HUMBO: Bridging Response Generation and Facial Expression Synthesis

Shang-Yu Su*  Po-Wei Lin*  Yun-Nung Chen
Department of Computer Science and Information Engineering
National Taiwan University
{f05921117, r09922a24}@csie.ntu.edu.tw  y.v.chen@ieee.org

Abstract

Spoken dialogue systems that assist users to solve complex tasks such as movie ticket booking have become an emerging research topic in artificial intelligence and natural language processing areas. With a well-designed dialogue system as an intelligent personal assistant, people can accomplish certain tasks more easily via natural language interactions. Today there are several virtual intelligent assistants in the market; however, most systems only focus on textual or vocal interaction. In this paper, we present HUMBO, a system aiming at generating dialogue responses and simultaneously synthesize corresponding visual expressions on faces for better multimodal interaction. HUMBO can (1) let users determine the appearances of virtual assistants by a single image, and (2) generate coherent emotional utterances and facial expressions on the user-provided image. This is not only a brand new research direction but more importantly, an ultimate step toward more human-like virtual assistants.

1 Introduction

The recent advance of deep learning has inspired many applications of neural dialogue systems (Wen et al., 2017; Bordes et al., 2017). A typical dialogue system pipeline can be divided into several components: a speech recognizer that transcribes a user’s speech input into texts, a natural language understanding module (NLU) to classify the domain along with domain-specific intents and fill in a set of slots to form a semantic frame (Hakkani-Tür et al., 2016). Following a dialogue state tracking (DST) module that predicts the current dialogue state according to the multi-turn conversations, then the dialogue policy determines the system action for the next step given the current dialogue state (Su et al., 2018). Finally the semantic frame of the system action is then fed into a natural language generation (NLG) module to construct a response utterance to the user.

Nowadays, several virtual intelligent assistants show up in the market, such as Apple Siri, Google Assistant, Microsoft Cortana, and Amazon Alexa. However, most of these systems only focus on single or monotonous modality, such as textual or vocal interaction. Although the existing systems have shown capability of enabling users to perform basic information inquiries and helping simple daily activities, real human-human conversation actually involve multiple modalities of information. Communication between humans is complex and often requiring mixture of expression mode to easily precisely exchange information, for example, using both gestures and voice. Multimodal dialogues reflect more human-like behavior, however, this research topic is barely explored due to its difficulty in data collection, cross-modality reasoning, and various aspects. In this paper, we explores a brand new research direction, which aim to bridge response generation and facial expression synthesis. The idea is inspired by talking head tasks (Suwajanakorn et al., 2017), the line of research in synthe-
sizing talking faces from speech, in which the face is animated to mimic the continuous time-varying context (i.e. talking) and affective states carried in the speech.

The proposed task is to generate natural language utterances and then construct realistic faces based on the generated sequences. In other words, the synthesized facial expression should be relevant to certain semantic concept in the generated sentences, in this paper, we model the shared semantics of the two modalities by emotion. Since emotions are expressed through a combination of verbal and non-verbal channels, like gestures, facial expression, speech, and spoken content, therefore it could be viewed as the intersection and the bridge of various modes.

The proposed concept is a new research direction of multimodal dialogues and also an ultimate step towards more human-like virtual assistants. We believe such characterization (Figure 1) would be one of the important developing direction of chatbots in the future. We hereby propose HUMBO (HUMAN-like BO), a framework consisting of two main components: (1) a GAN-based facial expression generator, and (2) a GPT-based multi-task language generator. HUMBO can let users determine the appearances of virtual assistants by a single image, and generate coherent emotional utterances and facial expressions on the user-provided image.

2 HUMBO

In this section, we first describe the data preparation strategy and then detail the technology we adopted in HUMBO.

2.1 Data Preparation

In this work, we focus on response generation, however, most of the textual emotional datasets consist of emotion labels of only individual words, sentences or documents, which makes it challenging to discuss the contextual flow of emotions. Although the IEMOCAP database (Busso et al., 2008) provides emotion labels for each utterance, it was created by actors performing emotions, and hence carries the risk of overacting (Chen et al., 2018). Moreover, the annotators label the emotions by watching the videos instead of reading the transcripts, which means the annotators may make the decision only depend on the facial expression or the prosodic features without realizing the meaning of the words. Considering such potential bias, we decide to combine separate vision and language datasets according to our needs.

