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To cite this version:
Mireille Fares, Catherine Pelachaud, Nicolas Obin. Transformer Network for Semantically-Aware and Speech-Driven Upper-Face Generation. EUSIPCO, 2022, Belgrade (Serbia), Serbia. hal-03996465

HAL Id: hal-03996465
https://hal.science/hal-03996465
Submitted on 20 Feb 2023

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Transformer Network for Semantically-Aware and Speech-Driven Upper-Face Generation

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Abstract—We propose a semantically-aware speech driven model to generate expressive and natural upper-facial and head motion for Embodied Conversational Agents (ECA). In this work, we aim to produce natural and continuous head motion and upper-facial gestures synchronized with speech. We propose a model that generates these gestures based on multimodal input features: the first modality is text, and the second one is speech prosody. Our model makes use of Transformers and Convolutions to map the multimodal features that correspond to an utterance to continuous eyebrows and head gestures. We conduct subjective and objective evaluations to validate our approach and compare it with state of the art.

Index Terms—Semantically and Speech Driven Gestures, Transformers, Visual Prosody, Embodied Conversational Agents

I. INTRODUCTION

A. Context

The human face is a key channel of communication in human-human interaction. During speech, humans spontaneously and continuously display various facial and head gestures that convey a large panel of information to the interlocutors. These gestures are known as "visual prosody" [1]: facial or head movement are produced in conjunction with verbal communication. During speech, the Fundamental Frequency (F0) variations and upper-facial movements are highly correlated [2]; they are the results of linguistic and conversational choices. Eyebrow motion can also occur during pauses. Another kinematic–acoustic relation that happens during production of speech is between F0 and head motion [2]. Natural and rhythmic head movements are one of the key factors in producing natural animations [3], [4].

B. Related works and our contributions

A large number of head motion generation systems has been proposed in previous works [5]–[11]. A variety of generative statistical models aimed to predict the multimodal behavior of a virtual agent. Hidden Markov Models (HMM) [5], Recurrent Neural Networks (RNN) [6], [11], and Dynamic Bayesian Networks (DBN) [9], [10] have been used to generate head motion from speech; Generative Adversarial Networks (GAN) have been proposed to produce facial gestures from speech [8], [12], [13] generates continuous 3D hand gestures based on acoustics and semantics. However, most of the aforementioned approaches exploit as input one modality only, namely speech, and neglect to render their approach using semantic information. Also, most of them focus only on facial expressions while the correlation between facial expressions and head movements are crucial to produce a natural behavior. For instance, [5]–[7], [10] do not generate eyebrow motion along with head motion, which are both correlated to F0 [2], and therefore are correlated to each other. On the other hand, transformer networks and attention mechanisms have been recently proved to be very efficient for sequence-to-sequence modelling, with particular advances for modelling multimodal processes. For instance, Transformers were previously used for translating speech to text (ASR) [14], [15], and multimodal learning of images based on text [16]. To overcome those limitations, we propose a novel approach for upper-facial and head gestures generation based on a multimodal transformer network. Our contributions can be listed as follows: 1) a transformer network operating on multi-modal input text and speech information in order to generate upper-facial and head movements, and 2) a cross-attention module that can efficiently exploit semantic and speech information.

The paper is organised as follows. The next section describes the proposed architecture of our model and its multimodal features. Then our objective and subjective evaluation experiments are presented including the LSTM-based Baseline Model. We finally discuss our results.

