Trapezoidal Segment Sequencing: A Novel Approach for Fusion of Human-Produced Continuous Annotations

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Overview

1. Introduction
   - Background: Continuous Annotation
   - Signal Warping (Our Previous Work)
2. Proposed Method
3. Validation
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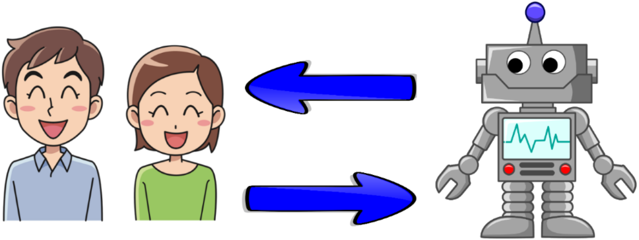
Introduction

Introduction

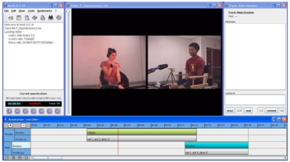
- Interested in human behavior and experiences and training machines to perceive and predict them
- At present, we are dependent on supervised learning using labels of experience provided by humans



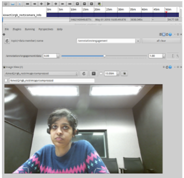
Introduction

- Many types of human-produced annotations
  - Discrete or continuous-scale (emotion categories, dimensional affect)
  - Discrete or continuous-time (images, videos)
- We **focus** on continuous-scale and continuous-time
  - e.g., dimensional affect from video

OASIS
(*Dimensional Valence + Arousal*)



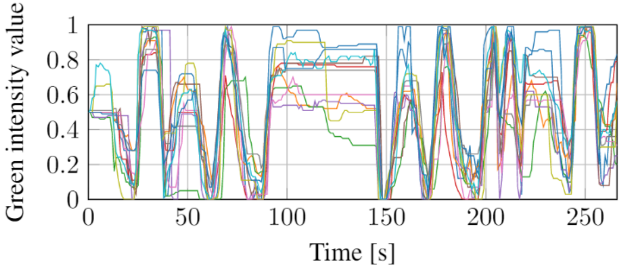
IEMOCAP
(*Dimensional Valence + Arousal Emotion Tags*)



Distance Learners
(*Engagement*)

Background: Continuous Annotation

- Typical procedure:
  1. Collect multiple annotations from different people
  2. *Fuse* the annotations to produce a single time series
- Why?
  - Mitigate individual biases and annotation artifacts



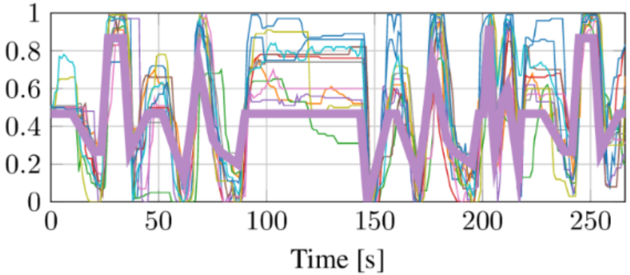
Background: Existing Fusion Techniques

- Many options for fusion, but **no consensus on best approach**
  - Simple averaging
  - Time-align, then average (*EvalDep*, *DTW*)
  - Annotator modeling + latent state recovery (HMM)
  - Correlated spaces regression
  - Canonical correlation analysis
  - *RankTrace*-based preference fusion
  - More...
- Each method **makes its own assumptions**

- Two-step fusion: Signal warping (previous work)
  - Assumes particular **structure to annotator reliability**

Background: Signal Warping Method Intuition

- Signal warping idea (previous work) based on observation that annotators **capture trends more reliably** than they assign values

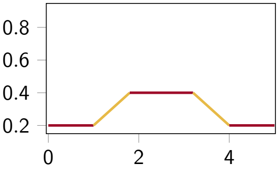


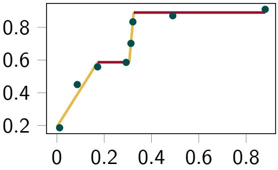
Target signal (bold magenta) and individual annotations (thin lines)

