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# Multimodal Learning for Detecting Stress under Missing Modalities

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## Abstract

Dealing with missing modalities is critical for many real-life applications. In this work, we propose a scalable framework for detecting stress induced by specific triggers in multimodal data with missing modalities. Our method has two key components: (i) aligning all modalities in the space of the strongest modality (the video) for learning a joint embedding space and (ii) a Masked Multimodal Transformer, leveraging inter- and intra-modality correlations while handling missing modalities. We validate our method through experiments on the *StressID* dataset, where we set the new state of the art while demonstrating its robustness across various modality scenarios and its high potential for real-life applications.

## 1. Introduction

Monitoring physiological changes is crucial for assessing individuals' well-being, especially in safety-critical contexts. Examples include stress, a response to emotional and physical challenges [14], and a triggering or aggravating factor for various pathological conditions [4]. Physiological changes may be detected visually (videos), acoustically (audio), or via biomedical signals (e.g., electrocardiograms). Yet, specific modalities may be unavailable during testing and sporadically absent during training. Thus, a method that can handle missing modalities during training and testing while balancing modalities' contributions for robustness is pivotal. A few existing methods address the challenge of handling missing modalities. However, they may suffer from notable limitations, including (a) requiring all modalities during training [10], (b) not being easily generalizable to more than two modalities [8, 9], or (c) considering the same input dimension for all modalities [17, 19]. In this work, we propose (i) a framework that aligns multimodal representations to a common rich feature space, (ii) a fusion strategy to handle missing modalities during training and inference, (iii) we set the new state of the art on *StressID* [1] in various modality settings.

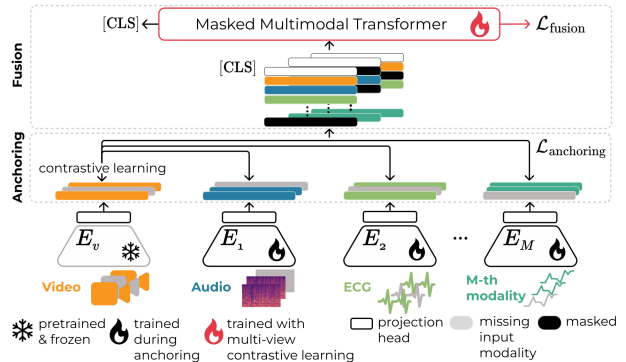


Figure 1. **Overview of our method.** (i) Contrastive learning aligns unimodal representations to the video. (ii) Fusion models multimodal interactions and handles missing modalities.

## 2. Anchored Multimodal Transformer

This study addresses stress detection using multimodal data, including video, audio, and biomedical signals. Real-world scenarios often involve missing modalities, motivating our goal to develop a modality-agnostic representation. Let  $\mathcal{D} = \{(x_m^i)_{m=1}^M, y^i\}_{i=1}^N$  be our dataset, with  $M$  modalities and  $N$  labeled observations, where  $x^i = (x_m^i)_{m=1}^M$  is the  $i$ -th observation (i.e., a family of  $m$  modality values) and  $y^i \in \mathcal{Y} = \{0, 1\}$  the corresponding label (i.e., *stressed* or *not*). An overview is presented in Figure 1.

**Anchoring.** We train modality-specific encoders with a contrastive learning objective to align their representations to the one of the *video* (the strongest modality). Let us consider a pair of modalities with aligned observation  $(\mathcal{V}, \mathcal{M}_m)$ , where  $\mathcal{V}$  the video, and  $\mathcal{M}_m$  another modality. The video  $x_v^i$  and its corresponding observation  $x_m^i$  are encoded using  $z_v^i = E_v(x_v^i)$  and  $z_m^i = E_m(x_m^i)$ , respectively, where  $E_v$  is a pre-trained and frozen video encoder and  $E_m$  a DNN. Projection heads map the embeddings to  $f_a^i, f_m^i \in \mathbb{R}^d$ . The loss is computed on  $f_a^i$  and  $f_m^i$  [5]:  $\mathcal{L}_{\mathcal{V}, \mathcal{M}_m} = -\sum_{i=1}^B \log \frac{\exp(\cos(f_a^i, f_m^i)/\tau)}{\sum_{k=1}^B \exp(\cos(f_a^i, f_k^i)/\tau)}$ ,  $\tau \in \mathbb{R}^+$  the temperature parameter,  $\cos(\cdot, \cdot)$  the cosine similarity, and

$B$  the batch size. In practice, we use a symmetric loss:  $\mathcal{L}_{\mathcal{V}, \mathcal{M}_m} + \mathcal{L}_{\mathcal{M}_m, \mathcal{V}}$ . We define the anchoring loss for  $M$  modalities:  $\mathcal{L}_{\text{anchoring}} = \sum_{m=1, \mathcal{M}_m \neq A}^M (\mathcal{L}_{\mathcal{V}, \mathcal{M}_m} + \mathcal{L}_{\mathcal{M}_m, \mathcal{V}})$ .

**Masked Multimodal Transformer.** To effectively build modality-agnostic representations, we resort to the transformer architecture [16]. For each sample, we stack the modality-specific representations,  $f_m^i \in \mathbb{R}^d, \forall m \in [1, M]$ , into a single matrix and prepend a special token [CLS], yielding a matrix  $F \in \mathbb{R}^{(M+1) \times d}$ . Similarly to Liu et al. [7], the query, key and value are derived from  $F$  via:  $Q = W^Q F$ ,  $K = W^K F$  and  $V = W^V F$  where  $Q, K \in \mathbb{R}^{(M+1) \times d_k}$  and  $V \in \mathbb{R}^{(M+1) \times d_v}$ . Our modularization of inter-modal interactions differs from the usual cross-attention [2, 6], which asymmetrically combines two separate embedding sequences of same dimension. Using stacked features  $F$  allows to generalize to any number of modalities, with linear scalability in the number of modalities instead of quadratic.

