

Outline - Contributions

- Explore new aspects of assistive living on smart human-robot interaction (HRI) involving automatic recognition and online validation of speech and gestures in a natural interface.
- New experimental framework and resources of a real-life scenario for elderly users, within the framework of I-SUPPORT bathing robot, addressing health and hygiene care issues.
- New domain specific dataset and a suite of tools used for data acquisition and a state-of-the-art pipeline for multimodal learning with emphasis on audio and RGB-D visual streams, considering also privacy issues by evaluating the depth visual stream, using Kinect sensors.

Goal:

Development of a robotic bathing system that will assist towards independent living and improved life quality for elderly.

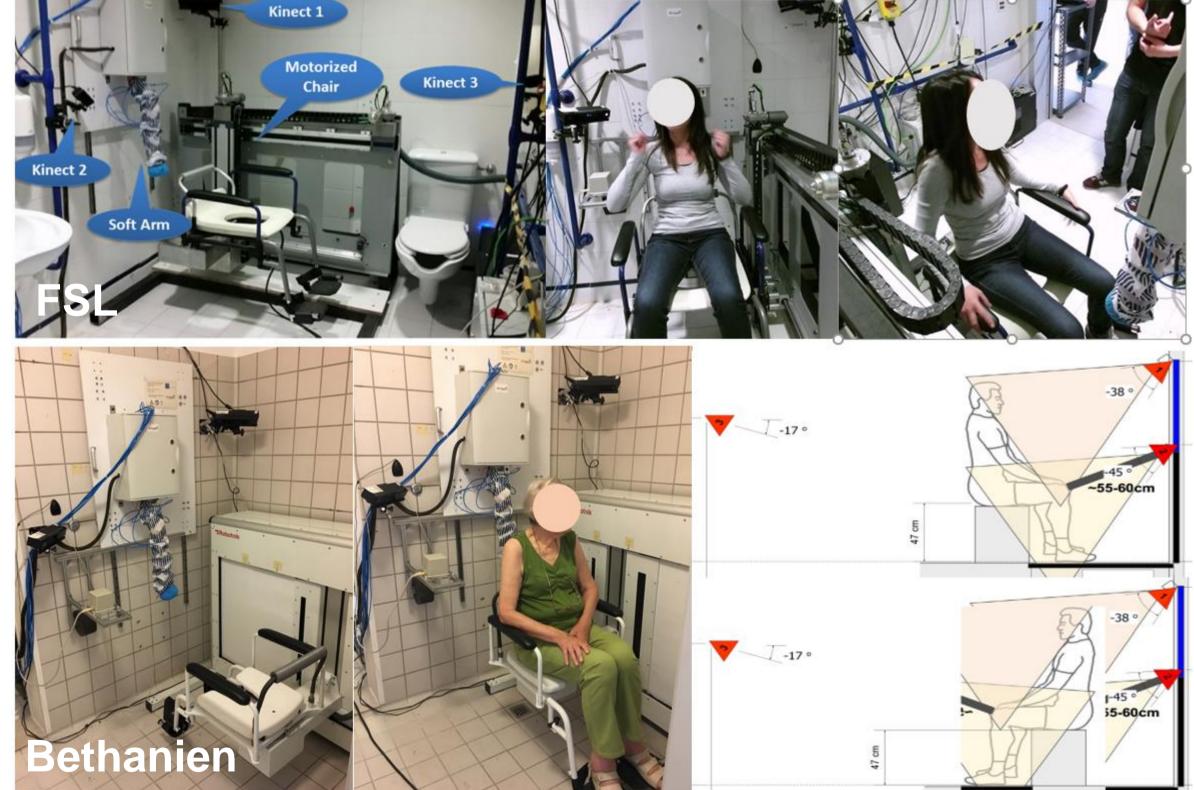
• Enhancement the communication making it natural, intuitive and easy to use, thus, enhancing it with respect to social aspects.

2. I-Support: Robotic Shower System

• Core system functionalities: tasks for bathing the legs and the back (taking into account impairments, limitations and user requirements).

Multi-view system architecture

- ➢ 3 Kinect sensors for 3D pose reconstruction of the scene (user and robot) and identification of user gestures;
- Audio system including 8 distributed condenser microphones



I-Support automatic bathing environment. Setup of the Kinect sensors as installed in the two validation sites: FSL (top) and Bethanien (bottom) hospitals.