For language part, we choose the Emotion Detection dataset from Emory NLP (Zahiri and Choi, 2017), which is collected from the transcripts of the TV show Friends. The corpus comprises 97 episodes, 897 scenes, and 12,606 utterances, where each utterance is annotated with one emotion label. The emotions have 7 types in total, the six primary emotions in the Feeling Wheel (Willcox, 1982), sad, mad, scared, powerful, peaceful, joyful, and a default emotion of neutral. Each label was accomplished by 4 crowd workers, and for each utterance in a label, the emotion with the highest number of votes was set as the gold label of the utterance.

On the other hand, Radboud Faces Database (RaFD) (Langner et al., 2010) has 8 binary labels for facial expressions, namely sad, neutral, angry, contemptuous, disgusted, surprised, fearful and happy. In total, the set contains 67 models: 20 Caucasian male adults, 19 Caucasian female adults, 4 Caucasian male children, 6 Caucasian female children, and 18 Moroccan male adults. All models in the dataset show the above eight facial expressions with three gaze directions, photographed simultaneously from five different camera angles. The photos were taken in a highly controlled environment. All displayed facial expressions were based on prototypes from Facial Action Coding System (FACS) (Ekman and Friesen, 1976). FACS was developed for describing facial expressions in terms of the so-called Action Units (AUs), which are anatomically related to the contractions of specific facial muscles. We select frontal images, crop the head regions, and use OpenFace 2.2.0 (Baltrusaitis et al., 2018) to recognize Action Units from the images. The images in RaFD are high-quality and suitable for facial expression generation where each model was asked to make different facial expressions in a clean white background. However, RaFD only has 535 images in total, hence we further utilize CelebA (Liu et al., 2015) in training.

2.2 Pipeline

In this section, we design a pipeline composed of two main components: (1) a multi-task NLG model based on DialoGPT (Zhang et al., 2020) and (2) a GAN-based model for facial expression generation (Pumarola et al., 2018).
2.2.1 Multi-task Language Generator

The framework of the proposed NLG model is illustrated in Figure 3, where the model architecture is based on DialoGPT (Zhang et al., 2020). DialoGPT models are trained on the basis of the GPT-2 (Radford et al., 2019) architecture, they are both self-regressive language model and uses the multi-layer transformer as model architecture. The difference between two models is that DialoGPT focuses on dialogues where is trained on large-scale dialogue sessions extracted from Reddit discussion threads. Therefore we choose DialoGPT as our dialogue response generator and finetune it on the language dataset described in the previous section. The emotion prediction is also a classification problem, where we aim to use the predicted emotion signal to bridge the language and facial expression. Given a dialogue pair \( \{(u_t, e_t), (u_{t+1}, e_{t+1})\} \), each utterance \( u_t \) has its corresponding emotion label \( e_t \) and dialogue context \( D \). We utilize DialoGPT to build a multi-task language generator,

\[ u_{t+1}, e_t = \text{DialoGPT}(D), \]

where the goal of the generator is to generate the next utterance and identify the emotion of the current turn. As depicted in Figure 3, the end-of-sentence token \(<\text{EOS}>\) will be appended to the dialogue context before feeding into the model, the encoded feature at the position of \(<\text{EOS}>\). The predictor is a simple full-connected layer. The multi-task loss is the combination of the language generation loss and the emotion prediction loss.

\[ L_{\text{MLG}} = \lambda_u \cdot L_u + \lambda_e \cdot L_e, \]

where \( \lambda_u \) and \( \lambda_e \) are the weight for the language generation loss and the emotion prediction loss respectively. When doing inference, the emotion of next turn \( e_{t+1} \) is what we want, hence the next utterance \( u_{t+1} \) will be fed into the model again for identifying the emotion label.

