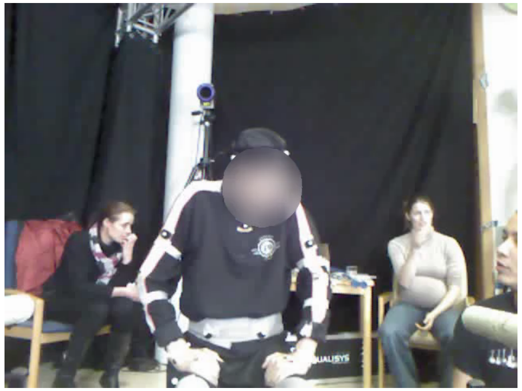
Intelligent assistive devices (robotic Rollator) aiming to provide ***context-aware*** and ***user-adaptive*** mobility (**walking**) assistance



MOBOT rollator

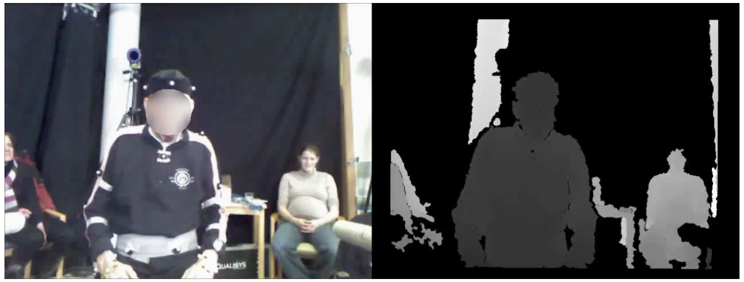
Multi-Sensor Data for HRI

Kinect1 RGB Data



Kinect Depth Data

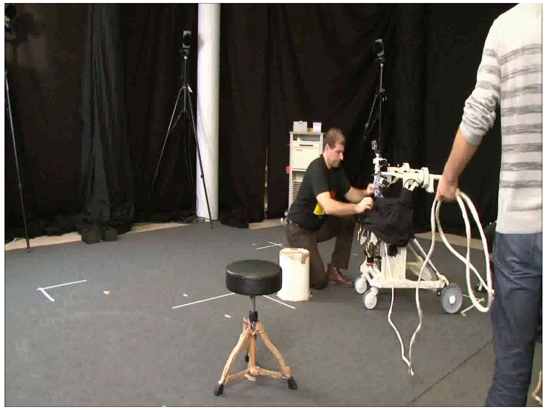
Kinect1 RGB
Kinect1 Depth
MEMS Audio Data



Go Pro RGB Data

HD1 Camera Data

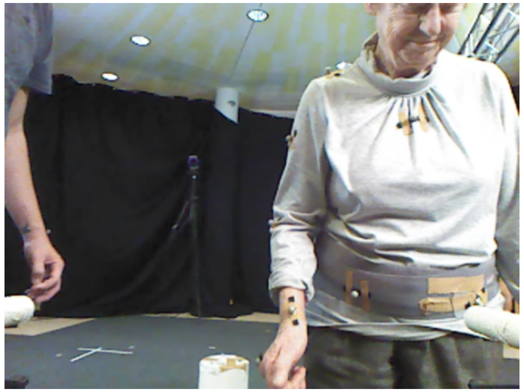
HD2 Camera Data



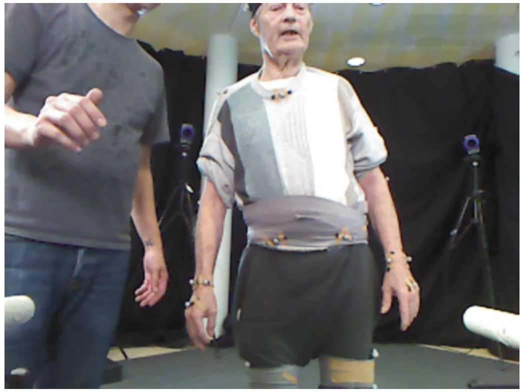
Action Sample Data and Challenges

- Visual noise by intruders
- Multiple subjects in the scene, even in same depth level
- Frequent and extreme occlusions, missing body parts (e.g. face)
- Significant variation in subjects pose, actions, visibility,

