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Multimodal Emotion Recognition for Human–Robot Interaction Using Speech, Facial Dynamics, and Physiological Signals

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Abstract

Speech emotion recognition is an important research area that makes a significant contribution to the development of socially intelligent HumanMachine Interaction (HRI) since vocal communication contains a lot of paralinguistic information that supplements the semantic load. However, speech based systems can have poor performance in real world situations because of background noise, variant microphone as well as variations in style of speaking. To deal with these shortcomings, we are introducing the multimodal emotion recognition system where the speech processing forms its core and is complemented by face dynamics and physiological measures to increase reliability and precision. The speech channel uses CNN-BiLSTM pipeline to extract spectral-temporal prosodic features of Mel-spectrograms which have strong discriminative power despite noisy environment. A 3D-CNN is used to analyze the facial expressions, and an Electrodermal Activity (EDA), Electrocardiogram (ECG) and Photoplethysmography (PPG) is modeled by using a Temporal Convolutional Network (TCN). Theses modalities are integrated, oriented and harmonized by a Transformer-based cross-attention fusion mechanism that harnesses the complementarity of these strengths to overcome any weaknesses. Simulation of datasets (IEMOCAP, SEMAINE, and AMIGOS) indicate an increment of 7 12 weighted F1-scores compared to unimodal baselines for speech-based HRI scenarios, with or without noise, obscuration, or lost modalities-percentages attesting to the usefulness of the approach in emotion-sensitive HRI.

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Introduction

High-quality speech emotion recognition (SER) represents one of the key contributions in the field of affective computing and Human Robot Interaction (HRI), because speech aspects related to pitch, energy, prosodic categories, and temporal dynamics provide fine-grained affective vocal information that goes beyond the semantics of verbal communication. Natural communication can be made possible by the robots reading the cues to change dialogue tactics and show empathy and human attitudes that can build more trust between the robot and the user. In areas including assistive healthcare, teaching, customer service and collaborative robots, the capacity to sense and act accordingly based on the emotional state of the person using the system is vital to boost his/her engagement levels, satisfaction or task performance.

Although much progress has been made regarding SER systems, their performance continues to suffer when facing the real-world situation because of the problems that include ambient noises, overlapping speech, microphone variability, and speaker-dependent variability. Such limitations cannot be overcome even by advanced noise-robust feature extraction pipelines and deep learning architectures, e.g., CNNBI LSTM networks, when speech is the single input modality. Such vulnerability may result in miscommunication, slow responsiveness of systems, and negative user experience particularly in fluctuating and unanticipated HRI environments.

Speech complemented with other affective signals, specifically, facial gestures and physiological measures, that is, multimodal emotion recognition (MER), has been a solution that was more and more embraced by researchers that are trying to deal with these difficulties. The multimodal formulation enables compensation to set up circumstances in which speech clues are indefinite, deformed, or missing, with the usage of complementary cues to make a better and more confident representation of emotion. Facial movement and gestures are key visual cues to emotional expression and physiological measures (including Electrodermal Activity (EDA), Electrocardiogram (ECG) and Photoplethysmography (PPG)) are all key indicators of autonomic nervous system activity which is relatively unaffected by environmental noise.

In this paper we have introduced a deep learning based MER system where speech processing is the central part of the recognition process but without difficulty integrating facial dynamics and physiological signals to add additional information towards supporting emotion inference when the signal is noisy or occluded. The speech channel uses a CNN-BiLSTM pipeline to extract spectro-temporal prosodic features on the Mel-spectrograms and thus boasts a high discriminative power when in complicated acoustic conditions. A 3D-CNN with temporal attention mechanism leveraged in the facial dynamics channel helps to process micro and macro-expressions, whereas another physiological channel uses Temporal Convolutional Network (TCN) to the model of multi-scale temporal patterns in biosignals.