II. PROPOSED ARCHITECTURE

A. Multimodal Input/Output Features

The upper-facial movements and head rotations are represented by mean of Action Units (AUs) as defined in the Facial Action Coding Systems (FACS) [17] and 3D head angles. The work presented in this paper only considers the AUs that represent eyebrows movements which are: inner raise eyebrow AU1, outer raise eyebrow AU2, frown AU4, upper lid raiser AU5, cheek raiser AU6, and lid tightener AU7. Head rotations have three degrees of freedom, represented by the Euler angles roll, pitch and yaw. They are represented by RX, RY and RZ which are the rotation of the head with respect to the X, Y and Z axes. In this paper, F0 values were extracted from the speech signal at a 5ms audio frame rate, 1

1Video samples of our model's gestures predictions and other related material can be found in: https://github.com/mireillefares/VAAnimation/blob/main/README.md
linearly interpolated between unvoiced segments, and clipped to the range of 50 to 550Hz which represents the F0 range of human speech. Since F0, AU intensities (AU) and head rotations (R) are continuous, they were quantized to produce a finite set of discrete values to reduce the model size and energy consumption [18]. Finally, BERT word embeddings were extracted from the text transcription.

**B. Face Gesture Generation Model Architecture**

The proposed architecture aims at mapping multimodal speech and text feature sequence into continuous facial and head gestures. This problem is treated as a multimodal sequence-to-sequence problem, for which a transformer network operating at the word level is presented as illustrated in Fig.1 (a). The inputs and outputs of the transformer network consist of one feature vector for each word \( W \) of the input text sequence. The input text corresponds to an Inter-Pausal Unit (IPU) which is a sequence of words separated by silent pauses longer than 0.2 seconds. F0 input sequence as well as AU intensities \( AU \) and head rotations \( R \) output sequences have a variable length. We set the maximum F0 input sequence length to 100, and the maximum \( AU/R \) output length to 124. Shorter sequences were padded to the maximum length, and longer ones were truncated. In order to handle continuous flow of input and output information with different timing, the transformer is wrapped with a F0 encoder module at its input and to a \( AU/R \) decoder at its output. The objective of the F0 encoder is to encode the continuous F0-values at the word level and the objective of the \( AU/R \) decoder is to reconstruct the continuous values for \( AU \) and \( R \) from a word-level encoding. Each spoken word \( W \) is represented by a word-level F0 embedding vector \( X_W^{(1)} \) which at its turn corresponds to the sequence of F0-values \( X^{(1)} = (F0_1, \ldots, F0_{N_W}) \), where \( N_W \) is the number of F0-values corresponding to the spoken word \( W \); and \( X_W^{(2)} \) is the BERT word embedding vector corresponding to the spoken word \( W \) - including silences. Silences less than 0.2 secs may belong to IPUs. They do not have a contextual BERT embedding. Hence, we replaced them by a comma `,`. Each spoken word \( W \) is also represented by a word-level \( AU \) vector \( Y_{W,AU}^{(j)} \) (resp. \( R \) vector \( Y_{W,R}^{(j)} \)) which in turn corresponds to the sequence of values \( dY_{AU}^{(j)} = (AU_1^{(j)}, \ldots, AU_{N_W}^{(j)}) \) (resp. \( Y_{R}^{(j)} = (R_1^{(j)}, \ldots, R_{N_W}^{(j)}) \)) where \( j \) denotes the \( j^{th} \) \( AU/R \) and \( N_W \) the number \( AU/R \)-values corresponding to the word \( W \).

**F0 Encoder:** As depicted in Fig.1 (a), for each \( W \), three one-dimensional convolutional layers are applied to project the input F0 sequence \( X^{(1)}_W \) into a word-level representation of F0 contours covering local context of F0 variations. These convolutional layers include 64 filters, with a *kernel size* equal to 3. The generated output vector of the latter layers \( X^{(1)}_W \) is then fed as an input to the Transformer Encoder.

**Transformer Encoder:** The transformer encoder architecture is depicted in Fig.1 (b); it is similar to the one proposed in [19]. In our work, it is composed of a stack of \( N = 4 \) identical layers. Each layer has two sub-layers: the first one is a multi-head self attention mechanism with 4 *attention heads*, and the second one is a position-wise fully connected feed-forward network. As the original transformer encoder, we employ a residual connection around each of the 2 sub-layers, followed by layer normalization.