Stand-to-Sit – P1



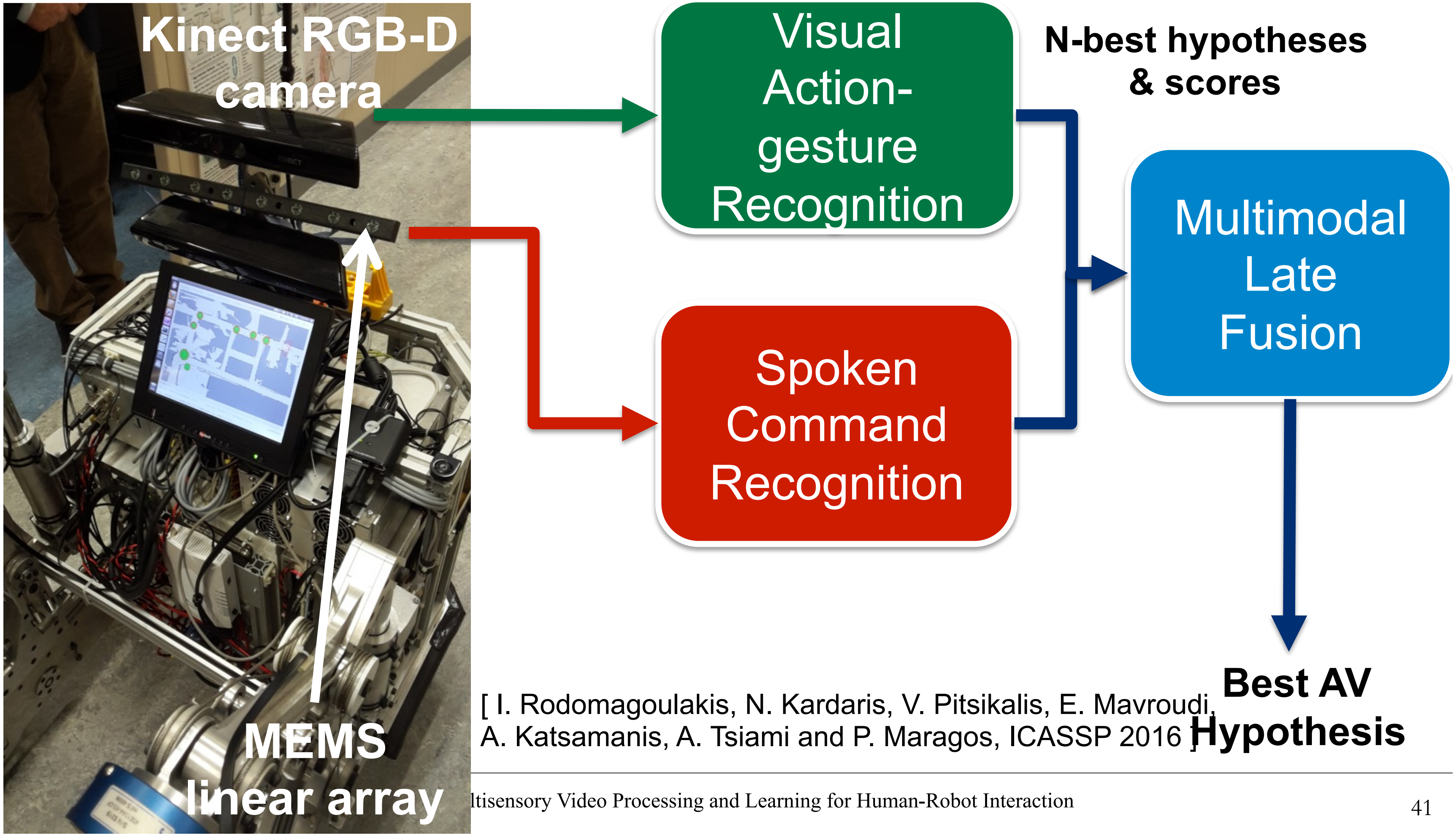
Stand-to-Sit – P3



Stand-to-Sit – P4

Audio-Gestural Command Recognition: Overview of our Multimodal Interface

MOBOT robotic platform



Kinect RGB-D camera

MEMS linear array

Visual Action-gesture Recognition

Spoken Command Recognition

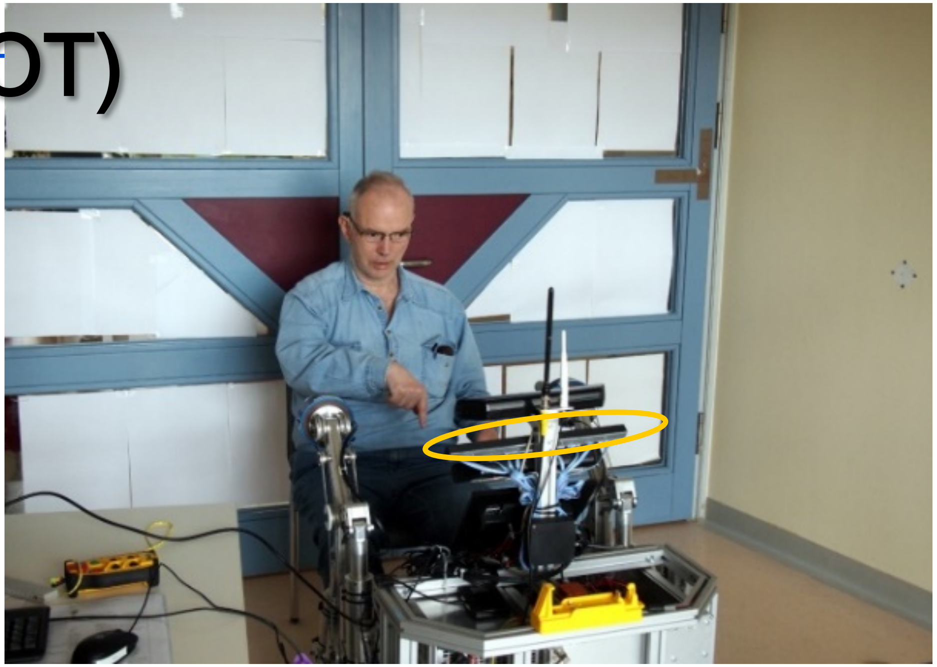