- Audio-gestural data acquisition –

.. for modeling the user-robot interaction

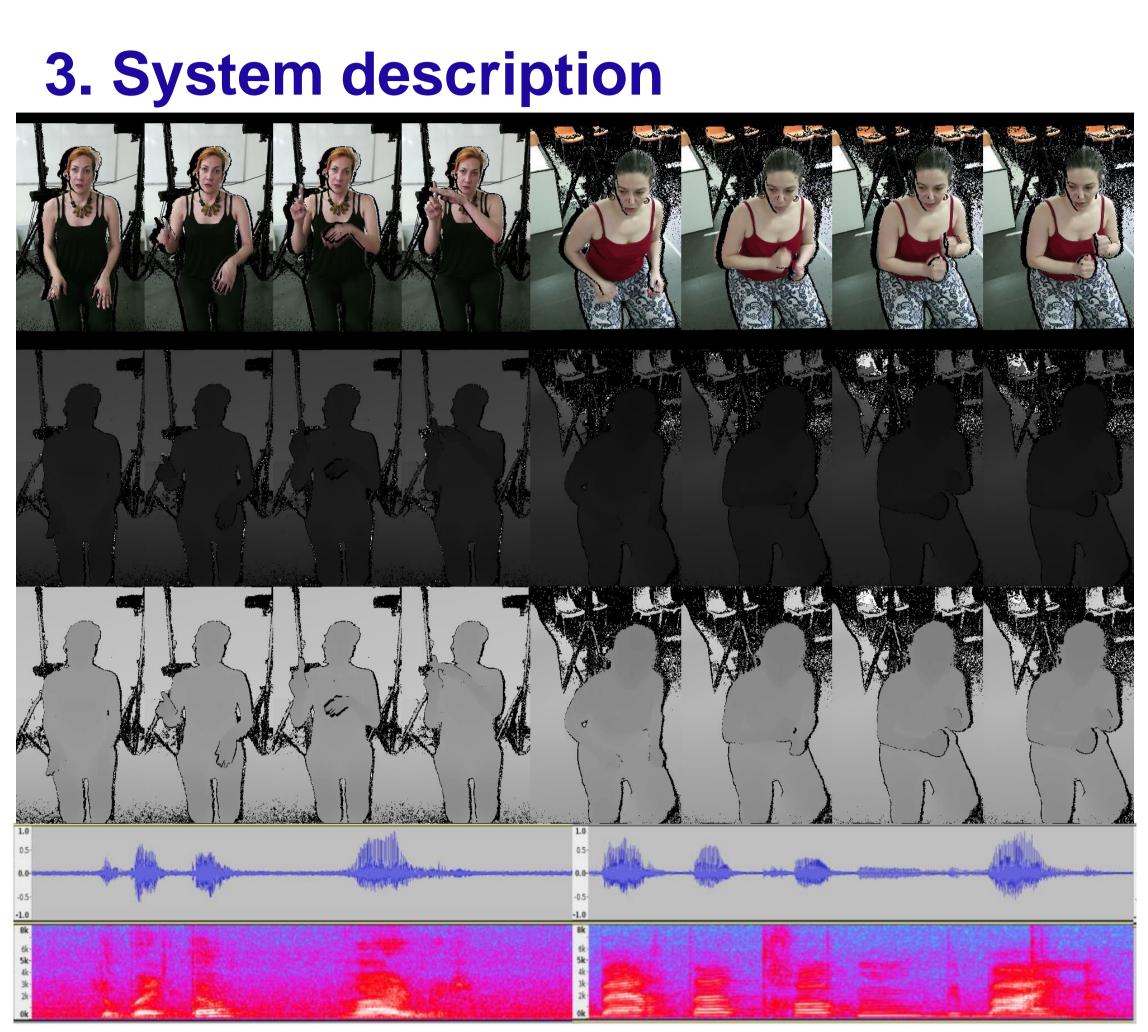
Core bathing tasks: washing/scrubbing/wiping/rinsing the back or legs changing base settings of the system, i.e., temperature, water flow etc. spontaneous/emergency commands and a background model

- Visual data: 23 users performing predefined gestures
- Audio data: 8 users uttering predefined spoken commands (German)

Total number of commands for each task:

• 25 and 27 gesture commands for washing the legs and the back, resp. • 23 spoken commands – preceded by a keyword ("Roberta")

