KOÇ UNIVERSITY

Use of Affect Based Interaction Classification for Continuous Emotion Tracking

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Outline

- Related Studies and Motivation
- JESTKOD Database
- GIT-CER system
- Experimental Evaluations
- Conclusion and Future work

Related Studies and Motivation

Observations

Dyadic interaction type helps Valence estimation [1]

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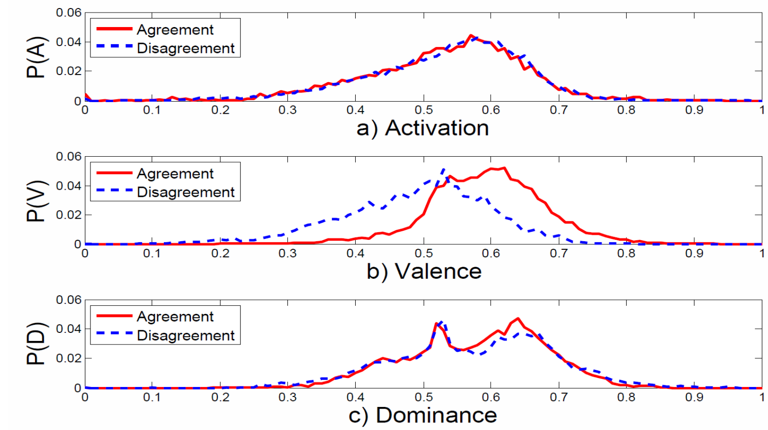
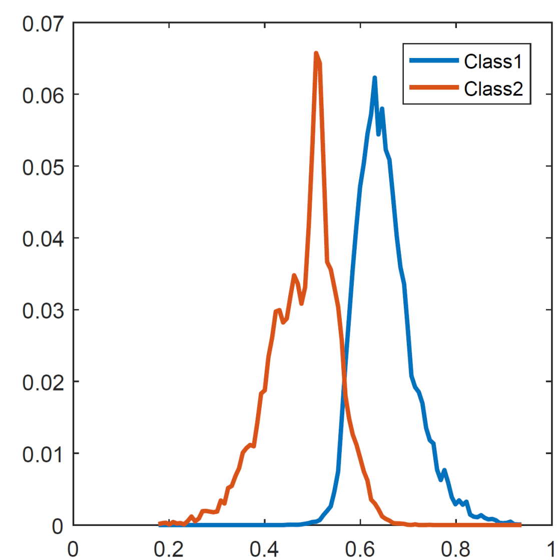
Locating temporal segmentation to cluster AVD in two general high/Low classes

Problem

Does general high/Low classes help to estimate AVD better?





[1]- H. Khaki and E. Erzin, “Use of agreement/disagreement classification in dyadic interactions for continuous emotion recognition,” in INTERSPEECH, 2016.

JESTKOD database

- A natural and affective dyadic interactions
- Equipment:
  - A high-definition video recorder
  - Full body motion capture system with 120 fps
  - Individual audio recorders
- 5 sessions, totally 56 agreement and 42 disagreement clips
- In each clips: 2 participants, around 2~4 minutes
- Totally 10 participants
  - 4 female/6 male, ages: 20 - 25
- Language: Turkish
- Annotation
  - Activation
  - Valence
  - Dominance

