Snapture - a Hybrid Hand Gesture Recognition System

Hassan Ali

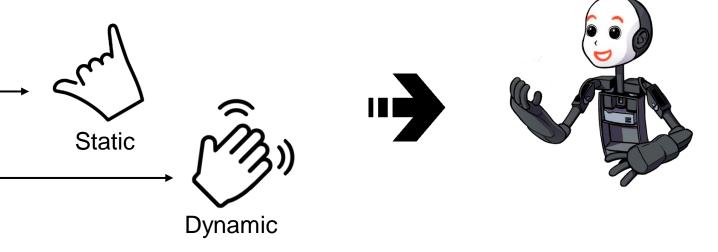
Examiners: Prof. Dr. S. Wermter, Dr. D. Jirak



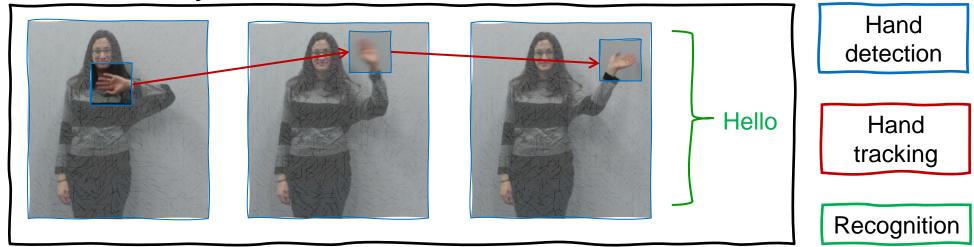
http://www.informatik.uni-hamburg.de/WTM/

Motivation

- Hand gesture applications
- Gesture taxonomy



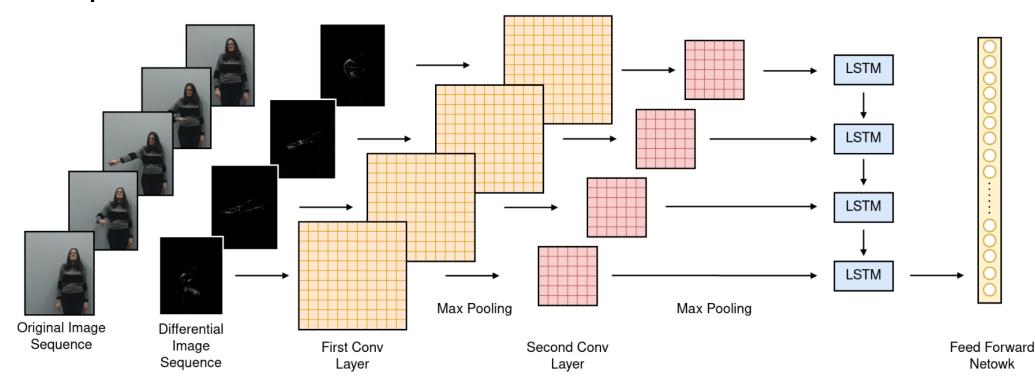
Vision-based systems



Hassan Ali

CNNLSTM

- Evaluated using the Tsironi GRIT dataset (available on WTM website)
- We reproduce the results.



Research Questions

CNNLSTM

- How influenced is the CNNLSTM network by subject variability?
- How efficient is the CNNLSTM network at learning co-speech gestures?

Snapture

- How to identify the peak of the gesture and extract the handshape using RGB data only?
- How to regulate the integration of the hand details into a dynamic gesture recognition system?