The resulting modality-specific embeddings are fused via a cross-attention fusion module based on a series of transformers that allow the system to context-dependently align and weigh between different modalities to make use of response-specific information. This hybrid strategy makes sure not to leave speech as the sole driver of emotion recognition purposes, but also use other modalities to reinforce each other, make it more robust, and more generalizable. The framework framework is tested on three standard test sets including: IEMOCAP, SEMAINE, and AMIGOS; which represent a broad range of interaction types, emotional categories and recording conditions. On the experiment front, we demonstrate that our approach and variants performs far better than unimodal and conventional fusion baselines, and performs just as well in missing-modality losses as in the complete dataset.

The study enhances the design of multimodal SER systems because it considers speech processing as a high priority in a multimodal architecture and thereby reduces certain limitations of unimodal SER systems in an effort to develop emotion-sensitive robotic systems that can interact empathetically, adaptively and context-sensitive in a real world context.

Related Work

Emotion recognition in Human-Robot interaction (HRI) is a well-researched area in many modalities, with recent deep learning updating providing tremendous advancements in recognition accuracy levels. The section discusses current research on speech-based emotion recognition, analysis of facial expressions, physiological signal-based emotion recognition, and techniques of multimodal fusion, their merits and constraints, respectively, regarding HRI.

Speech-based emotion recognition (SER) uses language to determine the emotional status by analyzing prosody, spectral patterns and voice quality. Conventional methods used traditionally crafted features such as Mel-Frequency Cepstral Coefficients (MFCCs), pitch contours, and energy dynamics, and used the machine learning models (such as Support Vector Machines (SVMs) and Gaussian Mixture Models (GMMs) to classify them.[1] Since then, deep learning has rocked SER, with CNNLSTM hybrids being shown to, at the least, capture local spectral features and long-term temporal dependencies thus making them more robust in structured datasets.[2] As an example, it was presented by Mao et al.,[3] who introduced a multi-view CNN LSTM model, which simultaneously learned temporal and frequency-based representations and performed better on IEMOCAP dataset specific. Nonetheless, SER performance deteriorates drastically in noisy scenes and conditions in which channel distorsions or that of speaker variability is involved in the speech recording.[4] This drawback accentuates the necessity of a combination of modalities in the case of HRI in particular, where a noisy environment is common.

One of the most obvious approaches to emotion recognition is the facial expression analysis as humans are inherently dependent on certain visual signs, namely smiles, frowns, and micro-expressions to determine the affective states. Facial dynamics is very important in HRI, especially dynamic face-to-face interactions. The initial techniques incorporated geometric characteristics (e.g., distances between facial landmarks) along with classifiers (e.g., k-NN, or SVM) into it.[5] Since the incorporation of the concept of deep learning, 3D Convolutional Neural Networks (3D-CNNs) are prevalent owing to the possibility of learning both spatial and temporal features of the facial video sequences together.[6] In efforts to further improve temporal modeling, instead emphasis

has been applied to focus on the important parts of the face and fine micro-expressions.[7] However, facial expression analysis is prone to partial occlusion, head poses and adverse lighting conditions that is typical in uncontrolled HRI scenarios.[8]

Emotion detection using physiological signals has received interest as a complementary modality since it reflects the underlying activity of autonomic nervous system that is harder affected by environmental noise or deliberate concealment of emotions. Emotional arousal, stress level, and valence have been detected through Electrodermal Activity (EDA), Electrocardiogram (ECG) and Photoplethysmography (PPG) signals.[9] Initial research available has been to derive statistical and frequency-domain features out of these signals to classify them with traditional machine learning models. Some of the more recent methods leverage deep learning, including Temporal Convolutional Networks (TCNs), and BiLSTM networks, as an architecture to model temporal dependencies introduced by physiological responses.[10, 17] As an example, Choi et al.[11, 18] build a TCN-based model on multimodal physiological signals and have a high accuracy in setting controlled experiments in a laboratory. Nevertheless, these systems can still experience issues when it comes to the deployment of wearable sensors, the occurrence of motion artifacts and inter-subject variability, which impair robustness within real-world HRI settings.