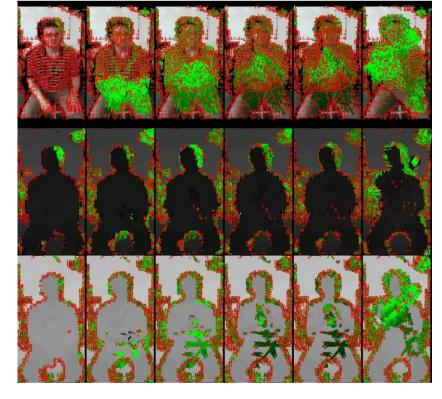
Multimodal Signal Processing and Learning Aspects of Human-Robot Interaction for an Assistive Bathing Robot A. Zlatintsi, I. Rodomagoulakis, P. Koutras, A.C. Dometios, V. Pitsikalis, C.S. Tzafestas and P. Maragos ICCS, School of ECE, National Technical University of Athens 15773, Greece http://robotics.ntua.gr http://cvsp.cs.ntua.gr



Data streams acquired by sensors #1 and #2: RGB (top), depth (2nd row) and log-depth (3rd row) frames from a selection of gestures ("Temperature Up", "Scrub Legs"), accompanied by the corresponding German spoken commands – waveforms (4th row) and spectrograms (bottom row) – "Wärmer", "Wasch die Beine".

Visual processing for system architecture —

- Emploing **Dense Trajectories** features along with a) Bag-of-Visual-Words (BoVW) framework and b) VLAD (Vector of Locally Aggregated Descriptors) encoding, using SVM.
- The Dense Trajectories method main concept consists in sampling feature points from each video frame on a regular grid and tracking them through time based on optical flow.



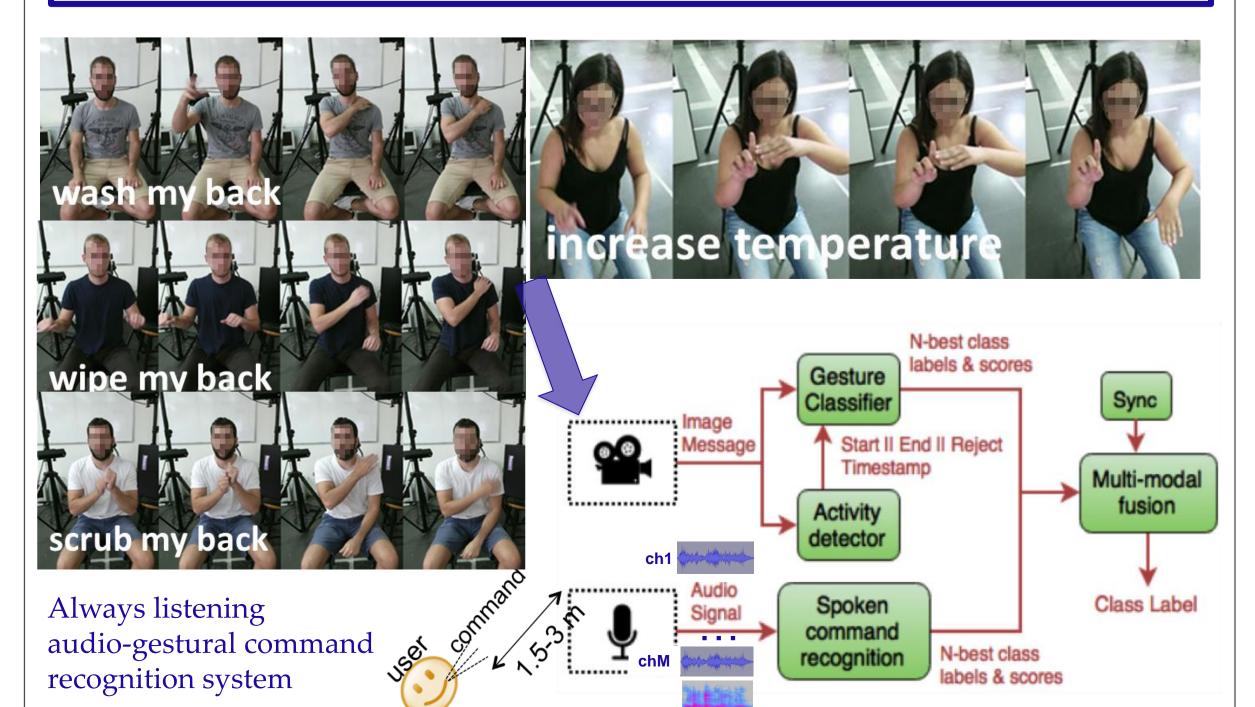
Employed descriptors: Trajectory descriptor, HOG, HOF and Motion Boundary Histograms (MBH).

A non-linear transformation of depth using logarithm (log-depth) enhances edges related to hand movements leading to richer dense trajectories on the ROI, close to the result obtained using the RGB stream.