1. How influenced is the CNNLSTM network by subject variability?









Prendere

Daccordo

Turn Left

No



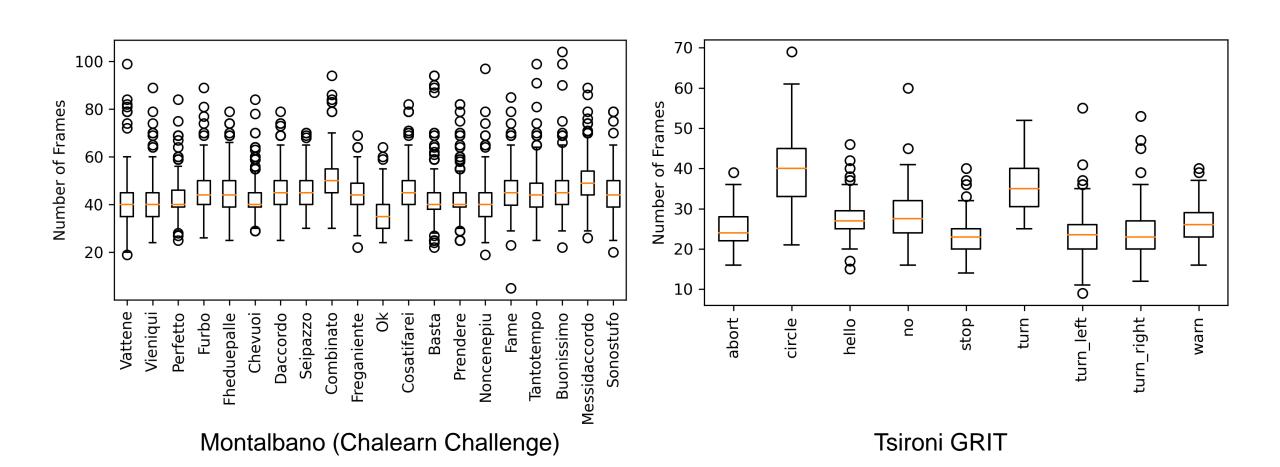






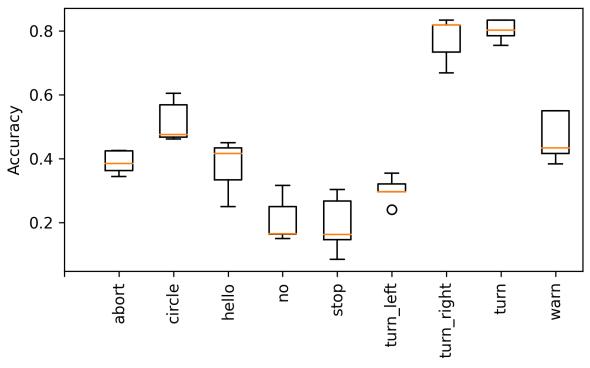
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CNNLSTM – Subject Variability



CNNLSTM – Subject Variability

- Experiment using the GRIT dataset
- Evaluate on unseen subjects (Leave-one-out approach)
- Low accuracy for most classes



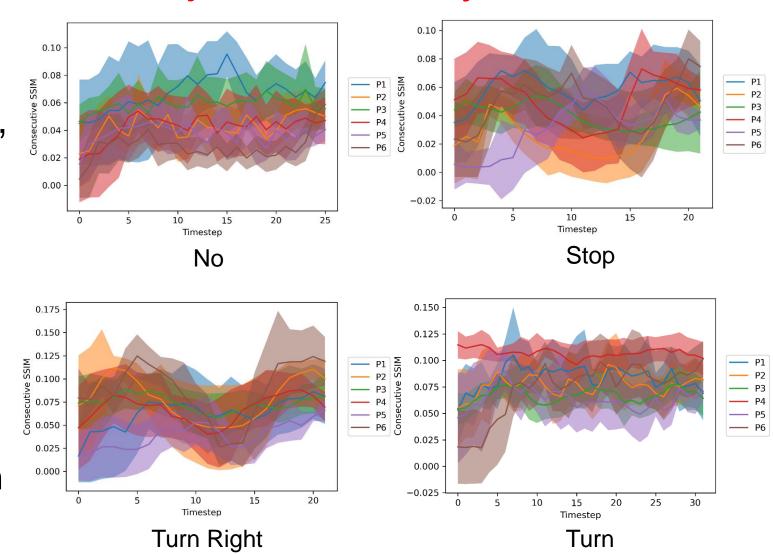
Accuracy per class, avg. over all subjects, avg. of 5 trials

CNNLSTM – Subject Variability

 Motion profile of the worst-case classes: No, Stop,

and the best-case classes: Turn Right, Turn

 Consequence: train on data of all subjects.

