Abstract—Multimodal emotion recognition is the task of detecting emotions present in user-generated multimedia content. Such resources contain complementary information in multiple modalities. A stiff challenge often faced is the complexity associated with feature-level fusion of these heterogeneous modes. In this paper, we propose a new feature-level fusion method based on self-attention mechanism. We also compare it with traditional fusion methods such as concatenation, outer-product, etc. Analyzed using textual and speech (audio) modalities, our results suggest that the proposed fusion method outperforms others in the context of utterance-level emotion recognition in videos.

I. INTRODUCTION

Infusion of the Internet in our lives and the subsequent presence of various online platforms has triggered the proliferation of user-generated multimedia content like videos. These videos often contain emotional content and act as useful resources for large-scale emotion detection. Affect and emotion detection is a significant pattern recognition problem that has emerged as an area of research for several domains like opinion-mining, healthcare, dialogue systems, etc. Traditional approaches for emotion detection in videos exploit individual modalities such as visual or audio signals. However, recent research has shifted its focus to multimodal processing which leverages information from multiple modalities. Linguistic information present in video transcripts along with para-linguistic traits present in speech (audio) provides excellent cues for detection of underlying affective states [1]. In this paper, we explore the role of these two sources in the task of emotion detection.

Utilizing multiple modalities brings forth the task of fusing these information channels for a unified prediction. This can be done in three ways, i.e., early, late or hybrid-fusion. Owing to the heterogeneity of the modalities, feature-level fusion has posed to be the most difficult amongst these methods.

In this paper, we propose a self-attention based fusion method. We hypothesize that an attention mechanism would be able to assign appropriate scores to the modalities. These scores would then be used as weights for a weighted combination. We also provide detailed analysis of multiple traditional fusion methods (element-wise addition/multiplication, outer-product, and concatenation.) and compare their effectiveness against our proposed method. Through this comparative analysis, we hope to aid researchers in choosing an appropriate method for feature-level fusion.

In the remaining paper, Section II enlists the related works; Section III introduces the multimodal approach for emotion recognition, including details of our proposed self-attentive feature-level fusion method. Section IV then provides experimental details, results and comparative analysis of the fusion variants. Finally, Section V concludes the paper.

II. RELATED WORKS

Emotion recognition as a field of research has seen contributions across several domains like machine learning, natural language processing, neuroscience, etc. [2]. Early works have individually explored facial expressions, auditory features and textual data as universal indicators of emotions [3, 4]. However, later works incurred improvements using combinations of these signals [5]. In the recent past, multimodal systems have dominated this field providing state-of-the-art networks. These systems typically use audio, visual and textual data and fuse them to get multimodal features [6]. A comprehensive review of such systems can be found in [7]. The advantage of decision-level fusion lies in the fact that the data to be fused is of similar type (predicted labels).

Multimodal fusion consists of combining data from various modalities. Such fusion can be done in three ways, i.e., early, late or hybrid-fusion. Amongst these, late or decision-level fusion involves the construction of multiple classifiers for each modality followed by a combination of their decisions to get a prediction. Various approaches such as Kalman-filters or weighted products are used for such fusion [8]. Early or feature-level fusion, on the other hand, requires the fusion of the feature representations in a single classifier [9, 10]. Considered to be more complex, works performing such fusion utilize numerous techniques such as concatenation [11], element-wise addition, inner/output product [12], etc. Combining both approaches we get hybrid-fusion [13]. In this paper, we focus on feature-level fusion and provide a deep analysis of its methods in our experiments. Similar analysis has been provided in [14], where they compare pooling methods in the context of valence prediction. Our work differs in the fact that we explore the domain of predicting emotion categories instead of valence and provide comparisons with our novel attention-based fusion.
Attention modules are an integral part of modern neural systems applied in various tasks [15, 16]. However, very few works have utilized attention for fusion [17]. Our work is different from [17] as we use self-attention mechanism whereas they utilize query-based attention to generate descriptions of a video (see Section III-C1). In another work [18], attention-based fusion between visual and audio signals is performed at the frame level. However, we posit that frame-level processing is not ideal for this task due to the presence of temporal-asynchrony between modalities. We thus, perform our analyses on video-level features for each utterance.