Comparison of dense trajectories extraction over the RGB (top), depth (middle) and log-depth (bottom) clips of gesture "Scrub Back".

Audio processing for system architecture _

- Robustness of the system via: a) denoising of the far-field multi-channel signals
- b) global MLLR adaptation of the acoustic models and
- c) combined command detection/recognition.



4. Online validation of the online A-G system with primary users

- Evaluation of the system's functionality and the HRI between the I-Support bathing robot and the primary end-users (elderly), using audio and audio-gestural commands.
- *Two simulated bathing scenarios*: bathing the legs and back at dry conditions.
- *Two pilot sites*:
- the Fondazione Santa Lucia (FSL) Hospital (Rome, Italy) • the Bethanien Hospital (Heidelberg, Germany).
- *Statistically significant number of users*: 25 and 29 patients (having various cognitive impairments).
- Results delivered as ROS messages to the system's finite state machine (FSM) to: a) decide the action to be taken after each recognized command, b) control the various modules and
- c) manage the dialogue flow by producing the right audio feedback to the user.
- *Challenges*: acoustic noise, low voice, weak/inaccurate motions/gestures, small variations in the camera setup, no additional data collection from the primary users

Vocabulary							
English	Italian	German					
Wash legs	Lava le gambe	Wasch meine Beine					
Wash back	Lava la schiena	Wasch meinen Rücken					
Scrub back	Strofina la schiena	Trockne meinen Rücken					
Stop (pause)	Basta	Stop					
Repeat (continue)	Ripeti	Noch einmal					
Halt	Fermati subito	Wir sind fertig					
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Audio-gestural commands incl. in the two scenarios, preceded by the keyword "Roberta".

	Distal F	Region	Back Region			
ID	Command	Modality	Command	Modality		
1	Wash Legs	A	Wash Back	A-G		
2	Stop	A	Halt	A-G		
3	Repeat	A	Scrub Back	A-G		
4	Halt	A	Stop	A-G		
5	Wash Legs	A-G	Repeat	A-G		
6	Halt	A-G	Halt	A-G		
7	Halt	A-G	Halt	A-G		

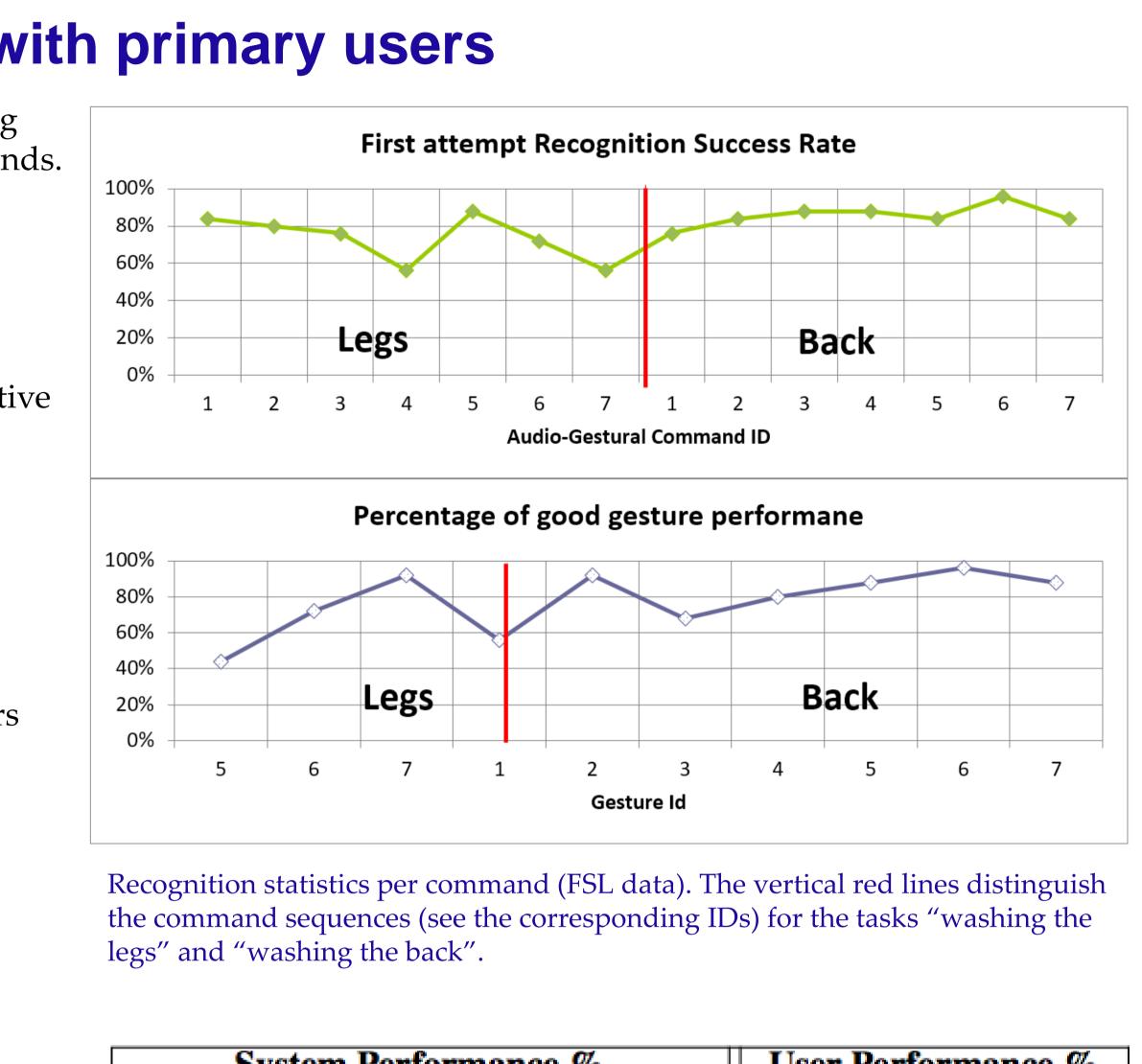
Betha Multimodal recognition evaluated in terms of 1) Multimodal Command Recognition Rate (MCRR): MCRR= # of commands correctly recognized by the system / # of commands correctly performed by the user, 2) accuracy (%) and 3) user performance/learning rate (%). Average Audio-Gestural Command Recognition Results; system performance (%) and user performance (%) averaged across 25 and 29 users at FSL and Bethanien Hospitals, respectively.