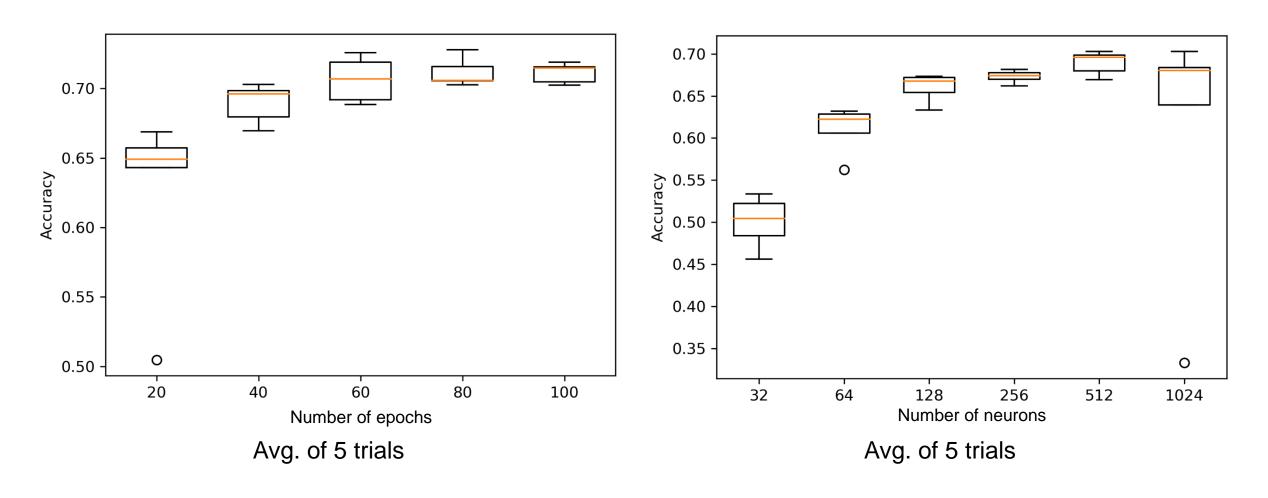


2. How efficient is the CNNLSTM network at learning co-speech gestures?

- Grit: suitable for robot commands, unique motion paths, lab settings
- Montalbano: co-speech (more profound)

Dataset	Chalearn Montalbano	Tsironi GRIT
#classes	20	9
#observations	13 342	542
#participants	48	6
#scenes	5	1

CNNLSTM – Upscaling



CNNLSTM – Upscaling

- Two Issues (Hypotheses):
 - It is challenging for the CNNLSTM model to distinguish classes with similar movement patterns.
 - It is challenging for the CNNLSTM model to distinguish subtle movements done at the peak of the gesture.
- Solution: Snapture architecture

3. How to identify the peak of the gesture and extract the handshape using RGB data only?

Gesture phases (Kendon)



1. Rest position



2. Pre-stroke



3. Stroke



4. Post-stroke



5. Rest position

Motion Profile

- Problem: analysis of motion/pause carried in a movement sequence
- Solution: structure similarity (SSIM) index

$$SSIM(x,y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

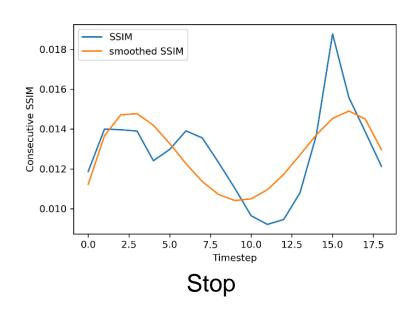
$$inverted_{SSIM} = 1 - \sum SSIM(\Delta_i, \Delta_{i-1})$$

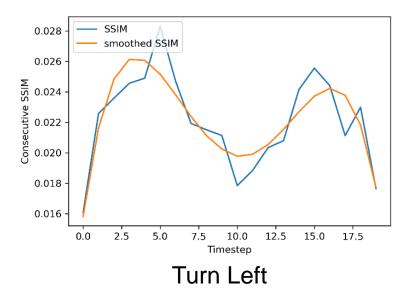
$$\Delta_i = (I_i - I_{i-1}) \wedge (I_{i+1} - I_i)$$

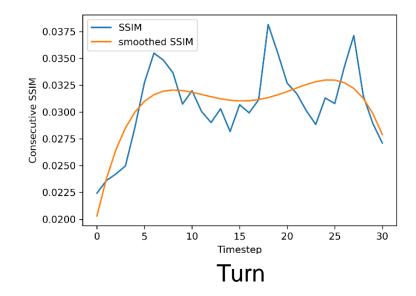
 μ : avg. intensity, σ^2 :variance C_1 , C_1 : stability constants Δ_i , Δ_{i-1} : differential images I_{i-1} , I_i , I_{i+1} : original frames