N-best hypotheses & scores

Multimodal Late Fusion

Best AV Hypothesis

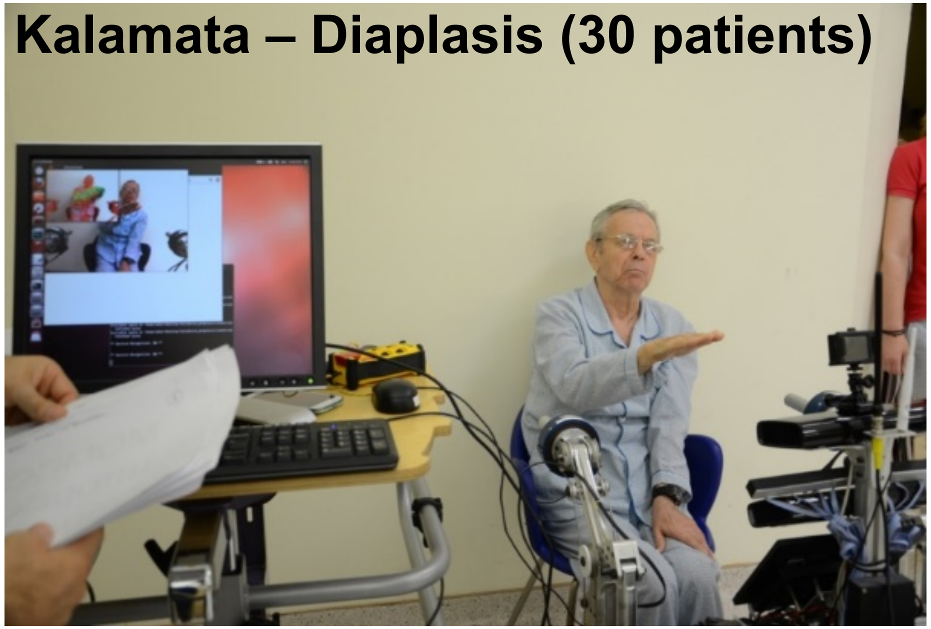
[I. Rodomagoulakis, N. Kardaris, V. Pitsikalis, E. Mavroudi, A. Katsamanis, A. Tsiami and P. Maragos, ICASSP 2016]

Clinical Studies (MOBOT)



Heidelberg – Bethanien (19 patients)

Kalamata – Diaplasis (30 patients)

