

# Mining Discriminative Intervals for Affective State Estimation

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## Abstract

**Problem Statement:** Affective state Estimation using wearable sensor signals.

**Motivation:**

- Computers that empathize with humans.
- Emotional channels for those with disabilities (e.g.: Autism)

**Limitations:**

- Unreliable labels
- Difference in personal response times to stimulus

**Objective:**

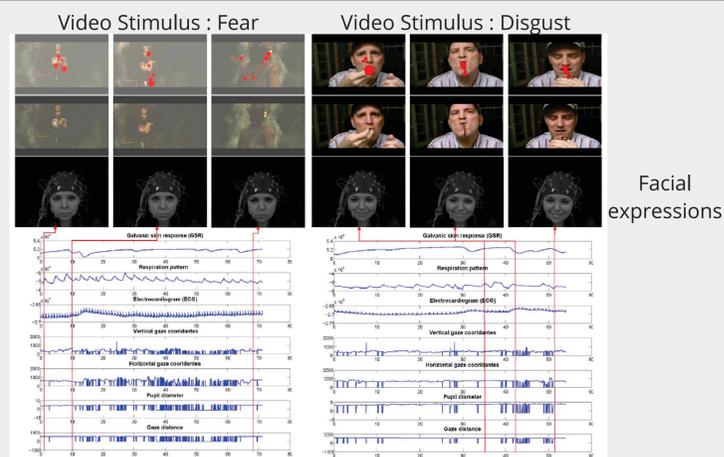
- Mine important signal segments
- Subject invariance

## Dataset description

We use MAHNOB-HCI, a publicly available multi-modal database with records of physiological signals from 27 participants who are shown 20 emotional movie clips. A neutral clip is played before every clip. Self-assessment follows every emotional clip.



## Data Collection



In the first row, red circles show the fixation points and their radius depicts the time spent on it. Red lines indicate the moments at which each snapshot was captured

## Feature Extraction

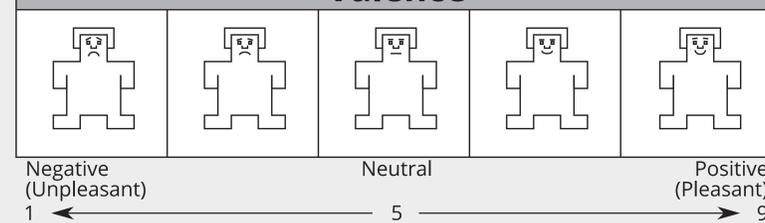
Sensor	No. of features extracted
ECG	576
EEG	216
GSR	39
Skin Temperature	4
Respiration	14
Eye Gaze	35

Number of features extracted from each physiological sensor

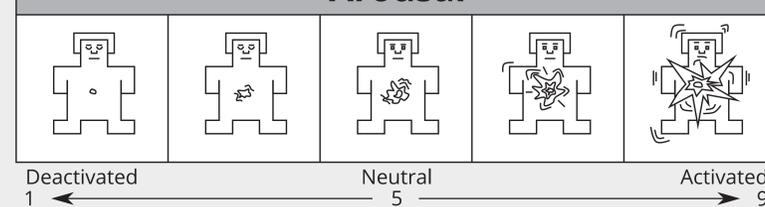
## Self-assessment Labeling

Russell's valence-arousal scale is used for self-assessment. Arousal ranges from inactive (e.g.: uninterested, bored) to active (e.g.: alert, excited), Valence ranges from unpleasant (e.g.: sad, stressed) to pleasant (e.g.: happy, elated).

### Valence



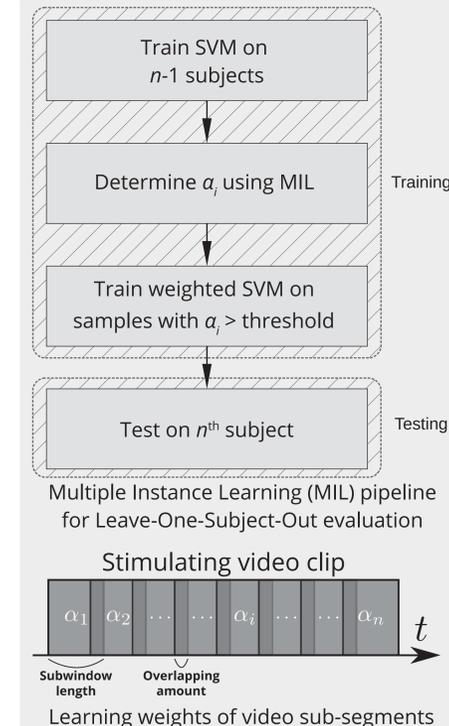
### Arousal



## Acknowledgment

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## Methodology



We use MS-SVM to determine  $\alpha$  for every sub-segment of the video clips. Sub-segments with  $\alpha_i >$  threshold are said to be important contributors to the emotional experience. These segments are selected for training. Majority voting strategy is used to determine the labels of videos. We classify high and low emotional states.

## Results

	LOSO	LOVO
<b>Linear SVM</b>	32.64%	30.47%
<b>Kernel SVM</b>	44.48%	49.32%
<b>MS-SVM</b>	<b>58.43%</b>	<b>49.38%</b>

Average classification accuracies of different SVM techniques on Arousal

	LOSO	LOVO
<b>Linear SVM</b>	39.53%	16.47%
<b>Kernel SVM</b>	<b>50.38%</b>	53.88%
<b>MS-SVM</b>	47.09%	<b>61.26%</b>

Average classification accuracies of different SVM techniques on Valence

## Future Work

- Feature Selection
- Analysis of response time delays of different signals to align temporal segments
- Sophisticated classification models