Motion Profile

- Tsironi GRIT data:
 - paused-gestures: the arm remains briefly in a fixed position at the peak
 - or gestures with *repeated-pattern:* include a motion pattern, usually circular

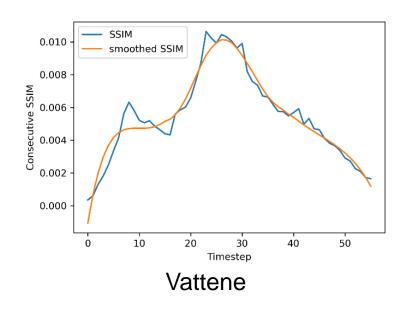


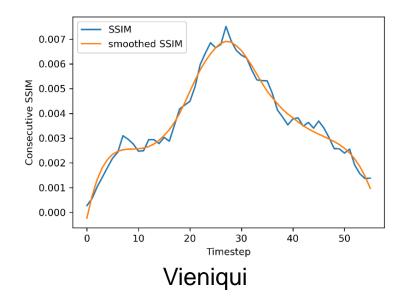


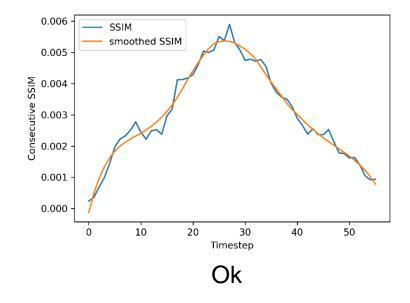


Motion Profile

- Chalearn Montalbano movements have comparable profile with pause at the peak
 - → Peak around the mean of the sequence length