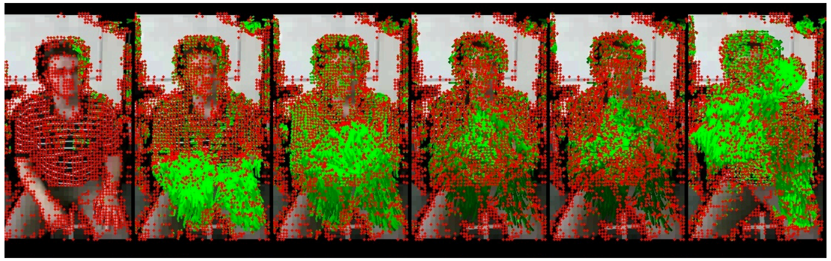


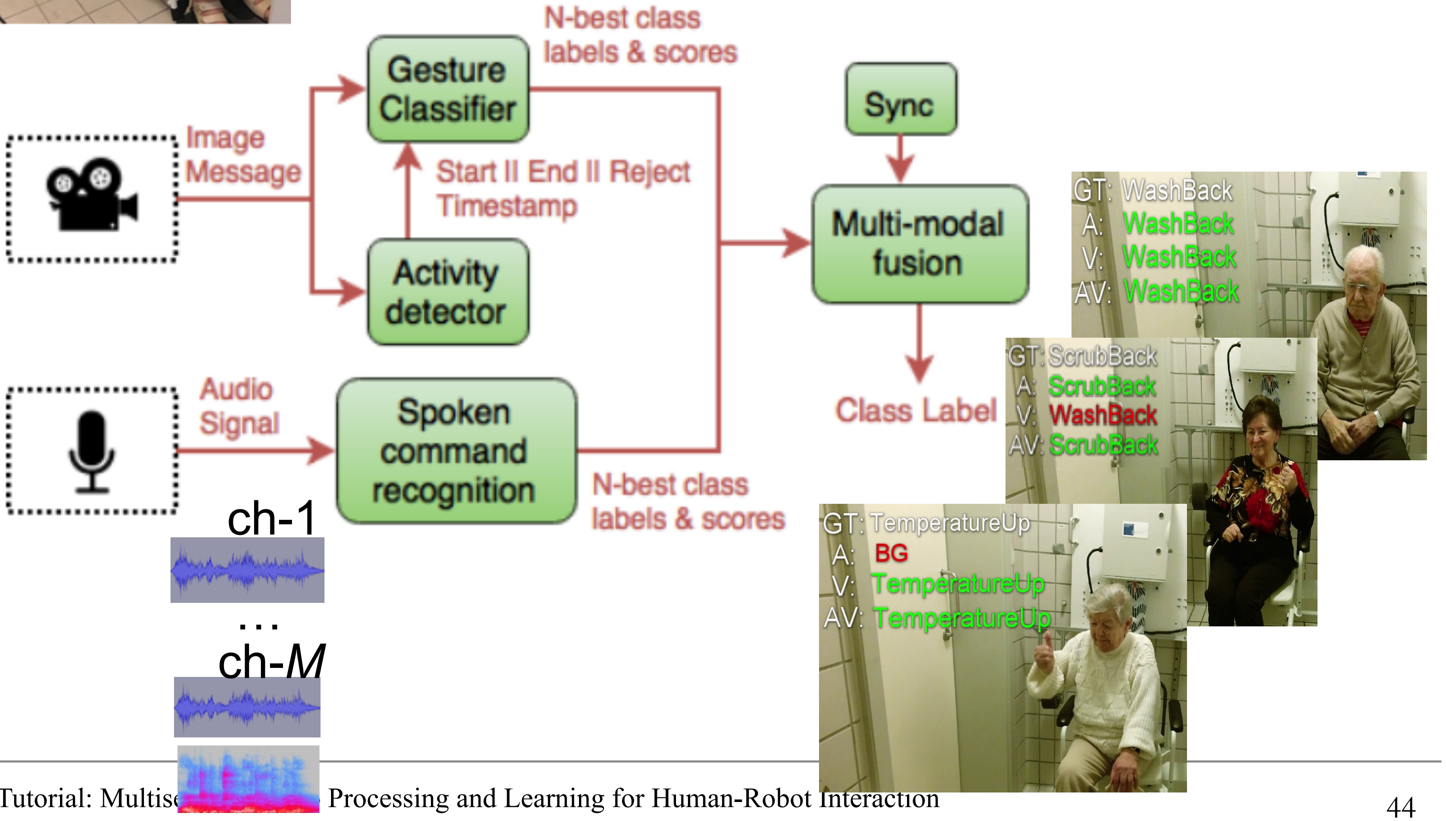
Speech, Gestures, Combination: 3 repetitions of 5 commands