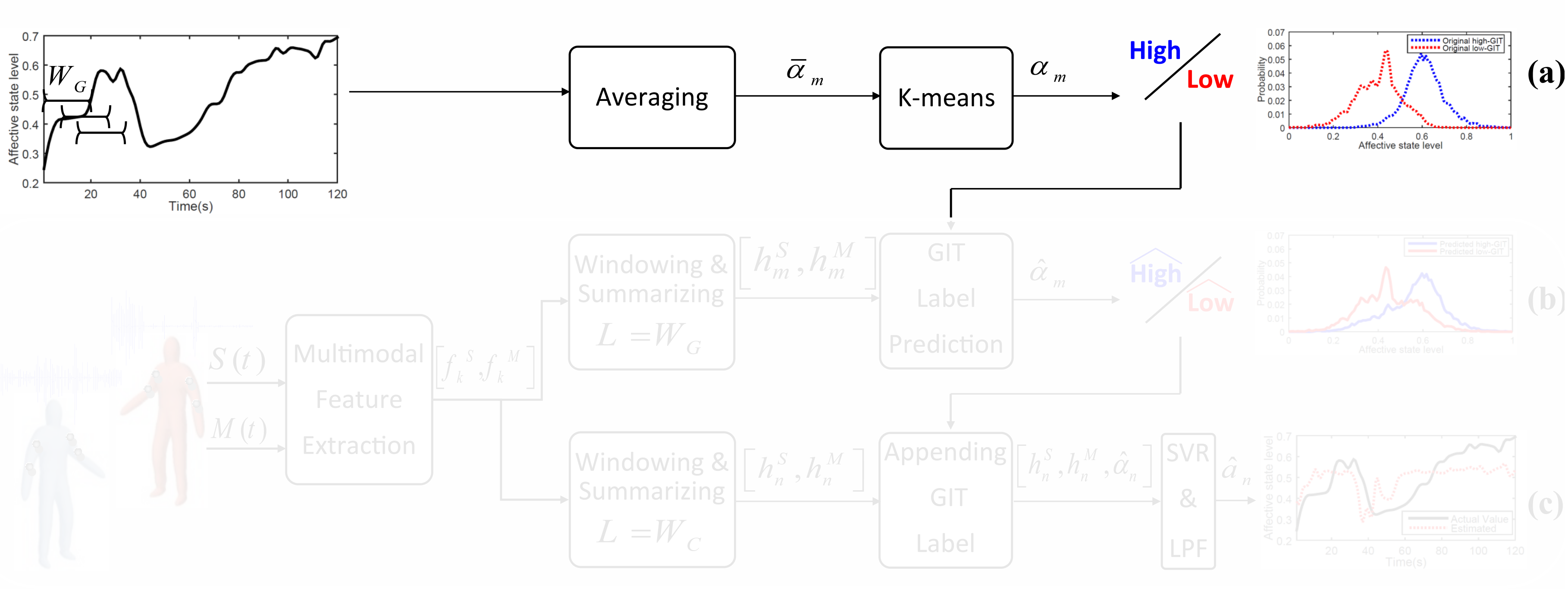
Mean Pearson's correlation between the consensus rating and individual annotations		
Activation	Valence	Dominance
0.5568	0.5638	0.7369

Topics in the JESTKOD database

Pair #	Agreement scenario	Num. clips	Disagreement scenario	Num. clips
1	Cinema, World cuisine, Holiday resorts, TV series	13	Football, Maths, Game consoles, PC Games	13
2	Football, World cuisine, Music, Cinema, Literature	13	Geography, Holiday resorts, PC Games, Theatre, Dance	16
3	Cinema, Sports, PC Games, Music, World cuisine	11	Cinema History, TV series, Animals, Education	17
4	World cuisine, Holiday resorts, Science-fiction, History, Theatre, Cities	16	Football, Cinema PC Games, TV series, Literature, Physics	17
5	Cinema, Languages, PC Games, Cities, Game consoles	13	Cinema, Sports, Holiday resorts, Nutrition, Musicals	16
Total		66		79

The JESTKOD database is available upon request for academic purposes.
http://mvgl.ku.edu.tr/databases