2.2.2 Action Units Mapping

To bridge the two models, we further design a tabular mapping from predicted emotion signal to the target attribute, which is activation of Action Units. Instead of utilizing the deterministic anatomical information in RaFD paper (Langner et al., 2010), like happiness would trigger the action unit 6 and 12, we build the tabular by sampling a photo with specific emotion in RaFD and using OpenFace to recognize action units. Since the process of recognizing AUs depends on two trained models: (1) a face detection toolkit\(^1\) and (2) OpenFace for action unit recognition, we observe that deterministic anatomical information of AU activation is not reliable. In contrast, extracting the AU information

\( ^1\text{https://pypi.org/project/face-recognition/} \)
from the dataset we are using would be a better choice. With the mapping, we can extract corresponding AU features for predicted specific emotion to pass into the facial expression generator.

### 2.2.3 Facial Expression Generator

We utilize the GAN-based model (Pumarola et al., 2018) as our face generator. As illustrated in Figure 4: the face generator is composed of two main modules: (1) a pair of generators ($G_A$ and $G_C$) is trained to change the facial expression in image $I$ according to the given desired attributes $z$ and (2) a pair of WGAN-GP-based discriminators ($D_I$ and $D_z$) to examine the photo-realism and desired expression fulfillment of the generated images.

Since our goal is to manipulate the facial expression in the image $I$, the generator should focus only on those regions of the image that are relevant to constitute facial expressions and keep the rest elements of the image such as hair, glasses, hats or background untouched. For this purpose, instead of directly regressing a full image, the generators predict two masks, a color mask $C$ and an attention mask $A$, by $G_A$ and $G_C$ respectively. Rather than directly constructing a full image as in the typical GANs, the image is now obtained by the following formula:

$$I_{zd} = G(I_{zo} \mid z_d) = (1 - A) \cdot C + A \cdot I_{zo}, \quad (1)$$

where $z_d$ and $z_o$ represent the desired and original attributes of facial expressions respectively, and the subscripts d and o denote the words *desired* and *original*. Note that the desired attributes $z_d$ are mapped from the predicted emotion tag as mentioned in the previous section. Both the color mask and the attention mask are predicted based on the original input image and the given desired attributes, $C = G_C(I_{zo} \mid z_d), A = G_A(I_{zo} \mid z_d)$. The generated attention $A$ is a single-channel mask, indicating the preserved region from the original image. On the other hand, the color mask $C$ is a RGB, three-channel mask, determining the actual facial movements. By (1), the model could focus on the pixels defining the facial movement and preserve the static region from the original image, which leads to sharper and more realistic synthesis.

Original GAN training utilizes Jensen-Shannon (JS) divergence as the loss function, which aims to maximize the probability of correctly distinguishing between real and generated data. Since the divergence is potentially not continuous hence resulting in vanishing gradients, in order to address the issue, we use WGAN-GP (Gulrajani et al., 2017) as our adversarial framework, which replaces JS divergence with Earth Mover Distance (Wasserstein Distance) along with a gradient penalty term. The gradient penalty term is an alternative way to enforce the Lipschitz condition, which directly constrains the gradient norm of the critic’s output with respect to its input. The adversarial objective is hereby formulated as below:

$$L_{adv} = \mathbb{E}_{I_{zo} \sim P_z}[D_I(G(I_{zo} \mid z_d)) - D_I(I_{zo})] + \lambda_{gp} \mathbb{E}_{\tilde{I} \sim P_{\tilde{I}}}[(\|\nabla_{\tilde{I}} D_I(\tilde{I})\|_2 - 1)^2], \quad (2)$$

where $\lambda_{gp}$ is the penalty coefficient, $P_0$ and $P_1$ represent original data distribution and the distribution of sampling uniformly along straight lines between pairs of points sampled from the original data distribution.

The attention mask $A$ and the color mask $C$ are both learned by direct end-to-end training driven by the signals provided by the discriminator. Because the discriminator would assess the photo-realism, the attention mask would tend to saturate to all 1, leading to a complete copy of the original input image. To circumvent the potential issue and improve smoothness of transformation, regularization $L_A$ is performed over attention mask distribution:

$$\lambda_{tv} \mathbb{E}_{I_{zo} \sim P_z} \left[ \sum_{i,j} ((A_{i+1,j} - A_{i,j})^2 + (A_{i,j+1} - A_{i,j})^2) - \mathbb{E}_{I_{zo} \sim P_z}[\|A\|_2] \right], \quad (3)$$

where $i$ and $j$ stand for the indexes of the attention mask matrices. The first term enforces the smooth-
ness, while the second term is the standard $l_2$ norm penalty.