Experimental protocol exhibiting a variety of 7Audio (A) and/or Audio-Gestural (A-G) commands. Sequence of the commands as performed by the participants.

$ \frac{MFCC}{75.8} = 67.6 $ Average (leave-one-out) classification results for the pre-defined spoken commands, performed by 8 subjects for the two bathing tasks. $ \frac{Feat. Encoding RGB D RGB D}{Traj.} = 69.64 + 60.52 + 77.84 + 60.87 + 1001 + 53.34 + 58.51 + 57.14 + 100G + 41.01 + 53.34 + 58.51 + 57.14 + 100G + 1011 + 53.34 + 58.51 + 57.14 + 100G + 1011 + 53.34 + 58.51 + 57.14 + 100G + 1011 + 53.34 + 58.51 + 57.14 + 100G + 1011 + 53.34 + 58.51 + 57.14 + 100G + 1011 + 53.34 + 58.51 + 57.14 + 100G + 1011 + 53.34 + 58.51 + 57.14 + 100G + 1011 + 53.34 + 58.51 + 57.14 + 100G + 1011 + 53.34 + 58.51 + 57.14 + 1011 + 53.51 + 57.14 + 1011 + 53.51 + 57.14 + 1011 + 53.51 + 57.14 + 1011 + 53.51 + 57.14 + 1011 + 53.51 + 57.14 + 1011 + 53.51 + 57.14 + 1011 + 53.51 + 57.14 + 58.51 + 57.14 + 58.51 + 58$	dio classificatior	۱ ——	Feat.	Task: Legs		Task: Back		
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erformed by 23 subjects. Results for the four features and their combination (Comb.), us e two encodings are shown for RGB data and D (depth) data for the two bathing tasks.	~						•	

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	System Performance %							· Perfo	orman	ce %
	MCRR %		Accuracy %		Speech		Gestures			
	L	B	Av.	L	В	Av.		B	L	B
FSL	80	87	83.5	86	73	79.5	98	9 9	81	78
anien	85	74	79.5	67	77	72	91	9 0	84	71

6. Conclusions

We presented a multimodal interface for an assistive bathing robot and a real-life use case, providing a rich set of tools and data.

- Such resources can be employed to develop natural interfaces for multimodal interaction between humans and robotic agents.
- We further investigate how the communication between end-users and the robot will be as intuitive and effortless as possible using co-speech gesturing, which is the most natural way for human-human communication, while also enhancing the recognition, in cases of speech dysfluencies or kinetic problems.
- The online results are really promising given the difficulties of the
- By sharing such resources, we aim to build a public crowdsourced library that shall open new perspectives in smart assistive HRI.
- Available software:
- http://robotics.ntua.gr/projects/building-multimodal-interfaces

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