Validation experiments (Bethanien, Heidelberg):

EU Project I-SUPPORT: Overview (Gesture & Spoken Command Recognition)

dense trajectories of visual motion



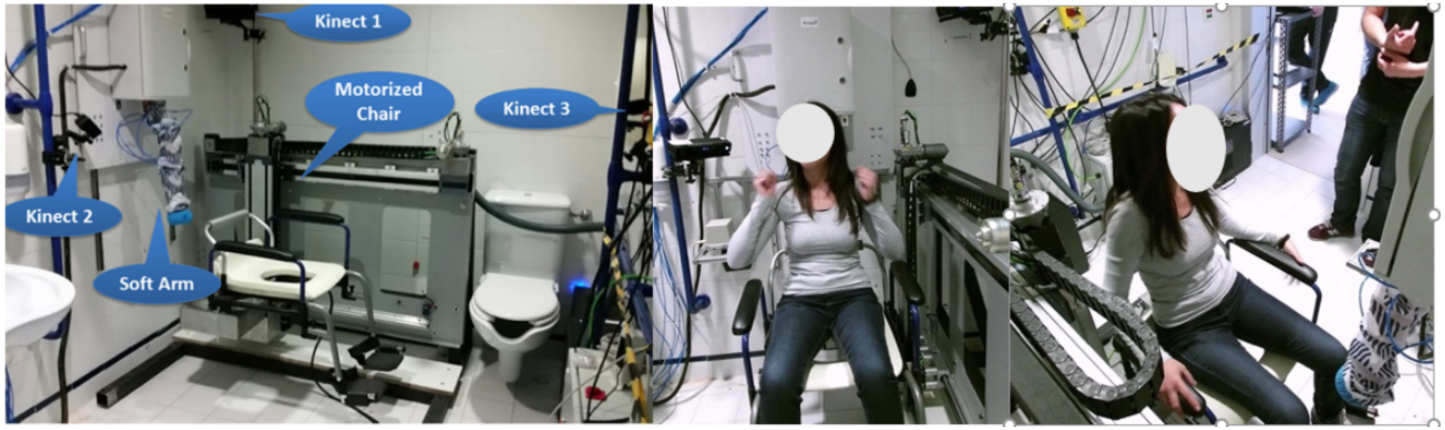


Audio-Gestural Recognition: Validation Experiments

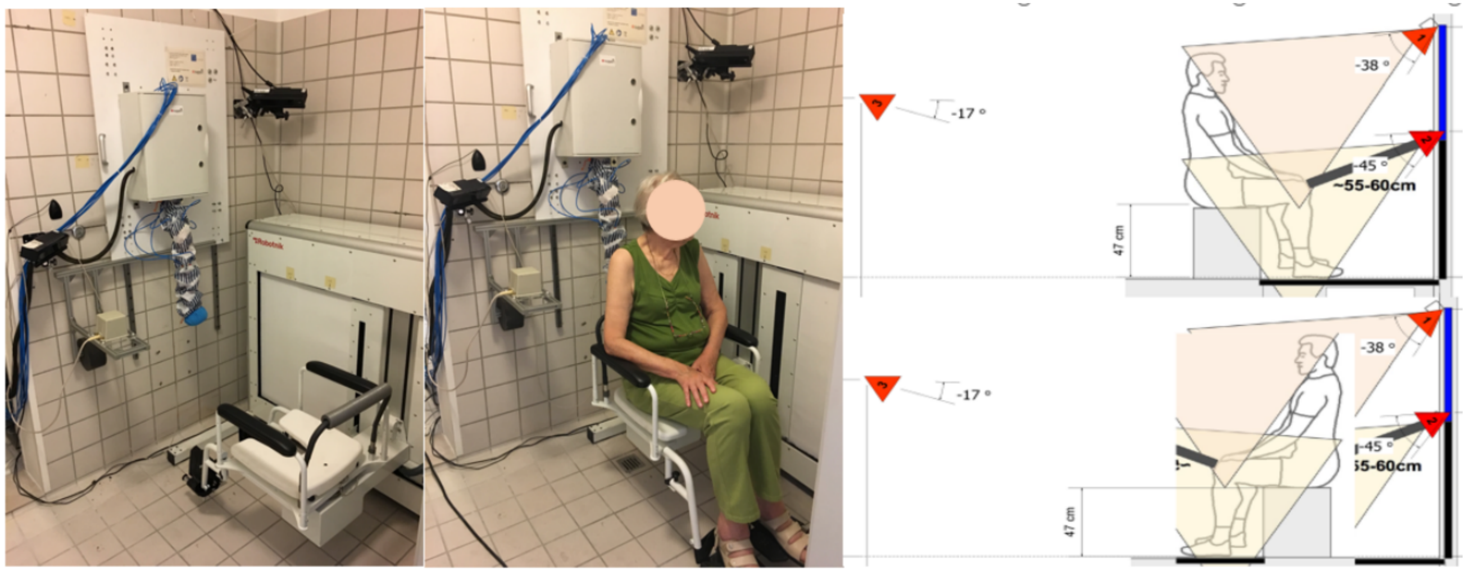
(FSL, Rome)