- **Key idea**: Partition the signal into reliable (trend) and less reliable (constant) regions

Background: Trapezoidal Segmented Regression

- Achieved using **trapezoidal signals** (previous work[1])
  - Piecewise cont. function of alternating sloped and constant lines



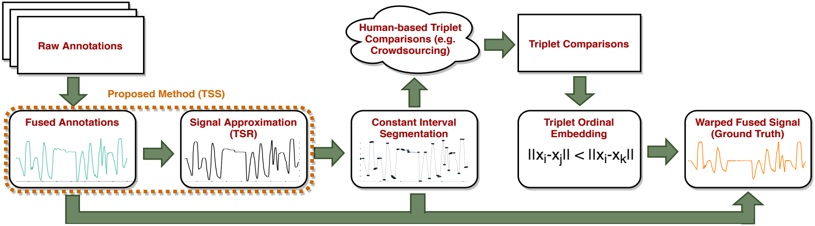


Simple trapezoidal signal (left) and a trapezoidal segmented regression (right)

- We show these signals are sensible annotation approximators
  - **Theorem 1:** Proof that trapezoidal signals are dense in $\mathcal{C}_C(\mathbb{R})$

[1] Brandon M Booth and Shrikanth S Narayanan. "Trapezoidal Segmented Regression: A Novel Continuous-scale Real-time Annotation Approximation Algorithm". In: *2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE. 2019, pp. 600–606.

Background: Signal Warping Pipeline



Signal warping algorithm[2]

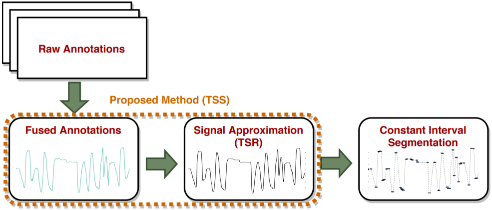
Two-step fusion:

1. Fuse annotations and partition into *trend* and *constant* intervals
2. Gather contrastive annotations for unreliable (constant) segments and use results to warp fused annotation

[2] Brandon M Booth, Karel Mundnich, and Shrikanth S Narayanan. "A novel method for human bias correction of continuous-time annotations". In: *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE. 2018, pp. 3091–3095.

Caveat: Initial Fusion Step

- **Prior approach**: Fuse annotations → TSR approximation
  - Problem: Fusion using some existing method, inconsistent with our observations and assumptions



- **Motivation for proposed method**: End-to-end implementation assuming trapezoidal-like annotation structure

Proposed Method

Method: Trapezoidal Segment Sequencing

Proposed method: Trapezoidal segment sequencing

1. Compute TSR approximation for each annotation A_i^a:
   - Compute the forward difference sequence: $D_i^a : 1 \le i \le N-1$
   - Normalize the differences:

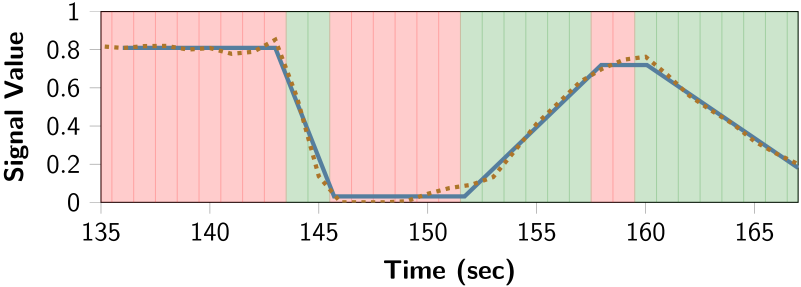
$$TSS_i^a = \begin{cases} -1 & D_i^a < 0 \\ 0 & D_i^a = 0 \\ 1 & D_i^a > 0 \end{cases}$$

2. Fuse by majority voting
   - $TSS_i = \text{mode}(TSS_i^a)$

- **($*$)** Extracting less reliable (constant) regions from TSS_i **is easy**

Method: Example Signal

Example annotation signal sampled at 1Hz:



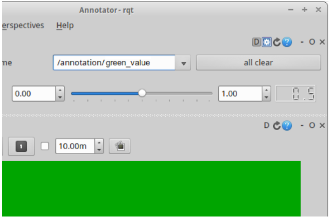
Sample annotation signal (dotted), TSR approximation (solid), and TSS render using green and red vertical bands. Red bands correspond to no change in the TSR, green bands correspond to a trend.