**Cross-Modality Attention Module (CMAM):** The output of the transformer encoder \( Z \), as well as \( X^{(2)}_W \) are fed as inputs to the Cross-Modality Attention Module (see Fig.1 (a)). This Module has the same structure as the Transformer Decoder in [19]. It generates a representation that can take into account both modalities, text and speech. The representation learning is done in a master/slave manner, where one modality - the master - is used to highlight the extracted features in the other modality - the slave. This module takes \( X^{(2)}_W \) - Text Modality - as master, and \( Z \) - Speech Modality - as slave. Thus, it performs cross-attention such that the attention mask is derived from text modality, and is harnessed to leverage the latent features from the speech modality.

**Transformer Decoder:** The decoder is composed of \( N = 4 \)...
identical decoding layers, with 4 attention heads. Similar to the
one proposed in [19], it is composed of residual connections
applied around each of the sub-layers, followed by layer
normalization. As depicted in Fig.1 (c), the self-attention sub-
layer in the decoder stack is modified to prevent positions
from attending to subsequent positions. The output predictions
which are offset by one position, and this masking ensure
that the predictions for position index \( j \) depend only on the
known outputs at positions less than \( j \). We use 6 Transformer
Decoders, one for each AU/R. For simplicity, Fig.1 (a) only
illustrates one decoder.

**AU/R decoder:** As depicted in Fig.1 (a), the Transformer
Decoder outputs are concatenated together, then fed to 3 one-
dimensional convolutional layers that include 64 filters, with
a kernel size equal to 3, to learn the correlation between the
6 output features, and therefore the correlation between facial
and head movements. Finally, a Dense layer with a Softmax
activation function is applied on each of the outputs, to convert
the outputs to predicted next-token probabilities. The final
output sequences are \( Y_{AU} \) and \( Y_R \).

**Transformer Sub-Layers and Hyperparameters:** the
transformer encoder and decoders have attention sub-layers,
and contain fully connected feed-forward networks which are
applied to each position separately and identically. Similarly
to other sequence to sequence models, we use learned embed-
dings to convert the input tokens and output tokens to vectors
of dimension \( d_{model} = 64 \). All sub-layers and embedding
layers therefore use this dimension. The inner feed-forward
layers are of dimension \( d_{ff} = 400 \). Positional encodings are
applied to the inputs of the transformer encoder and decoders.
They have the same dimension as the embeddings, so that
they can be added together. We use sine and cosine functions,
similar to [19].

**III. Experiments**

**A. Material and Experimental Setups**

We trained it on a subset of the TED dataset collected
in [20], containing preprocessed AUs/R, F0s, and BERT
embeddings of filtered shots where speakers’ face and head
are visible and close to the camera. Our subset consists of the
features of 200 videos. Videos vary between 2 and 25 minutes,
with a frame rate of 24 FPS, the total numbers of IPUs is 919,
and of words is 62307. We shuffled all the IPUs, then split
them into: training set (80%), validation set (10%) and test set
(10%). There are two test conditions: SD (Speaker Dependent)
and SI (Speaker Independent). The SD condition aims to assess
to what extent the model can generalize on new sentences
pronounced by a speaker seen during training. We considered
them since evaluating AU activity looks similar to VAD evaluation.
We assessed the full model using the SD test set. We additionally evaluated its capacity
to generalize on the SI set. To evaluate the different parts of
our architecture, we conducted an ablation study as follows:
(1) speech ablation, (2) text ablation, (3) CMAM ablation, and
(4) AU/R decoder ablation. The ablation study was evaluated
using RMSE metric.