Validation Setup

FSL, Rome



Bethanien, Heidelberg



Gesture Recognition

Challenges

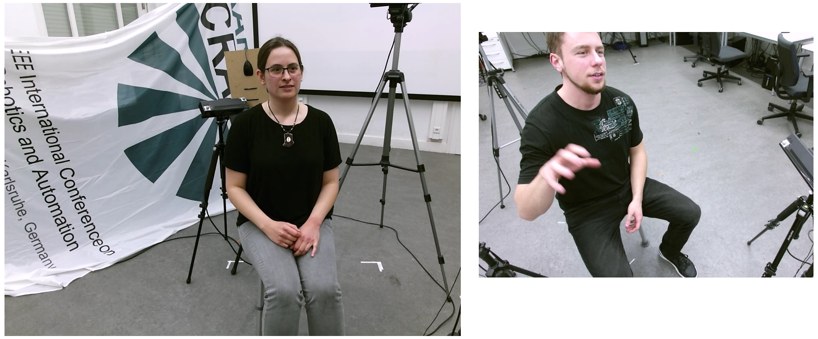
Different viewpoints

Poor gesture performance

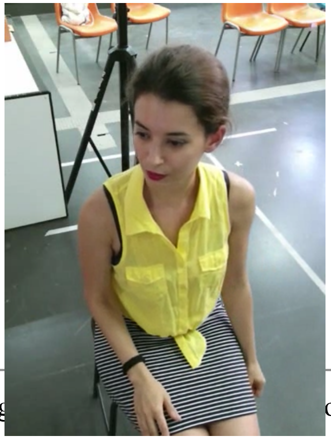
Random movements

Data collection

KIT



ICCS - NTUA



Pre-Validation

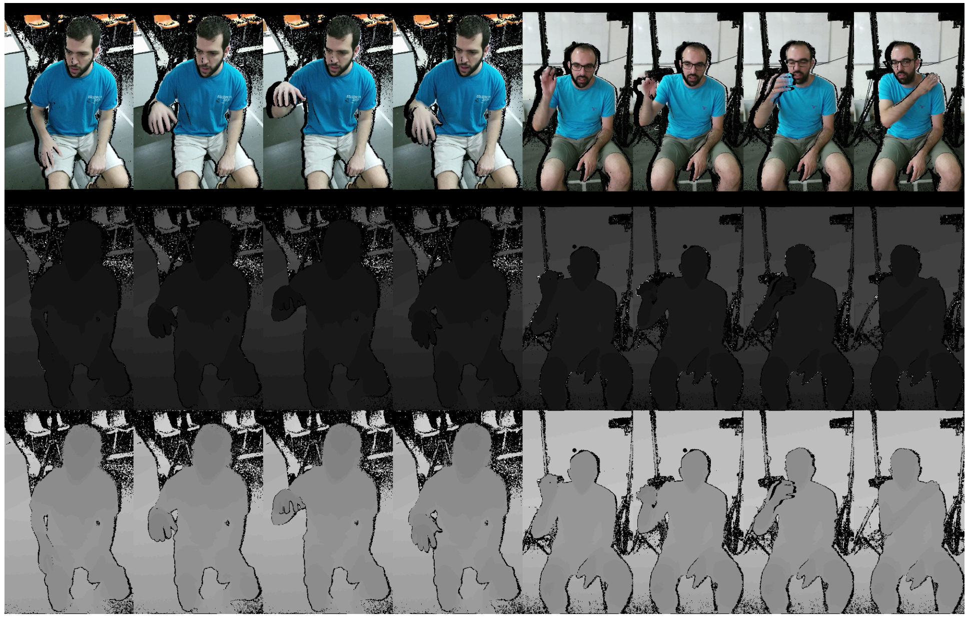
FSL -

Bethanien

Gesture Recognition – Depth Modality

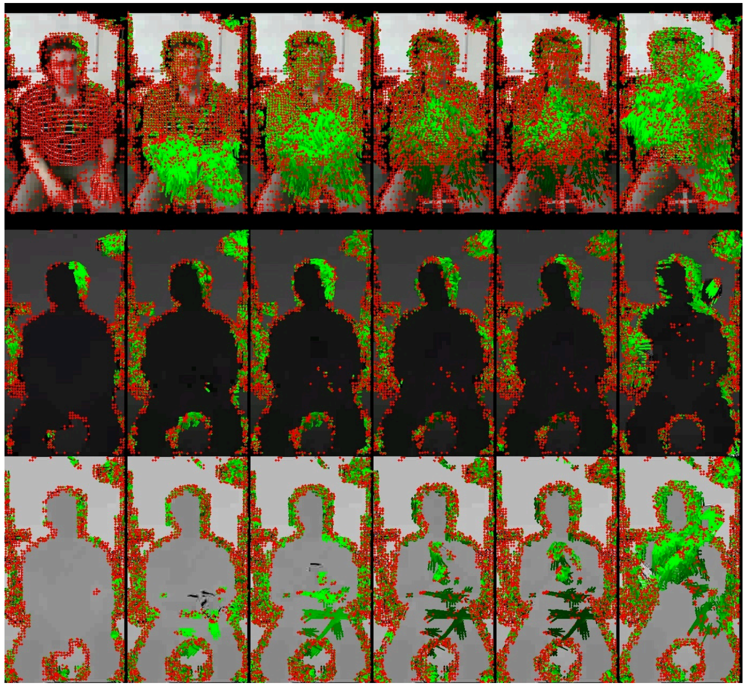
- Experiments with Depth and Log-Depth streams
- Extraction of Dense Trajectories performs better on the Log-Depth stream