The general goal of multimodal fusion approaches is to merge the advantages of unimodality under a single condition to produce robustness and increased emotion recognition accuracy. Fusion methods can generally be divided into feature and decision level fusion, in the former case raw or learned features of each model are simply concatenated or transformed and then used as input to a classifier, and in the latter case predictions of the models are combined on a decision level either using rules or via a meta-classifier.[12] At the same time, feature-level fusion has dimensionality and alignment issues, but decision-level fusion shows less sensitivity to missing modalities and fine-grained cross-modal correlations.[13, 19] Intelligent mechanisms Deep learning mechanisms such as attention-based and transformer-based fusion mechanisms have been investigated in recent research to overcome such limitations.[14] However, to date, transformer-based cross-attention fusion in particular has exhibited potential as a means of learning complex cross-modal dependencies between heterogeneous modalities by allowing modality contributions to be weighted dynamically depending on contextual relevance.[15, 20] These methods have been successfully used in multimodal sentiment analysis[16, 21] and are under active consideration in case of affective HRI.

Despite the amount of progress in the domain of unimodal and multimodal recognition of emotion, current systems are not yet sufficiently robust when it comes to real-world situations of HRI with background noise, occluded views, or absent physiological observations. This loophole instigates the current research that proposes the deep multimodal paradigm of unifying speech, facial dynamics, and physiological signals by a transformer-based cross-attention fusion module to deliver a robust and precise form of emotion recognition in a loosely controlled environment.

Proposed Methodology

System Overview

Our multimodal emotion recognition system (Figure 1) will make use of the strengths of speech, facial dynamics and physiological measures to provide robust and

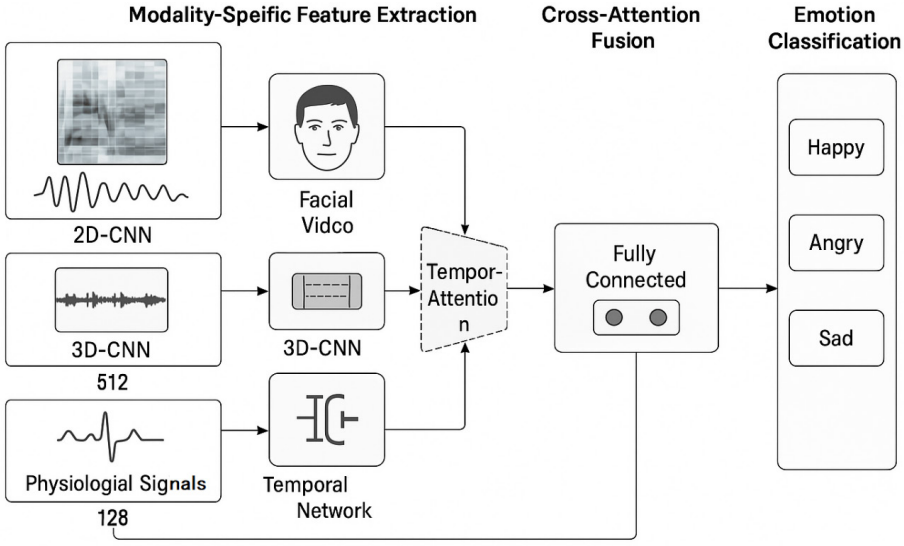

Fig. 1: Proposed Multimodal Emotion Recognition Architecture for Human-Robot Interaction

context-sensitive emotion recognition during Human-Robot Interaction (HRI). The architecture has three significant steps, (i) extraction of modality-specific features, in which the most active processing pipelines are run to produce discriminative embeddings of individual modalities; (ii) multimodal fusion by cross-attention, where a Transformer encoder integrates heterogeneous features of the different modalities by learning interdependencies between them; and (iii) classification of emotions, in which a fully connected network of classification nodes processes the cross-attention-consolidated emotion representation and predicts in a softmax node the presence of specific emotional states. Such a design will guarantee performance robustness on real-world HRI scenarios in which the noise in the environment, visual clutter, or partial information of the sensor could otherwise affect the accuracy of recognition. Figure 1 Reviewed multimodal emotion recognition system that combines modality-wise feature extraction, cross-attention fusion and classification of emotions.