*Handling missing modalities.* Inspired by Milecki et al. [11], we apply our strategy to the scaled dot-product, core of each multi-head self-attention sub-layer. We use a masking binary matrix  $Z$  that specifies which modalities are missing:  $z_{ij} = 1$  if  $i$  and  $j$  are available, else  $z_{ij} = 0$ . The output  $O$  of the attention mechanism, for  $O_i$  each line of  $O$  is :

$$O_i = \sum_j z_{ij} \frac{\exp(Q_i^T K_j / \sqrt{d_k})}{\sum_{\{j', z_{ij'}=1\}} \exp(Q_i^T K_{j'} / \sqrt{d_k})} V_j \quad .$$

We train the Masked Multimodal Transformer with a multi-view contrastive objective [3]. Inspired by Shi et al. [15], we mitigate the model’s over-reliance on a single modality while enhancing its robustness in the absence of modalities through the *modality dropout* augmentation technique.

### 3. Results & Discussion

**Dataset.** StressID [1] for stress identification contains physiological responses via electrocardiogram, electrodermal activity, respiration, audio, and videos. We denote  $X_{\text{train}}, X_{\text{test}}$  the entire train and test set (considering samples with and without missing modalities), and  $X_{\text{train}}^*, X_{\text{test}}^*$  for the train and test sets where all modalities are available. We follow the train, validation, and test splits provided in [1] and report the same metrics: balanced accuracy (ACC), weighted F1-Score (F1) in format mean(std).

**Implementation details.** The Anchoring and Masked Multimodal Transformer steps are trained separately on  $X_{\text{train}}^*$  and  $X_{\text{train}}$ , respectively. A linear classifier is trained using the [CLS] token output for the final task. At each step, we train for 70 epochs using AdamW optimizer, with a learning rate of  $1e-4$  and a batch size of 128. For the *Video* modality, we use the Hiera [13] pre-trained encoder. For *audio*, each sample is encoded into a mel-spectrogram and fed to

|                                  | ACC                | F1                 |
|----------------------------------|--------------------|--------------------|
| Video                            | 62(4) <sup>‡</sup> | 67(3) <sup>‡</sup> |
| Biomedical signals               | 58(4) <sup>‡</sup> | 66(5) <sup>‡</sup> |
| Audio                            | 62(4) <sup>‡</sup> | 67(4) <sup>‡</sup> |
| Feature Fusion [1]               | 61(3) <sup>‡</sup> | 66(4) <sup>‡</sup> |
| Decision Fusion <sup>†</sup> [1] | 65(5) <sup>‡</sup> | 72(5) <sup>‡</sup> |
| <b>Ours</b>                      | <b>69.5(3.7)</b>   | <b>75.9(4.3)</b>   |

Table 1. **Comparison to SOTA on  $X_{\text{test}}^*$ .** **Bold**, underlined indicate the top 1, 2 performing, respectively. <sup>‡</sup>Results from [1]. For decision fusion<sup>†</sup>, we report the best out of all 4 decision rules.

|                 | ACC       | F1        |
|-----------------|-----------|-----------|
|                 | 69.5(2.9) | 69.6(3.1) |
| <i>no video</i> | 61.2(4.6) | 63.0(4.2) |
| <i>no audio</i> | 68.3(2.9) | 68.4(3.0) |

Table 2. **Evaluation on two modality scenarios on  $X_{\text{test}}$ .** For each scenario, we systematically remove one modality from the test set.

BYOL-A [12]. *Biomedical signals* are processed using 1D CNNs as suggested by [18]. Projection heads encode each representation as a  $d = 64$  dimensional vector.

**Comparison to SOTA.** Table 1 presents the comparison to the SOTA in the presence of all modalities. We compare against ‘feature fusion’ and ‘decision fusion’ [1] (rows 4 & 5) and unimodal baselines for Video, audio, and the stacked biomedical signals (rows 1, 2 & 3). Our method outperforms all other methods by a notable margin. For instance, it outperforms ‘decision fusion’ by 4% in ACC and 6% in F1.

#### Robustness to missing modalities.

Table 2 reports the performances under missing modalities during inference. We remove audio or Video, the most cumbersome modalities to acquire, from  $X_{\text{test}}$  and compare the results and differences ( $\Delta$ ) to the ones obtained on  $X_{\text{test}}^*$ , the default test set (row 1). The results remain competitive for both *no-audio* and *no-video*:  $|\Delta| < 8.6\%$ , even-though these modalities individually perform the best on  $X_{\text{test}}^*$  (Table 1). Additionally, Figure 2 shows ACC and F1 under different missing modality ratios  $\eta$  among  $M * N$  with  $M$  the number of modalities and  $N$  the number of observations for training and inference. Our approach can successfully handle high ratios of missing modalities. More precisely, we report a delta of 2% between  $\eta = 12.5\%$  (i.e.,  $\eta$  inherent to the dataset) and  $\eta = 30\%$  for ACC and F1.

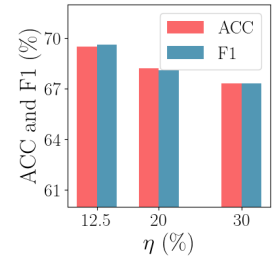


Figure 2. **Robustness to missing modality on  $X_{\text{test}}$ .**

**Conclusion.** We propose a modality-agnostic representation learning framework tailored to operate under missing modalities during training and testing. Applied to stress detection, our approach outperforms current SOTA and showcases robustness to missing modalities.

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