As the training scheme is based on conditional GANs, the generators should learn to synthesize realistic data and simultaneously satisfy the given attributes $z$, which are activation of Action Units. Specifically, the discriminators should identify $z_d$ from generated examples and $z_o$ from original data. Another condition loss $L_z$ is hereby formulated as below:

$$E_{I_{zd} \sim P_o}[\|D_z(G(I_{zd} \mid z_d)) - z_d\|^2_2 + \|D_z(I_{zd}) - z_o\|^2_2]. \quad (4)$$

The above described objectives encourage the generators to render realistic facial expression $I_{zd}$ according to desired attributes $z_d$. However, the generated face is not guaranteed to correspond to the same person in the input original image $I_{zo}$. In this work, the cycle consistency loss $L_{cycle}$ (Zhu et al., 2017) is utilized to regularize the learning inclination to preserve the identity in the original input:

$$E_{I_{zo} \sim P_o}[\|G(G(I_{zo} \mid z_d) \mid z_o) - z_o\|_1]. \quad (5)$$

Markovian discriminator (PatchGAN) (Isola et al., 2017) is introduced to restrict attention to the structure in local image patches to model high-frequency region, while $l_1$ norm it utilized to capture low-frequency structure. Next, equations (2) to (5) with their corresponding coefficients are combined into the full objective:

$$L_{FEG} = L_{adv} + \lambda_A L_A + \lambda_z L_z + \lambda_{cycle} L_{cycle},$$

where $\lambda_A$, $\lambda_z$, and $\lambda_{cycle}$ are the hyperparameters controlling the importance of each loss term. Finally, we aim to solve the following minimax problem:

$$G^* = \arg \min_G \max_D L_{FEG}.$$

3 Demo and Discussion

HUMBO is a web-based system: (1) the front-end is built by the JavaScript framework ReactJS$^2$, and (2) the back-end is built by Python library Flask. The usage flow of HUMBO is designed to be very intuitive: (1) first, select the image and upload it to determine the appearance of your virtual assistant (Figure 5); (2) next, press the start button to start a conversation (Figure 6). At each turn, the facial expression of the virtual assistant would change along with the emotion of the generated utterance.

The demo video is available

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$^2$https://reactjs.org/
Figure 8: The generated results of the facial expression generator, the underlying emotions are surprise, happy, and contemptuous (left to right).

at https://youtu.be/Qy9mvyfc8eQ.

3.1 Training Details

In the experiments, we train the language generator by Adam optimizer with each batch of 2 examples, 8 training epochs were performed without early stop. The learning rate is 1e-6, and the weights for losses $\lambda_u$ and $\lambda_e$ are 1e-7 and 1 respectively. The entire implementation was based on PyTorch and HuggingFace transformers\textsuperscript{3} package. The medium size of DialoGPT is adopted as the basis of the model.

For the facial expression generator, we use Adam as the optimizer with each batch of 8 examples, 1300 training epochs were performed without early stop. The learning rates of discriminator and generator are both 1e-4. The image size is $256 \times 256$, and the dimension of the action unit vector is 35. The other hyper-parameters and implementation details of the facial expression generator are same as the original work (Pumarola et al., 2018).

3.2 Challenges Ahead

HUMBO is a complex system consisting of multiple research problems, hence the data would be the key problem. For example, one of the data sources of EmotionLines (Chen et al., 2018) is also the TV show Friends, but the emotions are labeled according to Ekman’s basic emotions (Ekman and Keltner, 1997), which is slightly different to the dataset we conduct (Zahiri and Choi, 2017). The reason why we discard EmotionLines is because it has severe data-imbalance issue.

In language part, we could imagine that there might be some easy methods to improve the performance, for example, conducting a more powerful and public pre-trained language model like GPT-3 (Brown et al., 2020). However, it would be much more difficult to improve the facial expression generator. Facial expression generation is the main highlighted feature of HUMBO, the goal is to endure users with the ability of determining the appearances of the virtual assistants by a single image. Figure 8 shows different generated faces of a person, we could observe that though not being perfect, the overall results are acceptable. There are some obvious defects like unexpected shading and wrinkle, especially around the lips and eyebrows, we speculate that it is because those areas contain many Action Units. The characteristics of original user-uploaded images are also important, Figure 9 shows some failure cases, where we could observe that skin colors, wrinkles, and original facial expressions are critical.