Snapture Architecture

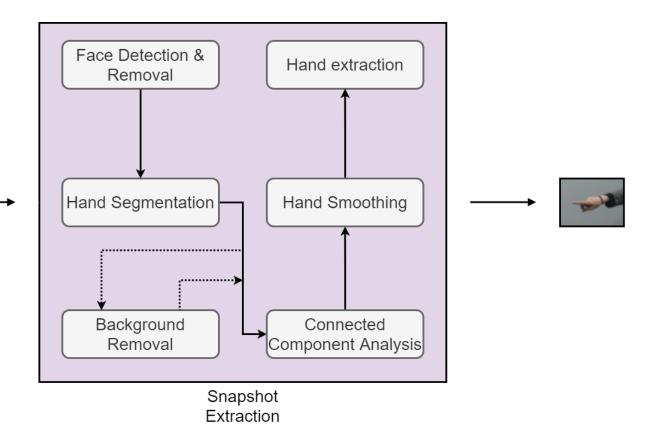
Static Channel

- Gesture Peak Detection
- Gesture Peak Extraction



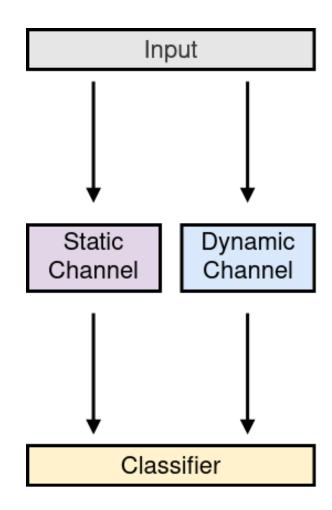
Frame at the peak of the gesture

 Independent of subject's dominant hand

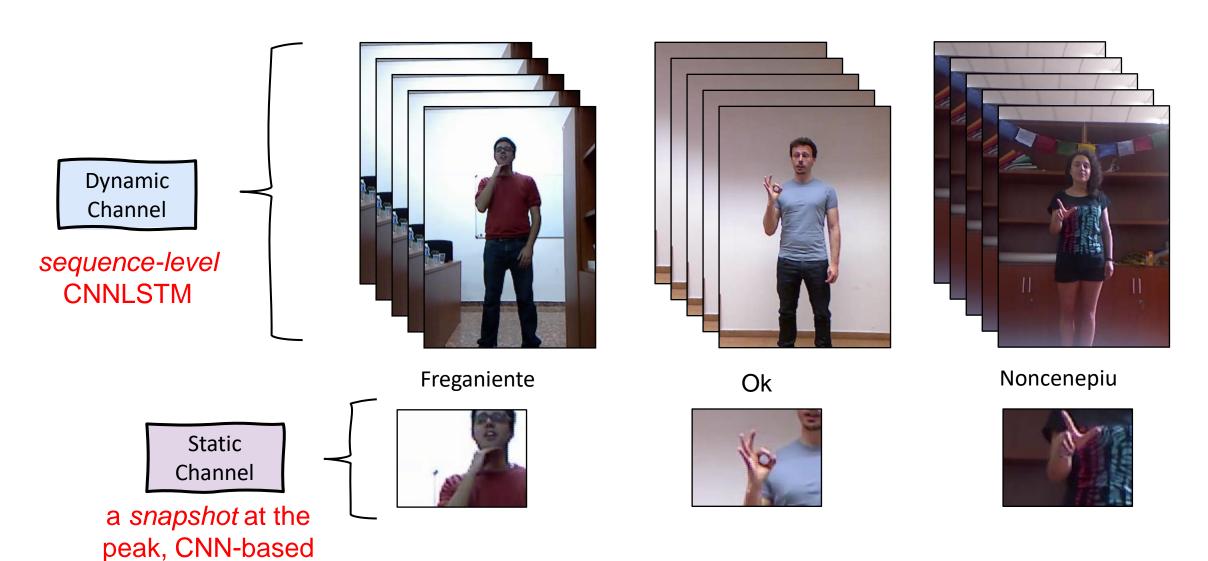


Snapture Architecture

- SNAPshot capTURE is our proposed architecture
- Hybrid (static/ dynamic) gesture recognition
- Input: isolated sequences



Snapture Architecture



4. How to regulate the integration of the hand details into a dynamic gesture recognition system?

- Some gestures, e.g., Circle are strictly dynamic.
- Low camera frame-rate
 - → blurriness issue
- Solution: threshold-controlled approach based on sufficient pause

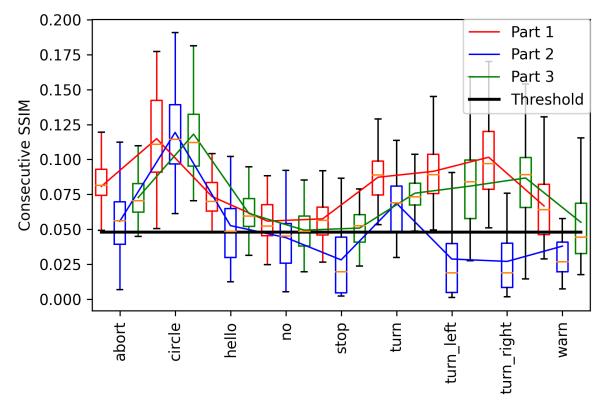




Stop

Regulating the static channel

- Lower values represent longer pauses.
- More pronounced for Stop,
 Turn Left and Turn Right
- Approx. only 44% of the GRIT samples include a pause

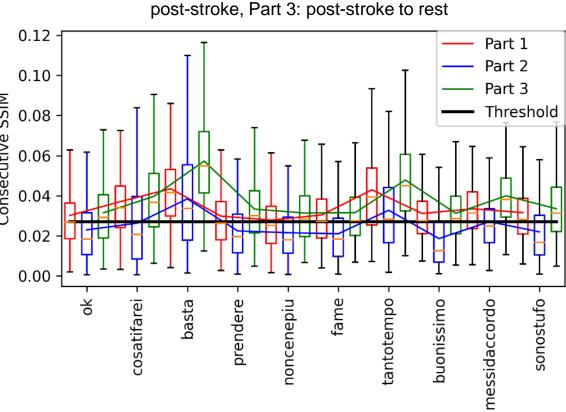


Part 1: rest to pre-stroke, Part 2: pre-stroke to post-stroke, Part 3: post-stroke to rest

Regulating the static channel

Co-speech movements include more pause at the peak (approx. 70% of the Montalbano samples).