III. METHOD

In this section, we define the architecture of our system (Figure 1). We first describe the feature extractors for textual (III-A) and audio (III-B) modalities. This is followed by a general description of query-based attention (III-C1). We then propose two variants of self-attention mechanism for multimodal fusion, uni/multi-dimensional self-attentive fusion.

A. Textual features

Let us take an utterance video $U$ whose textual modality is its transcript, i.e., a sentence $S = [w_1, w_2, ..., w_n]$ composed of $n$ words. To extract textual features, we use a Convolutional Neural Network (CNN). CNNs generate abstract representations of text by extracting location-invariant local patterns.

Each word $w_i \in \mathbb{R}^V$ is initially represented as a one-hot vector of dimension $V$ which denotes the size of the vocabulary. This creates sparse word vectors that suffer from the curse of dimensionality. To overcome this issue, we embed the words into low-dimensional real-valued vectors, popularly known as word embeddings. We use the pre-trained FastText [19] embedding dictionary as $W_{em} \in \mathbb{R}^{d_{em} \times V}$. Word embeddings can then be computed as $x_i = W_{em} w_i \in \mathbb{R}^{d_{em}}$, transforming $S$ into a sequence of vectors $X = [x_1, x_2, ..., x_n]$.

We apply a single-layered CNN on $X$ [20]. Its convolution layer contains three filters $F_1 \in \mathbb{R}^{d_{em} \times h_1}, F_2 \in \mathbb{R}^{d_{em} \times h_2}$, and $F_3 \in \mathbb{R}^{d_{em} \times h_3}$ of heights $h_1, h_2,$ and $h_3$, respectively. Each filter $F_i$ slides across the input sequence and extracts $h_i$-gram features at each instance. This constitutes a feature map vector $m_i$ of size $\mathbb{R}^{[X] - h_i + 1}$, whose each entry $m_{i,j}$ is obtained as,

$$m_{i,j} = \alpha(F_i \cdot X_{[j:j+h_i-1]} + b_i)$$

with $j = 1, ..., ([X] - h_i + 1)$. Here, $b_i \in \mathbb{R}$ is the bias and $\alpha(\cdot)$ is a non-linear activation function. Each filter $F_i$ is used to create $M$ such feature maps thus giving a total of $3M$ feature maps. Following this, we apply max-pooling operation across the length of each of the $M$ feature map vectors of Filter $F_i$. This results in an output vector $o_i \in \mathbb{R}^M$ which is denoted as,

$$o_i = \left[ \max(m_1^i), ..., \max(m_M^i) \right]$$

Next, we concatenate each $o_i$ to get $o = [o_1 \oplus o_2 \oplus o_3] \in \mathbb{R}^{3M}$, where $\oplus$ represents concatenation and then follow it with another dense layer with $d_3$ neurons. This generates the overall textual representation $t_u \in \mathbb{R}^{d_3}$ for utterance $U$ as,

$$t_u = \alpha(W_t o + b_t)$$

where, $W_t \in \mathbb{R}^{d_3 \times 3M}$ and $b_t \in \mathbb{R}^{d_3}$ are projection parameters.

B. Audio features

To extract the audio features for an utterance video $U$, we consider its audio in 16-bit PCM WAV format. We extract informative features from this audio by using the open-source tool openSMILE\(^1\). openSMILE provides high dimensional audio vectors comprising of features such as loudness, pitch, voice quality (jitter, shimmer), Mel-spectra, MFCC, etc. These extracted features for the entire utterance video are represented in a bag-of-words format to summarize the whole audio signal. This summarized vector of statistical measures thus contains indicative features that have a direct correlation to the emotional state of the speaker [21]. Earlier findings in the literature also suggest the existence of such correlations [22]. For example, anger is often denoted by fast speaking and high pitch. Whereas, slow speech rates and low pitch deviation relate to sadness. We call this feature vector as $a_{in}$.