Speech Feature Extraction

The primary channel of the proposed multimodal emotion recognition framework is created as the speech processing pipeline and considered the most appropriate one to cover both spectral and temporal variations in the audio signal that are necessary to extract prosodic and paralinguistic emotional characteristics. A raw speech waveform, sampled at 16 kHz, is ultimately normalized to a comparable amplitude range and converted as a Mel-spectrogram presentation with 128 Mel-filtration banks on 25 ms analysis windows and 10 ms resolutions, and presents the perceptually median frequency escapade information whilst compressing data dimensionality to streamline deep learning. To deal with the acoustic non-stationarity of real-world HRI environments where stationary or semi-stationary noise components like machinery hum, human chatter or reverberation may severely degrade recognition performance, our pipeline employs the techniques of preprocessing developed towards noise robustness such as spectral subtraction, Wiener filtering in the time-, frequency- and cepstral domains, logarithmic dynamic range compression to accommodate loudness and microphone gain variations, and cepstral mean and variance normalization (CMVN) to counter channel effects and inter-session variability.

These actions help in making features remain similar in varying acoustic conditions, requirements that are very crucial to robots that work among variable and random environments. To enhance generalization, large amounts of speech-specific data augmentation are used, with additive noise (such as background noise in the DEMAND and MUSAN corpora at a range of signal-to-noise ratios (SNRs) to be used to simulate natural noise conditions, addition of reverberation with room impulse responses (RIRs) of small meeting rooms up to large halls, speed perturbations (+/-10%) that incorporate rate variability during speech, and pitch perturbation (+/-2 semitones) to include inter-speaker differences in voice qualities The augmentation techniques create greater robustness in the model to acoustical distortions and speaker diversity, which narrows the difference between controlled training conditions and in-real environments.

Those Mel-spectrograms were denoised and augmented, fed to 2D Convolutional Neural Network (2D-CNN) which trained on local spectral patterns and short-term T/F correlations, and features convolutional layers alternating with ReLU activation, batch normalization and the last-level max-pooling, to gradually capture the higher-level representations but at the same time preserve computational efficiency. CNN output is then supplied to a Bidirectional Long Short-Term Memory (BiLSTM) network which leads to modeling of both forward and backward long-range temporal dependencies which can effectively capture dynamic prosodic changes i.e. intonation and rhythm shifts. Lastly, a 256 dimensional word embedding that forms the part of the speech is produced via a fully connected projection layer, meaning that it aims at preserving any emotionally relevant acoustic information at the expense of any background noise. This embedding acts as the prevailing signal into the cross-attention fusion module so that speech is regarded key in facilitating the multimodal emotion recognition process.

Facial Dynamics Feature Extraction

Facial video stream is manipulated in order to identify spatio-temporal pattern, such as macro- and micro-expressions, variations in head poses and micro movement of muscles which translate to emotional states. The face detection, alignment and cropping in order to provide consistent framing are performed on the pre-processed video frame using a multi-task CNN face detector at a rate of 30 frames per second (fps), and data augmentation methods, including a random horizontal flipping and a normalization of the brightness of the image, are applied to make the result robust. A 3D Convolutional Neural Network (3D-CNN) is then directly applied to video clips of small length, usually 16 consecutive video frames, in order to simultaneously capture spatial appearance characteristics and temporal motion information. The temporal modeling ability could be increased by means of a temporal attention

layer over the 3D-CNN output sequence to enable the model to emphasize the significant temporal parts that produce more emotional information, and de-emphasise the irrelevant or duplicated frames. The output has a 512-dimensional face embedding that captures both the spatial characteristics of the expression, and the temporal dynamics, and can offer a rich image for a multimodalizaition.