0.12 0.10 Part 1 0.10 Consecutive SSIM Consecutive SSIM 0.08 0.06 0.02 0.00 0.00 fheduepalle daccordo combinato freganiente perfetto



Part 1: rest to pre-stroke, Part 2: pre-stroke to

Results

Tsironi GRIT Dataset

Model	Accuracy	F1-score	Time*
CNNLSTM	0.91 (0.012)	0.913 (0.012)	140.612 (0.255)
Snapture	0.924 (0.006)	0.927 (0.005)	170.012 (1.027)
Snapture thold	0.926 (0.008)	0.913 (0.012)	125.156 (1.117)

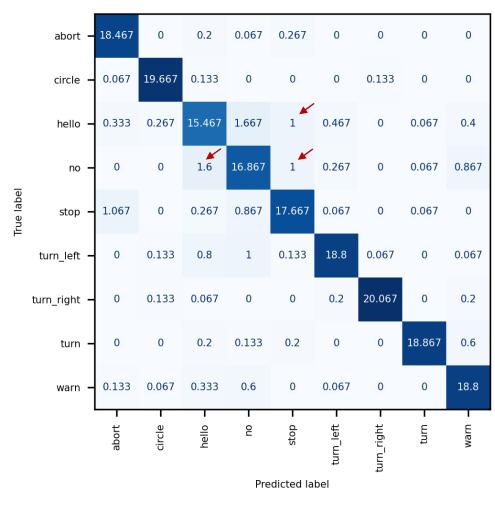
^{*}In seconds.

Chalearn Montalbano Dataset

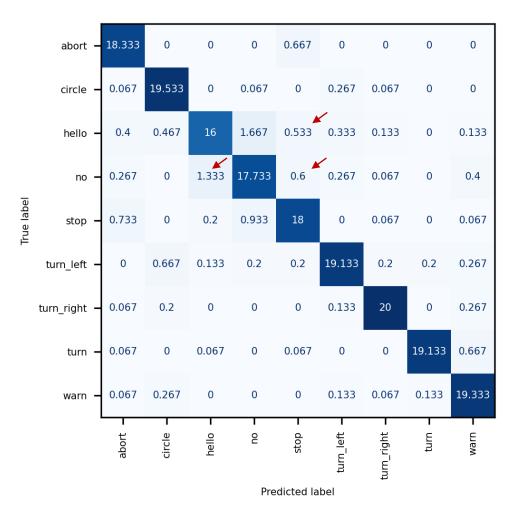
Model	Accuracy	F1-score	Time*
CNNLSTM	0.699 (0.014)	0.701 (0.013)	234.762 (0.115)
Snapture	0.755 (0.021)	0.752 (0.021)	318.578 (0.428)
Snapture thold	0.77 (0.008)	0.772 (0.007)	744.953 (0.724)

^{*}In minutes.

Results Analysis - GRIT

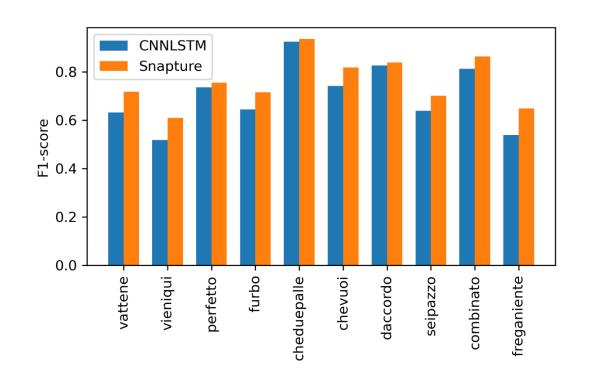


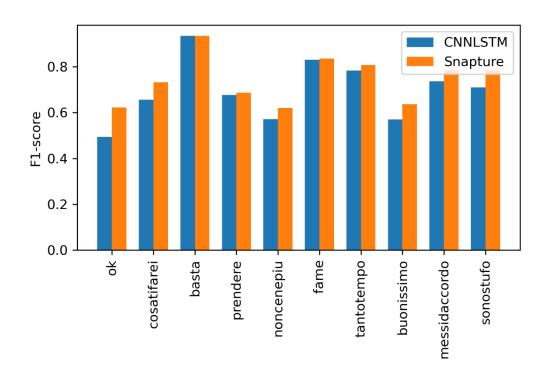
CNNLSTM (avg. 5 trials)