**B. Objective Evaluation**

To assess the quality of the generated gestures, we used
the following measures: Root Mean Squared Error (RMSE),
Pearson Correlation Coefficient (PCC), Activity Hit Ratio
(AHR) and Non-Activity Hit Ratio (NAHR). AHR and NAHR
were proposed by Freeman et al. [21], to evaluate the perfor-
mance of Voice Activity Detector (VAD) systems. We also
considered them since evaluating AU activity looks similar
to VAD evaluation. We considered an AU as “Activated”
when its value is greater than 0.5, otherwise it is “Not-
Activated”. AHR is the percentage of predicted AU activation
with respect to ground truth. If it is greater than 100%, it
means that the model is predicting more activation than
the amount of activation that is in the ground truth. NAHR
is the same but for non-activity. We assessed the full model
using the SD test set. We additionally evaluated its capacity
to generalize on the SI set. To evaluate the different parts of
our architecture, we conducted an ablation study as follows:
(1) speech ablation, (2) text ablation, (3) CMAM ablation, and
(4) AU/R decoder ablation. The ablation study was evaluated
using RMSE metric.

**C. Comparing to LSTM-based Baseline Model**

We compared our approach to a sequence to sequence
LSTM-based model [20] to predict upper-face movements
based on speech and text. This LSTM model [20] was de-
veloped only for predicting eyebrows movements (AUs).
We extended it to include head movements (R). This extended
model consists of mapping sequences of F0 and the Bert
embedding that correspond to a Word (W), to the sequences
of (AUs/R) of that corresponding W. It employs 2 layers of
Bidirectional LSTMs to encode the concatenation of word-
level F0 contours and Bert embeddings. The hidden internal
states are then transmitted to 6 decoders to produce the
corresponding AUs and R for a given input. The decoders
are followed by Dense Layers with Softmax Activation. The
hyperparameters of the extended LSTM model are as follows:
the first layer of bidirectional
LSTM has 200 units, and the second one has 100 units.
The activation function used in these layers is LeakyReLU
with \( \alpha = 0.01 \). We trained and tested this model using the same
training, validation and test sets described in Section III - A.
We trained it on 300 epochs, using a batch size = 128. We
used Root Mean Squared Propagation (RMSProp) optimizer,
and Categorical Cross Entropy Loss. We used the same metrics
described in III.B to compare this SOTA Baseline model to
our Transformer-based model.

**D. Subjective Evaluation**

To investigate human perception of the facial gestures pro-
duced by our model, we conducted two different experimental
<table>
<thead>
<tr>
<th>Prop. Transformer Model (SD)</th>
<th>SOTA Baseline (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>PCC</td>
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<td>AU02</td>
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<td>RY</td>
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<tr>
<td>RZ</td>
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</tr>
</tbody>
</table>

TABLE I: Objective Evaluation: comparison of proposed transformer model vs. SOTA baseline model

We additionally performed a post-hoc Fisher’s LSD Test to do pair-wise comparisons of the means between the factors of all conditions. Significant results ($p<0.001$) were found for...
all the factors when comparing the condition GT with the 3 other conditions and when comparing our model M with SOTA and E. In particular, there were significant differences between M and SOTA in terms of the 5 factors (p<0.007). This constitutes experimental validation that when used with SD data, condition M is perceived significantly better than SOTA and E for all the factors. The difference for the 5 factors between M and GT is not significant. For our second perceptive study conducted on SI data, Fig. 2 (b) shows the means scores obtained on all factors for conditions M and GT: for the 5 factors M is perceived as close to GT. As our data were not normally distributed (Shapiro test’s p<0.5), we conducted a post-hoc unpaired Wilcoxon test on each factor for the two conditions. For all tests, we could not find significant differences (p>0.05). Thus our model when used with SI data and GT received similar values for the 5 factors.

V. CONCLUSION

We have presented a new approach for modelling upper facial and head gestures using Transformer model. We conducted objective and subjective evaluations that showed that our model produces animations that are close to the ground truth in term of expressivity while ensuring that speech and computed gestures are aligned and synchronized. In a next future, we plan to expand our model to learn different speaker styles for gesture generation.

REFERENCES