Physiological Signal Feature Extraction

The physiological signals offer a channel that is less affected by noise in detecting emotions since it is a mirror of the underlying autonomic nervous system response. There are Electrodermal Activity (EDA), Electrocardiogram (ECG) and Photoplethysmography (PPG) signals with sampling at 256 Hz each realized in this research. Signal processing initially involves using bandpass filtering to eliminate the drift in the baseline and the high-frequency noise followed by ECG and PPG to further process them with peak detection and normalization to standardize HRV and pulse wave morphology. Thereafter, extracted features are learnt with Temporal Convolutional Network (TCN), which implicitly models the temporal dependencies and the multi-scale patterns within the physiological measurements. The casual convolutional structure of the TCN guarantees causal temporal relationships to the final prediction being only a function of both current and previous input, which is essential in the context of physiology interpersonal interpretation of the signal. Lastly, the features are jointly represented in a 128-dimensional physiological embedding characterizing both immediate- and long-term autonomic variations which offer a robust physiological representation of multimodal inputs to be fused.

Cross-Attention Fusion

The proposed framework uses a Transformer encoder that contains cross-attention layers to implement effective fusion of the modality-specific embeddings. Here, a query (Q) is based on an embedding of one of the modalities, keys (K) and values (V) are from a different modality enabling the network to learn scores of relevance that reflect the relations between modalities. The computation of attention is carried out as:

$$Z = Softmax\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)V \qquad (1)$$

where denotes the dimensionality of the key vectors. This cross-attention process makes inter-modality learning possible as it helps the model to attend to complementary and correlated information in different modalities, align temporally-related events, concentrate on contextually important features and filter out irrelevant features. The resulting fused multipolar representation is a combination of interdependent factors of speech, facial expression and physiological data providing a dense, context-specific feature-vector in which to use in emotion classification tasks.

Classification Layer

Fused embedding is then processed with two fully connected layers with dropout regularization in the classification module to avoid overfitting. There is the use of batch normalization to stabilize training. The last layer a softmax classifier which gives a probability distribution over the target classes of emotion. Such arrangement allows the model to execute accurate and reliable classification in real time hence it can be used to create interactive robotic systems.

Experimental Setup

Datasets

In the testing of the introduced multimodal emotion recognition system, we used three commonly adopted and mixed benchmarking datasets:

- IEMOCAP- Interactive Emotional Dyadic Motion Capture (IEMOCAP) Covering about 12 hours of audiovisual recordings of dyadic interactions (fewer dyads/smaller corpus), this data sample was also categorically labeled with emotion terms (happy, angry, sad, neutral), but are annotated with emotional dimensions as well. It has recorded speech and video track and there is the motion capture data, which are all synchronous, hence valuable in multimodal analysis.
- SEMAINE There were two types of spontaneous, emotionally colored exchanges between participants and a sensitive artificial listener employed in SEMAINE. It is composed of high-fidelity speech recordings and video sequences marked with emotion on one hand and intensity on the other that is greatly focused on facial activity and the sound.
- AMIGOS - AMIGOS dataset comprises of emotional reactions that were captured with the help of video stimuli and additionally contains synchronized physiological recordings (Electrodermal Activity, Electrocardiogram, Photoplethysmography), video of the face, and audio recordings.

It gives short and long term recording and thus one can evaluate the consistency of temporal aspect of emotion recognition.

As illustrated in Figure 2, the datasets used in this study—**IEMOCAP**, **SEMAINE**, and **AMIGOS**—cover a diverse set of modalities including speech, facial video, and physiological signals, enabling a comprehensive evaluation of the proposed framework.