RGB stream



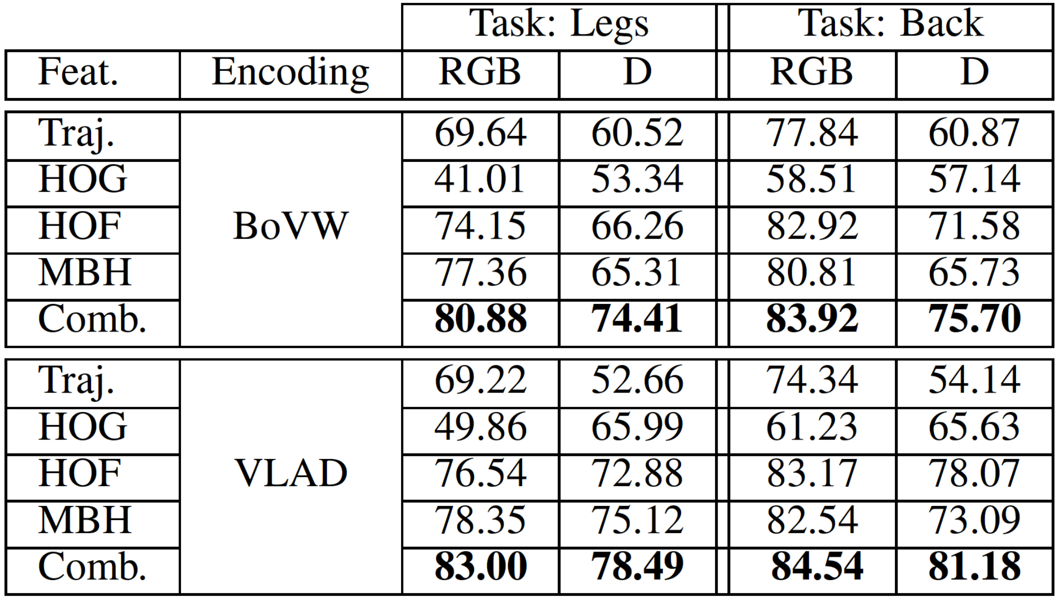
Log-Depth stream

Dense Trajectories



Gesture Offline Classification – Results

- **ICCS Dataset** (24u, 28g)
  - Two different setups
  - Two different streams
  - Different encoding methods
  - Different features
- **KIT Dataset** (8u, 8/10g)
  - Two different setups
  - Average gesture recognition accuracy:
    - Legs (8 gestures): 83%
    - Back (10 gestures): 75%
- **FSL Pre-Validation Dataset** (5u, 10g)
  - Train/fine-tuning the models for audio-visual gesture recognition
  - Average gesture recognition accuracy for the 5 gestures used in validation:
    - Legs: 85% , Back: 75%



		Task: Legs		Task: Back	
Feat.	Encoding	RGB	D	RGB	D
Traj.	BoVW	69.64	60.52	77.84	60.87
HOG		41.01	53.34	58.51	57.14
HOF		74.15	66.26	82.92	71.58
MBH		77.36	65.31	80.81	65.73
Comb.		**80.88**	**74.41**	**83.92**	**75.70**
Traj.	VLAD	69.22	52.66	74.34	54.14
HOG		49.86	65.99	61.23	65.63
HOF		76.54	72.88	83.17	78.07
MBH		78.35	75.12	82.54	73.09
Comb.		**83.00**	**78.49**	**84.54**	**81.18**

Multimodal Fusion and On-line Integration

- Multimodal "late" fusion (Validation @ Bethanien, Heidelberg)

- ROS (Robot Operating System) based integration

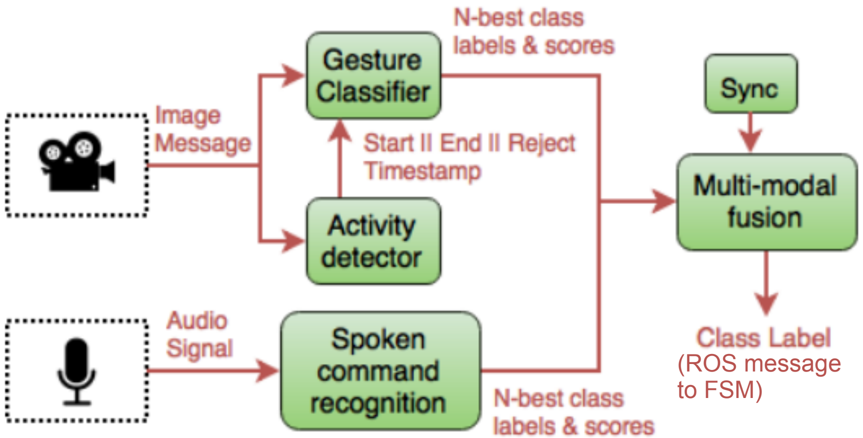


Image Message
Gesture Classifier