4 Conclusions

In this work, we present HUMBO, a system aiming at generating dialogue responses and simultaneously synthesize corresponding visual expressions on faces for better multimodal interaction. HUMBO can let users determine the appearances of virtual assistants by a single image, and generate coherent emotional utterances and facial expressions on the user-provided image. To bridge these two problem, we further propose to model the shared semantics of the two modalities by emotion signals. This is not only a brand new research direction but more importantly, an ultimate step toward more human-like virtual assistants.

References

Tadas Baltrusaitis, Amir Zadeh, Yao Chong Lim, and Louis-Philippe Morency. 2018. Openface 2.0: Facial behavior analysis toolkit. In 2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018), pages 59–66. IEEE.

3https://huggingface.co/transformers/
Antoine Bordes, Y-Lan Boureau, and Jason Weston. 2017. Learning end-to-end goal-oriented dialog. In Proceedings of ICLR.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. OpenAI blog, 1(8):9.

Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeannette N Chang, Sungbok Lee, and Shrikanth S Narayanan. 2008. Iemocap: Interactive emotional dyadic motion capture database. Language resources and evaluation, 42(4):335.

Sheng-Yeh Chen, Chao-Chun Hsu, Chuan-Chun Kuo, Lun-Wei Ku, et al. 2018. Emotionlines: An emotion corpus of multi-party conversations. arXiv preprint arXiv:1802.08379.

Paul Ekman and Wallace V Friesen. 1976. Measuring facial movement. Environmental psychology and nonverbal behavior, 1(1):56–75.

Paul Ekman and Dacher Keltner. 1997. Universal facial expressions of emotion. Segerstrale U, P. Molnar P, eds. Nonverbal communication: Where nature meets culture, 27:46.

Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, and Aaron C Courville. 2017. Improved training of wasserstein gans. In Advances in Neural Information Processing Systems, pages 5767–5777.

Dilek Hakkani-Tür, Gökhan Tür, Asli Celikyilmaz, Yun-Nung Chen, Jianfeng Gao, Li Deng, and Ye-Yi Wang. 2016. Multi-domain joint semantic frame parsing using bi-directional rnn-lstm. In Proceedings of INTERSPEECH, pages 715–719.

Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. 2017. Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1125–1134.

Oliver Langner, Ron Dotsch, Gijsbert Bijlstra, Daniel HJ Wigboldus, Skylar T Hawk, and AD Van Knippenberg. 2010. Presentation and validation of the radboud faces database. Cognition and emotion, 24(8):1377–1388.

Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. 2015. Deep learning face attributes in the wild. In Proceedings of International Conference on Computer Vision (ICCV).

Albert Pumarola, Antonio Agudo, Aleix M Martinez, Alberto Sanfeliu, and Francesc Moreno-Noguer. 2018. Ganimation: Anatomically-aware facial animation from a single image. In Proceedings of the European Conference on Computer Vision (ECCV), pages 818–833.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9.

Shang-Yu Su, Xiujun Li, Jianfeng Gao, Jingjing Liu, and Yun-Nung Chen. 2018. Discriminative deep dyna-q: Robust planning for dialogue policy learning. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3813–3823.

Supasorn Suwajanakorn, Steven M Seitz, and Ira Kemelmacher-Shlizerman. 2017. Synthesizing obama: learning lip sync from audio. ACM Transactions on Graphics (TOG), 36(4):95.

Tsung-Hsien Wen, Milica Gasic, Nikolaj Mrksic, Lina M Rojas-Barahona, Pei-Hao Su, Stefan Ultes, David Vandyke, and Steve Young. 2017. A network-based end-to-end trainable task-oriented dialogue system. In Proceedings of EACL, pages 438–449.

G. Willcox. 1982. The feeling wheel a tool for expanding awareness of emotions and increasing spontaneity and intimacy. Transactional Analysis Journal, 12:274–276.

Sayyed M. Zahiri and Jinho D. Choi. 2017. Emotion detection on tv show transcripts with sequence-based convolutional neural networks.

Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2020. Dialogpt : Large-scale generative pre-training for conversational response generation. Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations.

Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE International Conference on Computer Vision, pages 2223–2232.