GIT-CER system

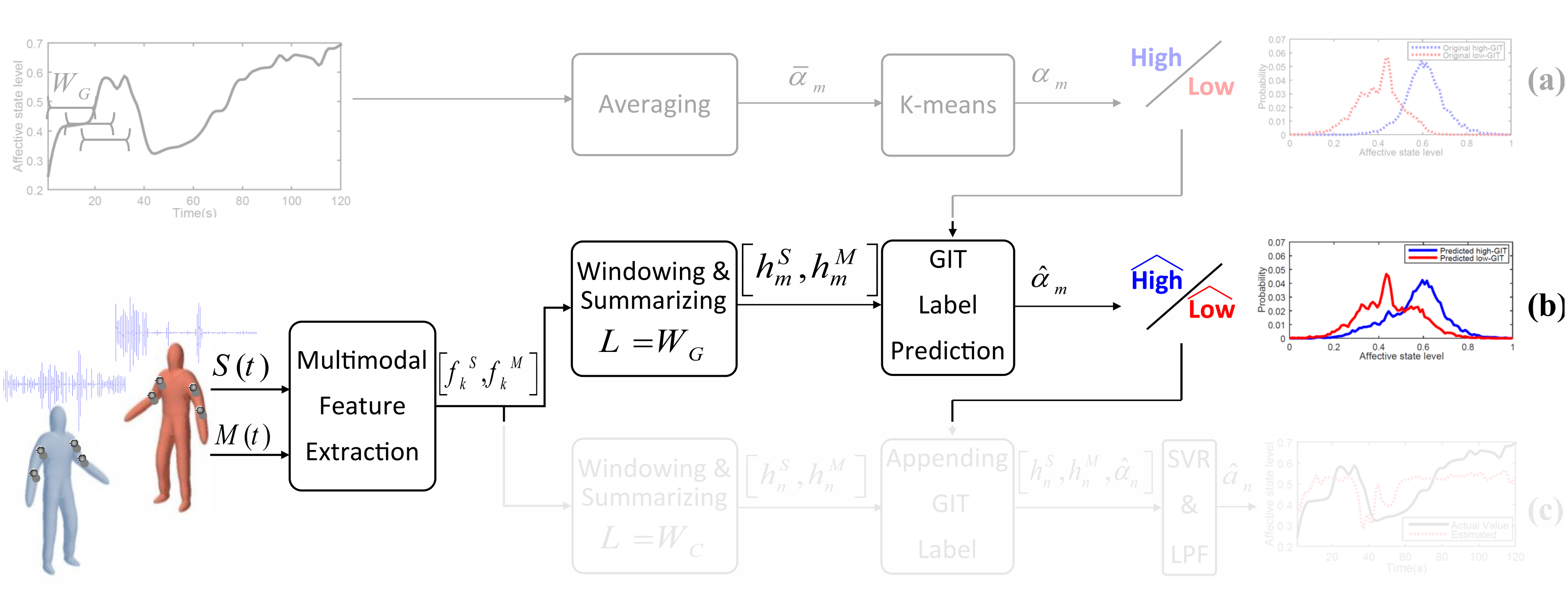


- a. Clustering:
  - Temporal segmentation
  - Splitting AVD into two general classes
  - Similar to DIT, Defining General DIT (GIT)