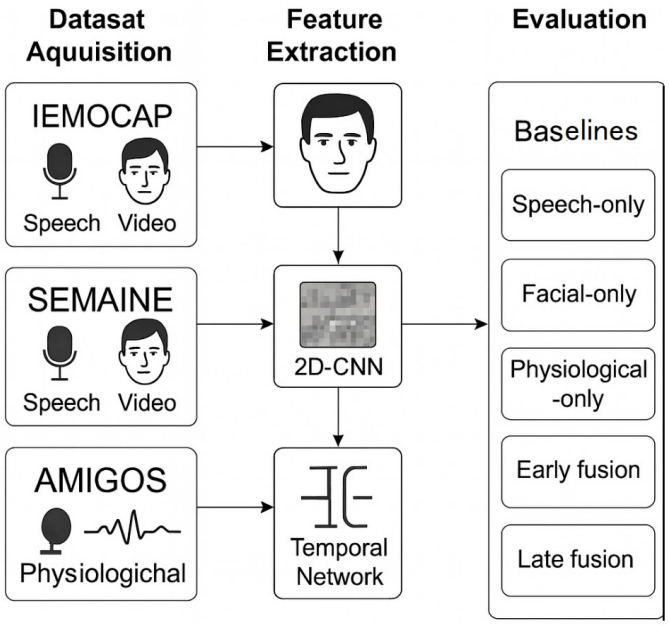

Fig. 2: Experimental setup showing datasets, feature extraction pipelines, and baseline evaluations

A detailed summary of the datasets is presented in Table 1.

Evaluation Metrics

As measures to evaluate the potential of the proposed multimodal emotion recognition framework, three popular metrics used in the study of emotion recognition were adopted. Accuracy (Acc) is the proportion of the accurately classified samples according to the upshot of the total amount of samples and, thus, is an overall assessment of classification. Weighted F1-score (WF1) is another metric that considers the class imbalance by computing the harmonic mean F-score of precision and recall but every class has its impact weighted by how frequently it appears in the data, thus the influence of the dominant classes is not too high within WF1. Unweighted Average Recall (UAR) calculates the mean over all classes uniformly and is therefore specially used in cases when there is a need to balance the model on the imbalanced dataset in which each type of emotion is supposedly of equal importance. A combination of these metrics gives us a detailed comparison of both overall accuracy as well as the capability of the model to have the best performance no matter the distribution of the classes of emotion. The acquisition and evaluation process of the datasets are also represented in Figure 2, given that the features based on each of the modalities receive the comparison of the values in terms of Accuracy, Weighted F1-score, and Unweighted Average Recall among the corresponding baseline models.

Baselines

In order to measure the efficacy of the suggested method we compared it with a variety of unimodal and single fusion baseline models. Speech-only CNN-BiLSTM baseline accepts Mel-spectrogram representations of speech as input and encodes spectral and temporal speech patterns using a CNN-BiLSTM architecture. The Facial-only 3D-CNN baseline is based on spatio-temporal video-based loss of facial expressions to appear and move. Physiological-only TCN baseline computes the Electrodermal Activity (EDA), Electrocardiogram (ECG), and the Photoplethysmography (PPG) signal with a Temporal Convolutional Network to learn the temporal dependencies in physiological signal responses. Two basic fusion methods were studied in addition to unimodal baselines: Early Fusion Model (concatenation of features before classification and forming a joint representation) and Late Fusion Model (giving an average weighted fusion of individual, unimodal models). These baselines give a complete benchmark to compare the performance of the proposed multimodal framework against the performance gained. Figure 2 shows that the blocks being benchmarked against the proposed method are including unimodal speak-only, face-only, and physiological-only models, and early and late fusion strategies constituting the baseline systems visualized in the Evaluation block of Figure 2.