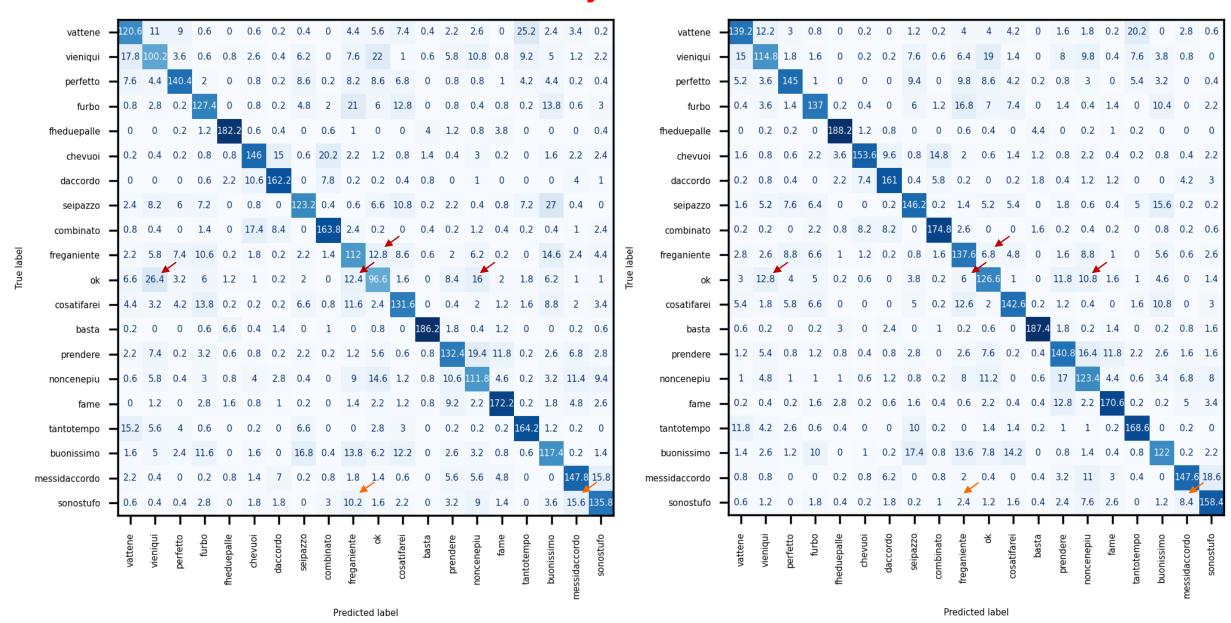


Snapture (avg. 5 trials)

- Snapture: superior results on all classes except for Basta
- Boosted F1-score for unique handshape classes (ex: *Ok*)







Snapture boosts the classification of indistinctive movements.











Cosatifarei



Vattene

snapshot

Perfetto

Freganiente



Ok



snapshot

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snapshot

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Snapture boosts the classification of subtle movements.



Basta (explicit hand movement



Sonostufo (subtle hand movement)

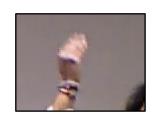




Vieniqui or Tantotempo?



snapshot



snapshot



Furbo or Buonissimo?



snapshot



snapshot

How influenced is the CNNLSTM network by subject variability?

- Network's limitation when presented with data of new subjects
 - → Train *Snapture* on data from all participants
 - → Satisfactory solution in the context of our work (we analyzed architecture rather instead of comparing to benchmark)

How efficient is the CNNLSTM network at learning co-speech gestures?

- Network's limitation
 - Main issues: similar motion patterns, missing hand details (pre-processing)
- Our Snapture architecture achieved superior results to CNNLSTM due to the static channel

How to identify the peak of the gesture and extract the handshape using RGB data only?

- Our algorithm worked well under the Kendon's model assumption.
- Independent of the hand
- Future work: additional channels (facial features, speech, body pose)
 - → simple (modularity of our architecture)

How to regulate the integration of the hand details into a dynamic gesture recognition system?

- Snapture thold bypassed the blurriness issue and improved the performance of Snapture even further.
- Future work: improve robustness of threshold values.

Thesis Contribution

- Thorough analysis of Tsironi GRIT and Chalearn Montalbano gestures
- New architecture proposal: Snapture (code available soon).
 - Emblematic gestures & co-speech domains.
- New algorithm based on SSIM for analyzing a gesture's motion profile and identifying its pause.
- Montalbano temporal segmentations (publicly available soon).
- A concrete step to support an immersive HRI scenarios without the lab restrictions.

The End

Thank you for your attention.

Any question?

Literature

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