To get $a_{in}$, we use the IS13_ComParE configuration file which contains a total of 6373 audio features. Similar to one-hot vectors (Section III-A), these high dimensional vectors explode the parameter sizes. We thus project these feature vectors into a dense neural layer to generate the audio feature vector $a_u$ for utterance $U$.

$$a_u = \alpha(W_a a_{in} + b_u)$$

\(^1\)http://audeering.com/technology/opensmile
where, \( W_a \in \mathbb{R}^{d_a \times 6373} \), \( b_a \in \mathbb{R}^{d_a} \) and \( d_a \) refers to the dimension of \( a_u \). As before, \( \alpha(\cdot) \) represents non-linear activation.

C. Attention

Attention modules, inspired from human visual-attention, present a mechanism to infer the relative importance of a set of memories with respect to a given query. Given that it provides complete differentiability and interpretability to observe where a network focuses, it presently serves as a default component in many state-of-the-art neural applications. Content-based attention mechanisms allow networks to scan through memory components and filter the ones which match with a given query. They can either be performed as hard-attention, where only a subset of memories are focused upon, or as soft-attention where a probability distribution signifying importance is assigned over all the memories. We chose the latter format in our further considerations.

Below, we first describe the general format of the attention mechanism which uses an explicit query. This is followed by the two self-attention schemes that we propose as feature-level fusion techniques.

1) Query-based Attention: Given an input element sequence \( E = [e_1, ..., e_n] \), this mechanism takes a query vector \( q \) and computes the alignment score with respect to each element \( e_i \) belonging to \( E \). In particular, this score is computed using a compatibility function \( f(e_i, q) \). Different compatibility functions have been proposed in the literature [15, 23]. The common compatibility function based on addition and multiplication are measured as,

\[
\begin{align*}
    f(e_i, q) &= w^T_{\text{attn}} \beta(W_{\text{attn}}(e_i + q) + b_{\text{attn}}) \quad (5) \\
    f(e_i, q) &= w^T_{\text{attn}} \beta(W_{\text{attn}}(e_i \times q) + b_{\text{attn}}) \quad (6)
\end{align*}
\]

where \( w_{\text{attn}}, W_{\text{attn}}, \text{and } b_{\text{attn}} \) are parameters in this auxiliary attention network, \( \times \) represents element-wise multiplication and \( \beta(\cdot) \) is a non-linear activation function.

Further, a softmax operation is applied to all the scores \([f(e_i, q)]_{i=1}^{n}\) to convert it into a probability distribution. We denote this distribution as \( p(z \mid E, q) \) where \( z \) is a random variable ranging from 1 to \( n \) with \( p(z = i \mid E, q) \) representing the importance of element \( e_i \) with respect to query \( q \).

The above process can be summarized by the following equations.

\[
\begin{align*}
    a &= [f(e_i, q)]_{i=1}^{n} \quad (7) \\
    p(z = i \mid E, q) &= \text{softmax}(a_i) = \frac{\exp(f(e_i, q))}{\sum_{j=1}^{n} \exp(f(e_j, q))} \quad (8)
\end{align*}
\]

Finally, these probability scores given by \( p(z \mid E, q) \) are used to perform a weighted sum of the input elements to get an overall representation that caters to the provided query. The whole pipeline of this attention framework is summarized in Figure 2a.

2) Self-Attention: Self-Attention is a special case of the general Query-based Attention where the external query \( q \) is generally replaced by another input element \( e_j \). Thus attention scores are calculated against each input element pair \( e_i \) and \( e_j \). A specific case of this setting is when the query is removed altogether. This forces the input elements to explore their dependency with the global representation of the sequence itself. This alleviates the need to provide a compatibility function, which is now derived implicitly from supervision provided by the final loss in the neural network. We focus in this kind of self-attention framework in our analyses. Below, we describe two versions of this attention framework.