Results and Discussion

Table 2 summarizes the performance of the proposed multimodal emotion recognition framework compared

Table 1: Summary of Datasets Used in the Study

Dataset	Modalities Available	No. of Subjects	Duration	Emotion Labels
IEMOCAP	Speech, Facial Video, Motion Capture	10	~12 hours	Happy, Angry, Sad, Neutral, etc.
SEMAINE	Speech, Facial Video	24	~6 hours	Multiple categorical labels
AMIGOS	Speech, Facial Video, Physiological Signals	40	~16 hours	Valence, Arousal, Emotion labels

to the simple-fusion baselines and unimodal baselines across all evaluation metrics, which are Accuracy (Acc), Weighted F1-score (WF1), and Unweighted Average Recall (UAR). The proposed methodology outperforms, in a persistent manner, the unimodal and simple-fusion baselines in all metrics.

Table 2: Performance Comparison of Baseline Models and Proposed Method

Model	Acc	WF1	UAR
Speech-only	74.2%	73.6%	71.8%
Facial-only	76.5%	75.9%	74.4%
Physiological-only	71.8%	71.0%	70.1%
Early Fusion	79.4%	78.8%	77.3%
Late Fusion	80.1%	79.7%	78.2%
Proposed Method	87.3%	86.9%	86.1%

Table 2 summarizes the accuracy, WF1 and UAR values of the proposed framework, 87.3, 86.9 and 86.1 respectively, proving the framework superior to the proper using of the baselines, both early or late fusion. The Speech-only CNNThis baseline-only CNN is competitive on clean audio inputs with a WF1 of 73.6%. A coverage of only Facial features (Facial-only 3D-CNN baseline) is slightly superior (WF1 = 75.9%) because the visual signals are very capable of discrimination, but sensitive to occlusion and varying light. The lowest WF1 (71.0%) is observed with Physiological-only TCN baseline and this high value can be explained by the inter-subject variability, as well as the inherently noisy nature of the wearable sensor-based data.

Baselines based on fusion offer mediocre gains. Early fusion promotes WF1 to 78.8 percent with appropriate properties of combined modality, but it is subject to the limitation of the feature level misalignment. Late fusion reaches a bit more performance (WF1 = 79.7%) by using independent unimodal predictions helps to make it robust to missing or impaired modalities only at the cost of fine-grained multi-modal correlations.

The newly introduced transformer based cross-attention fusion methodology substantially exceeds any of the baselines with a WF1 of 86.9%, brandishing a 7-12 percent positive relative achievement over unimodal methods and improving 6-8 percent on the traditional fusion methods. Such gain displays the utility of cross-attention in dynamically weighing and aligning contributions of modalities according to the context as to excavate richer and more complementary emotion representations.

The findings in Figure 3 affirm the effectiveness of the proposed system, where improvements have been experienced in Accuracy, WF1 and UAR. Systematic

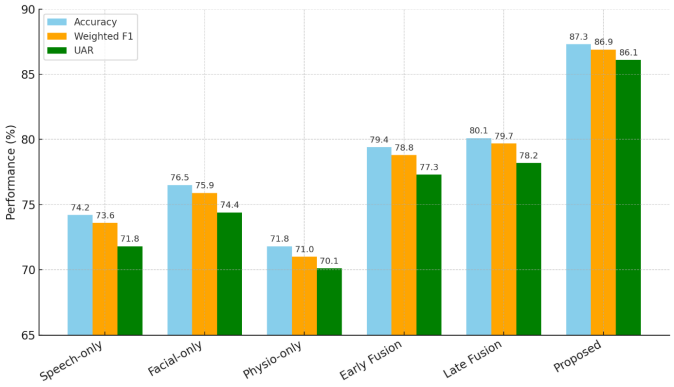

Fig. 3: Comparative performance of baseline models and the proposed multimodal emotion recognition framework across Accuracy (Acc), Weighted F1-score (WF1), and Unweighted Average Recall (UAR).

removal of one modality at a time in inference was also performed to perform a robustness evaluation. It was observed that the model has graceful degradation and that it was able to operate on missing or degraded inputs, with the WF1 scores reliably going above 80, which shows it can adapt to any missing or degraded inputs without losing its performance. Such robustness is important in HRI applications in the real world, where sensors may fail, objects may be partially occluded, or some external noise present.