N-best class labels & scores
Start II End II Reject Timestamp
Activity detector
Sync
Multi-modal fusion
Audio Signal
Spoken command recognition
N-best class labels & scores
Class Label
(ROS message to FSM)

Validation results

Command Recognition Rate (CRR)

(= accuracy only on **well** performed commands)

Bethanien, Heidelberg

Round 1 (no training, audio-gestural scenario)	
Back	73.8% (A)*
Legs	84.7%

Round 2 ("back" position)		
	Gesture-only scenario	**Audio-Gestural Scenario**
Without training	70.3%	86.2%
With training	84.6%	79.1%

FSL, Rome

Round 1 (no training, audio-gestural scenario)	
Back	87.2%
Legs	79.5%

Round 2 (no training, audio-gestural scenario, "legs" position)
83.5%

I-SUPPORT system video

Part 3&4: Conclusions

- **Synopsis**:
  - ❑ Multimodal Action Recognition and Human-Robot Interaction
    - Visual Action Recognition
    - Gesture Recognition
    - Spoken Command Recognition
    - Online Multimodal System and Applications in Assistive Robotics

- **Ongoing work**:
  - ❑ Fuse Human Localization & Pose with Activity Recognition
  - ❑ Activities: Actions – Gestures – SpokenCommands - Gait
  - ❑ Applications in Perception and Robotics

For more information, demos, and current results: http://cvsp.cs.ntua.gr and http://robotics.ntua.gr