a) Uni-dimensional Self-Attention (uSA): This particular setting is similar to Query-based Attention in the sense that both generate scalar scores for each input element \( e_i \). The attention score generation and the subsequent probability distribution \( p(z \mid E) \) for a given input element sequence \( E = [e_1, ..., e_n] \) is performed as follows,

\[
\begin{align*}
    f(e_i) &= w^T_{\text{attn}} \beta(W_{\text{attn}}e_i + b_{\text{attn}}) \quad (9) \\
    a &= [f(e_i)]_{i=1}^{n} \quad (10) \\
    p(z \mid E) &= \text{softmax}(a) \quad (11)
\end{align*}
\]
b) Multi-dimensional Self-Attention (mSA): This variant is an extension of the uSA, where instead of calculating a scalar score \( f(e_i) \) for each input element \( e_i \), we calculate attention scores for each feature of \( e_i \), i.e., \( f(e_i) \) is now a vector of dimensions \( \mathbb{R}^{d_e} \) where \( d_e \) is the dimension size of each input vector \( e_i \). This is achieved by replacing the vector parameter \( W_{attn} \) in Equation 9 with another matrix parameter \( W_{attn}^{(1)} \in \mathbb{R}^{d_e \times d_e} \). The motivation for this mechanism is to allow fine-grained control over the attention-weighing scheme which now functions at the feature level. The overall transformation process of mSA is summarized below,

\[
\begin{align*}
\hat{f}(e_i) &= W^{(1)}_{attn}\beta(W_{attn}e_i + b_{attn}) \\
\hat{a}_k &= [\hat{f}(e_i)]_k
\end{align*}
\]

(12)

\[
p(z_k | E) = \text{softmax}(\hat{a}_k)
\]

(13)

Here, \( k \in [d_e] \) and \( \hat{f}(e_i)_k, p(z_k | E) \) represents the score vector and probability distribution for the \( k^{\text{th}} \) dimension, respectively. This attention scheme is summarized in Figure 2c.

3) Multimodal attention fusion: Here we describe the process of applying either uSA or mSA as a feature-fusion method on the extracted unimodal features \( t_u \in \mathbb{R}^{d_t} \) and \( a_u \in \mathbb{R}^{d_a} \). For the sake of applicability, we first set \( d = d_t = d_a \). Following this, we model the input element sequence as \( E = [e_1 = t_u, e_2 = a_u] \) and apply the transformations mentioned in Equations 9-11 or Equations 12-14. This generates the probability distribution \( p(z) | E \) or \( [p(z) | E]_{k=1}^{d_e} \) for uSA and mSA, respectively. We then create the fused vector \( s_u \in \mathbb{R}^d \) by performing a weighted addition using these attention score probabilities. For uSA, the output vector \( s_u \) is calculated as,

\[
s_u = P_t \odot t_u + P_a \odot a_u
\]

(15)

where \( P_i = p(z = i | E) \) is a scalar which is broadcasted across \( d \) dimensions and \( \odot \) represents element-wise multiplication. Similarly, for mSA, the \( k^{\text{th}} \) element of \( s_u \), i.e., \( s_u[k] \) is calculated as,

\[
s_u[k] = P_{k,1} \odot t_u[k] + P_{k,2} \odot a_u[k]
\]

(16)

where \( P_{k,i} = p(z_k = i | [t_u, a_u]) \).

D. Final Prediction

After the generation of the fused vector \( s_u \), we proceed towards the classification of the emotion category by first projecting it to another dense layer which is followed by a softmax classification (Figure 1). This is summarized below,

\[
\hat{y} = \text{softmax}(W_f s_u + b_f)
\]

(17)

where, \( W_f \in \mathbb{R}^{C \times d} \) and \( b_f \in \mathbb{R}^{C} \) are parameters and \( C \) is the number of label classes. Batch-loss for backpropagation-based training is calculated using categorical cross-entropy,

\[
\text{Loss} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} y_{i,j} \log(\hat{y}_{i,j})
\]

(18)

Here, \( N \) is the total utterances in a batch and \( C \) is the number of emotion categories. \( y_i \) represents one-hot ground truth vector of \( i^{\text{th}} \) utterance from the training batch and \( \hat{y}_{i,j} \) denotes the predicted probability of class \( j \) for the same utterance.