$$\bar{\alpha}_m = \frac{1}{W_G} \sum_{k=1+(m-1)R_G}^{W_G+(m-1)R_G} a_k,$$

$$\alpha_m = \mathcal{Q}(\bar{\alpha}_m)$$

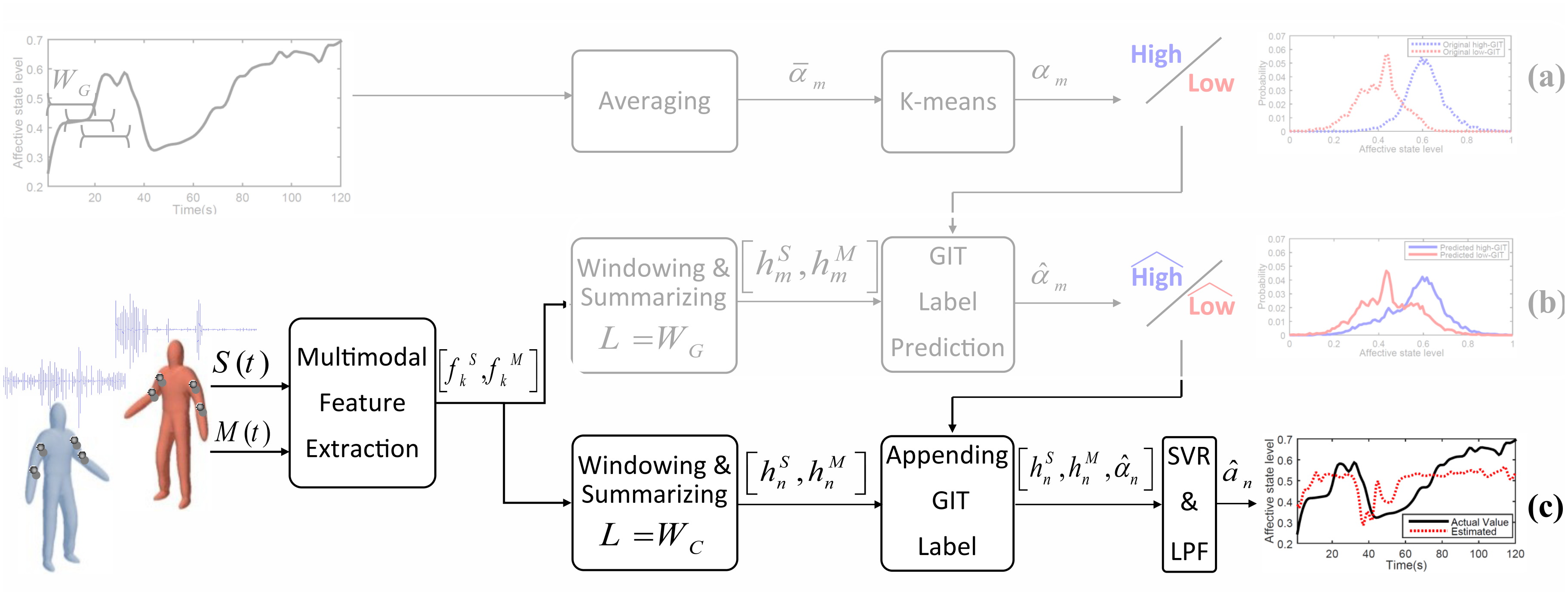
GIT-CER system



- b. GIT Label Prediction:
  - Linear SVM unimodal and multimodal system.

$$\hat{\alpha}_m = \Phi(h_m^S, h_m^M) \qquad 8 \leq W_G \leq 30\ sec$$

GIT-CER system



- c. Appending GIT label and Continuous Emotion Recognition

$$\hat{a}_n = \Psi(h_n^S, h_n^M, \hat{\alpha}_n) \qquad W_c = 1.5\ sec$$

Experimental Evaluations (parameters)

- **Feature extraction:**
  - **Speech**: 16.66 ms win with 8.33 ms frame shifts $\Rightarrow$ 39D $=$ (E $+$ 12MFCCs) $+ \Delta + \Delta\Delta$
  - **Motion**: 24D $= (\varphi, \theta, \psi)$ of the arm & forearm joints with their derivatives
- **Training and testing strategy:**

  Leave-one-session-out => Speaker independent

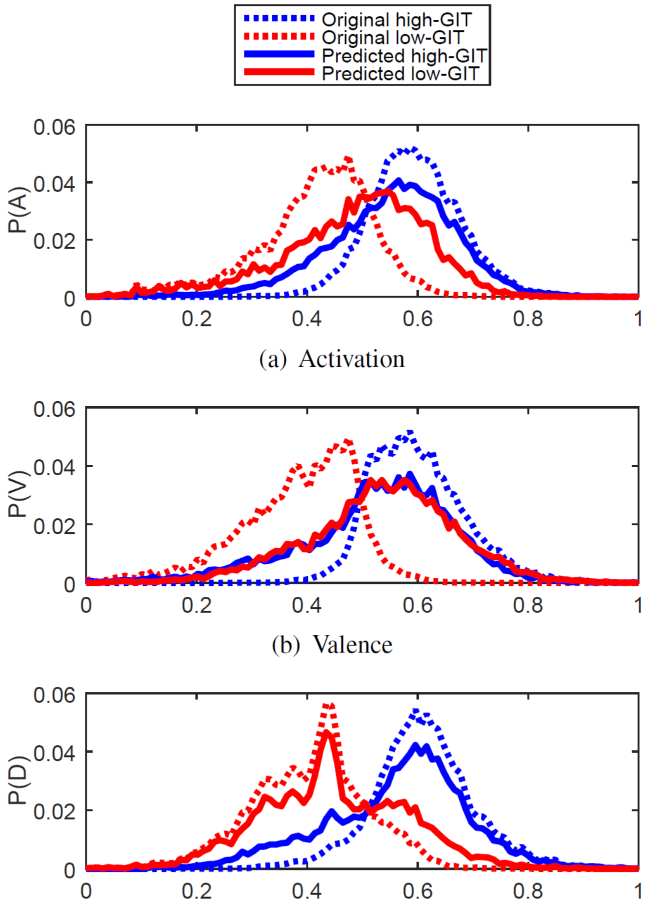
- **Feature Summarization:**
  - **Statistical functions:** Adjust the PCA output dimension to preserve 90% of the total variance
- **Prediction and regression:**
  - **GIT prediction:** Linear kernel SVM
  - **CER:** RBF kernel SVR
- **Performance metric:** The average Pearson correlation between consensus ratings and their estimation

Experimental Evaluations – GIT Prediction

- GIT predication phase:
  - Search over different $8 \leq W_G \leq 30$ sec to maximize the statistical difference between predicted high and low GIT
  - Statistical difference measure:
    Kullback-Leibler divergence (KLD)
  - GIT prediction from speech and motion