Validation

Validation: Simple Annotation Experiment

- Experiment where the true signal is known *a priori*
    - Task: Annotate the intensity of the shade of green

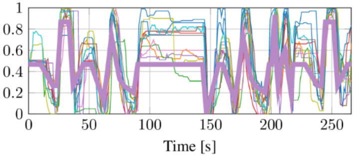
Video stimulus



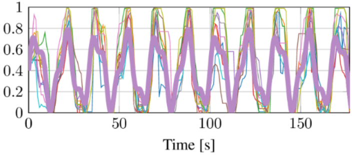
Annotation UI

Validation: Annotation Results

- Protocol
  - Ten annotators
  - Continuous-time and continuous-scale
- Results
  - High agreement: ICC(3,k) $= 0.97$

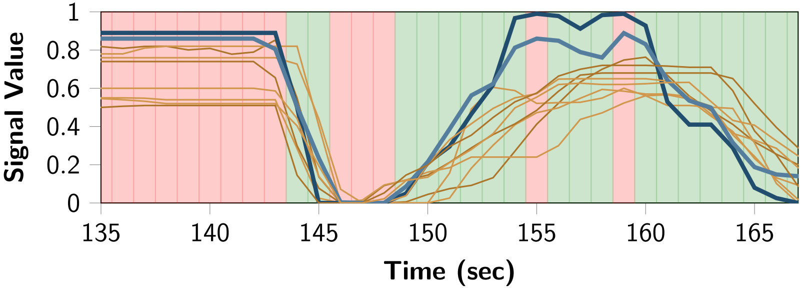


Task A: Objective truth and annotations



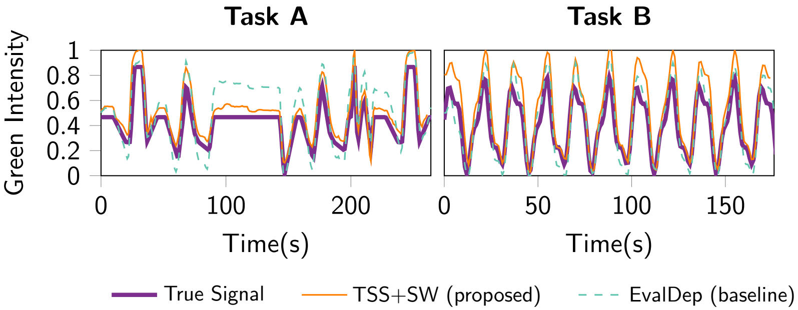
Task B: Objective truth and annotations

Validation: TSS Fusion Results



- Vertical bands = TSS after majority voting
  - Red bands: no change (constant)
  - Green bands: some change (up/down trend)

Validation TSS + Signal Warping Results



Task	Method	Pearson	Spearman	Kendall's Tau	NMI
A	EvalDep (baseline)	0.90	0.93	0.80	0.88
	TSS+SW(proposed)	**0.96**	0.92	0.80	0.88
	Fusion-first SW	**0.97**	0.94	0.83	0.82
B	EvalDep (baseline)	0.96	0.96	0.83	1.0
	TSS+SW(proposed)	0.96	0.96	0.83	1.0
	Fusion-first SW	0.99	0.99	0.91	0.99

Discussion and Future Work

Conclusion

- Introduced TSS fusion leveraging TSR
  - Exploits structure in variation of annotator reliability over time

- Signal warping with TSS enables end-to-end annotation fusion that is *internally consistent in its assumptions*

Future Work

- End-to-end signal warping on real-world data (external consistency)
- TSS representation provides foundation for new annotator agreement measures
  - Supports both global and localized agreement over interpretable partitions in annotation space (e.g., trend vs. no change)

Thanks and Code Link

Code available on GitHub:

https://github.com/brandon-m-booth/2019_continuous_annotations

- Optimum TSR
- Signal warping fusion with TSS

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