IV. EXPERIMENTATION

A. Dataset

IEMOCAP\(^2\) [24] is a multimodal dataset consisting of two-way dyadic conversations among 10 speakers (5 male and 5 female). The conversational videos are then segmented into utterances which result in smaller utterance videos. Each utterance is annotated using one of the following emotion tags: anger, happiness, sadness, neutral. To avoid speaker overlap in the training and testing set, we consider the conversations by first 8 speakers as the training fold and remaining as testing fold. In summary, the training and testing set comprises of 4290 utterances (from 120 conversational videos) and 1208 utterances (from 31 conversational videos), respectively.

B. Training Details

We use 10% of the training set as a held-out validation set for hyper-parameter tuning. To optimize the parameters, we use Adam optimizer [25], starting with an initial learning rate of 0.01. Termination is decided using an early-stop measure with a patience of 10 by monitoring the validation loss. Hyper-parameters are decided using Random Search [26]. The values of the hyper-parameters are summarized in Table I.

<table>
<thead>
<tr>
<th>( \alpha, \beta )</th>
<th>( d_{emb} )</th>
<th>( h_1, h_2, h_3 )</th>
<th>( M )</th>
<th>( d_t, d_a )</th>
</tr>
</thead>
<tbody>
<tr>
<td>ReLU</td>
<td>300</td>
<td>3,4,5</td>
<td>50</td>
<td>100</td>
</tr>
</tbody>
</table>

TABLE I: Hyper-parameter values set in the training stage.

C. Fusion Variants

In this section we introduce the variants that we analyze for feature-level fusion. Specifically, we discuss the methods to generate fusion vector \( s_u \).

a) Element-wise addition: Here we fuse the textual and audio representations using element-wise addition of the vectors \( t_u \) and \( a_u \). Thus \( s_u \) is calculated as,

\[
s_u[k] = t_u[k] + a_u[k], \forall k \in [1,d]
\]

(19)

b) Element-wise multiplication: The fusion process here involves the element-wise multiplication (also known as Hadamard product) of \( t_u \) and \( a_u \). Similar to element-wise addition,

\[
s_u[k] = t_u[k] \ast a_u[k], \forall k \in [1,d]
\]

(20)

c) Outer-Product: This method corresponds to the pairwise product of each feature from \( t_u \) and \( a_u \). Such mutual combination provides a rich feature set. This is especially beneficial since input representations’ features (individual dimensions) often do not align as they do not belong to the same hyper-space. Mathematically, outer-product is represented as,

\[
s_u = \text{flatten}(t_u a_u^T)
\]

(21)

Here, \( s_u \in \mathbb{R}^{d^2} \) and \( \text{flatten}() \) is a function that unravels a matrix into a vector following column-first order.

\(^2\)http://sail.usc.edu/iemocap/
A. Noise Stability

An important functionality of feature-level fusion methods is their stability against noisy inputs. To test the robustness of our proposed fusion methods $uSA$ and $mSA$, we simulate noisy signals in the testing set. In particular, we inject zero-mean Gaussian noise to either of the modalities while keeping the other one pure and test the performance of our system. Training of the models is done as before, i.e., without noise. Table II provides the UAR results for different levels of induced noise either in textual or audio modality. Here, we see an expected dip in performance with the increase in noise (increase of standard deviation) for both modalities. Both the $uSA$ and $mSA$-based systems provided better resistance to degradation in the case of textual pollution. This shows the importance of audio modality which provides complementary information despite textual unimodal being a better classifier. Also, $mSA$ performs better than $uSA$ in the presence of noise. Its ability to weigh modalities at the feature level provides it with this extra stability. However, degradation of the system with the increase of noise in a particular channel is unwanted and remains an open research problem.
In this paper, we proposed a novel self-attention based fusion procedure. Our results and comparative analysis reveal the capabilities of different fusion methods and also justify the superiority of our proposed attention scheme for feature-level fusion. We also performed a noise stability test where we found multi-dimensional attention module to perform best for fusion. Through this work, we aim to aid researchers in choosing the desired fusion procedure and hope for the adoption of our proposed fusion method in future multimodal systems.

ACKNOWLEDGMENT

This research has been supported in part by Singapore’s Ministry of Education (MOE) Academic Research Fund Tier 1, grant number T1 251RES1713.

REFERENCES