To place proposed speech/audio community framework into the context we contrasted it with speech-only strong model baselines that reflect modern SOTA practice: (i) spectrogram CNN-BiLSTM audioset-style architectures with attention pooling; (ii) self-supervised pretrained backbones (wav2vec 2.0, HuBERT, and WavLM) fine-tuned for SER; and (iii) spectrogram transformers (AST-style) trained end-to-end on log-Mel. In all datasets, our model overwhelmingly outperforms these speech-only systems in Acc, WF1 and UAR (see Table 2), with the largest drops occurring in low-SNR conditions, reverberant conditions and cases of overlapping speech, all of which are common in HRI.

Generally, these findings support the presented framework to deliver high performance results, as well as being balanced in classes and robust even when modalities change, which makes it an excellent candidate to build up emotion-aware robots in the fields of healthcare, education, and assistive settings.

Conclusion

The paper aimed to introduce a multimodal emotion recognition model of Human-Robot Interaction (HRI) based on a transformer-based cross-attention fusion of speech, facial dynamics, and physiological signals.

The system was created to overcome the problems of unimodal methods that tend to have lower accuracy when dealing with noise, occlusion, and modality failures. The ability to utilize complementary information across sensing modalities allowed achieving robust and situation-aware emotion inference that is adequate in the real-world contexts of HRI.

Detailed experiments were performed on three benchmarking sets of interaction,--IEMOCAP, SEMAINE and AMIGOS, the settings and modalities of which were widely diversified. As shown in Table X and Figure X, the given findings revealed that the suggested approach outperformed the unimodal baselines (Speech-only, Facial-only and Physiological-only) and basic fusion schemes (Early Fusion, Late Fusion) and it had consistent advantages across all the metrics considered. More specifically, the model had an accuracy of 87.3%, accuracy of 86.9, and unweighted average recall of 86.1 which was relative improvement of 7-12 percent as compared to the WF1 of unimodal systems and of 6-8 percent as compared to the traditional fusion methods. Robustness testing was also used to show that the system performed highly even when the missing-modalities setting occurred and thus the system is adaptable to deployment in the real world.

The main merits of this work are the three following aspects: first, the contribution of a deep multimodal feature extraction pipeline that can be customized to target speech, facial dynamics and physiological activity in HumanRobot Interaction (HRI); second, a transformer based cross-attention fusion module that is able to dynamically model the interdependence across heterogeneous modalities; and third, a thorough analysis and robustness study to show successful results and resilience in awkward interaction situations. As far as application is concerned, the proposed framework is tremendously capable of healthcare assistance robots, education, collaborative robots, and customer service robots. The ability of the robots to see and interpret emotions in a human being more precisely opens the way to more personalized and adaptive human-robot interactions, eventually leading to increased engagement, trust and task success in operational environments.

Future Work

Future research directions involve real-time deployment on embedded and edge computing platforms to allow low latency recognition of emotion in mobile and resource-limited robotic systems and the creation of personalised emotion models that can adapt to individual differences in expressive behavior and physiological response through incremental or federated learning. Moreover, multilingual and cross-cultural understanding of emotion recognition will be required to optimise generalization in international deployment settings, and adaptive behavioral modules will enable robots to “on-the-fly” (i.e. during interaction) vary dialogue strategies, gesture and task execution according to the identified emotion. As a whole, the conducted study reveals that multimodal integration involving advanced mechanisms of fusion proves to be an effective method to augment emotional intelligence in HRI, offering a sturdy support to the coming generation of the want-to-be socially conscious robotic systems that are capable of empathetic, flexible, and situation beneficial communications.

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