$D_{KL}(P_H, P_L)$ / (W_G)		
Activation	Valence	Dominance
0.31/(13)	0.11/(29)	0.81/(13)

- Dominance: Well separated ☺
- Activation Medium separated! 😐
- Valence: Not separated ☹



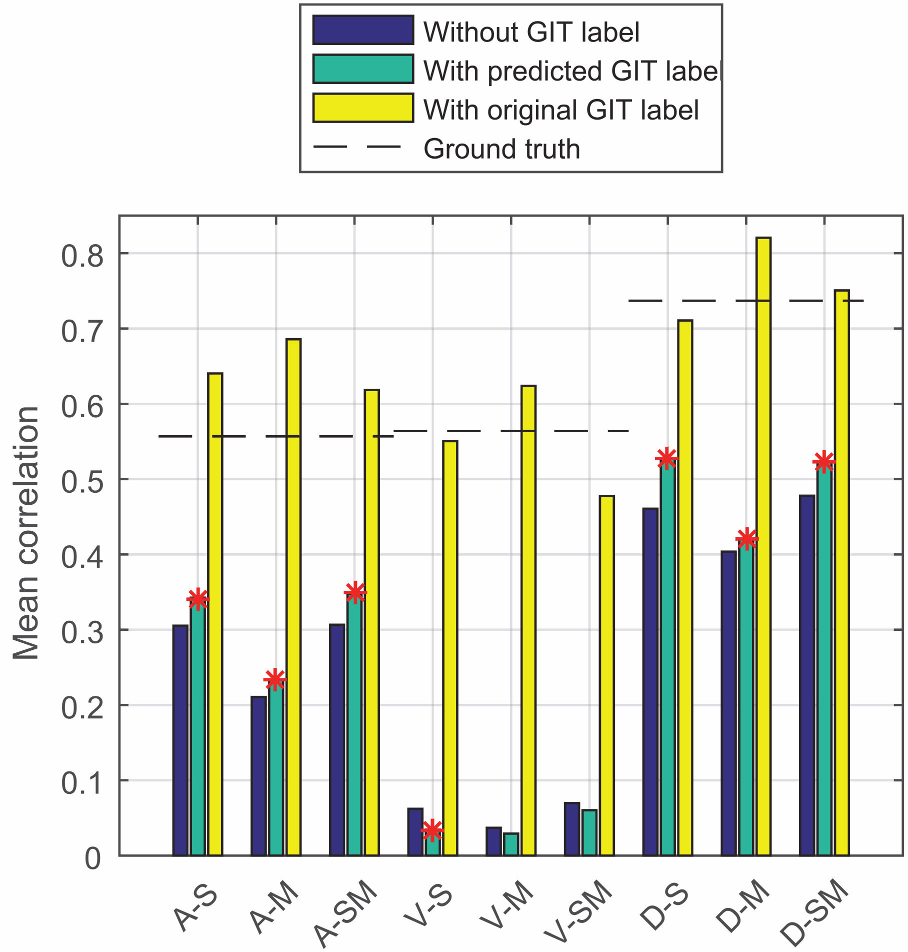
(a) Activation

(b) Valence

(c) Dominance

Experimental Evaluations – Emotion Recognition

- Continuous Emotion Recognition
  - From **S**peech, **M**otion and multimodal speech & motion (**SM**)
  - For **A**ctivation, **V**alence and **D**ominance
- Observations
  - Multimodal tests have almost always the highest correlation
  - Predicted GIT (green bars) improves dominance and activation
  - Valence regression is always poor (No facial expression data)
  - Yellow bars: Theoretical upper bounds



Star signs indicate the statistically significant ($p<0.05$) difference between CER without GIT labels and CER with predicted GIT labels

Conclusions and Future work

- Conclusions
  - Our hierarchical continuous emotion recognition system consist of:
    - Temporal clustering of AVD to form GIT label
    - Predict GIT Label with multimodal feature set
    - Append predicted GIT to multimodal feature for continuous emotion recognition
  - GIT labels provide useful discrimination for the activation and dominance attributes in the JESTKOD dataset
  - GIT labels introduce side information for CER problem

- Future work
  - Use of affect context, such as GIT, for continuous emotion recognition

Thanks.

!?QUESTIONS?!