

# Text2Action: Generative Adversarial Synthesis from Language to Action

Hyemin Ahn, Timothy Ha\*, Yunho Choi\*, Hwiyeon Yoo\*, and Songhwai Oh

**Abstract**—In this paper, we propose a generative model which learns the relationship between language and human action in order to generate a human action sequence given a sentence describing human behavior. The proposed generative model is a generative adversarial network (GAN), which is based on the sequence to sequence (SEQ2SEQ) model. Using the proposed generative network, we can synthesize various actions for a robot or a virtual agent using a text encoder recurrent neural network (RNN) and an action decoder RNN. The proposed generative network is trained from 29,770 pairs of actions and sentence annotations extracted from MSR-Video-to-Text (MSR-VTT), a large-scale video dataset. We demonstrate that the network can generate human-like actions which can be transferred to a Baxter robot, such that the robot performs an action based on a provided sentence. Results show that the proposed generative network correctly models the relationship between language and action and can generate a diverse set of actions from the same sentence.

## I. INTRODUCTION

“Any human activity is impregnated with language because it takes places in an environment that is build up through language and as language” [1]. As such, human behavior is deeply related to the natural language in our lives. A human has the ability to perform an action corresponding to a given sentence, and conversely one can verbally understand the behavior of an observed person. If a robot can also perform actions corresponding to a given language description, it will make the interaction with robots easier.

Finding the link between language and action has been a great interest in machine learning. There are datasets which provide human whole body motions and corresponding word or sentence annotations [2], [3]. In additions, there have been attempts for learning the mapping between language and human action [4], [5]. In [4], hidden Markov models (HMMs) [6] is used to encode motion primitives and to associate them with words. [5] used a sequence to sequence (SEQ2SEQ) model [7] to learn the relationship between the natural language and the human actions.

In this paper, we choose to use a generative adversarial network (GAN) [8], which is a generative model, consisting of a generator  $G$  and a discriminator  $D$ .  $G$  and  $D$  plays a two-player minimax game, such that  $G$  tries to create more

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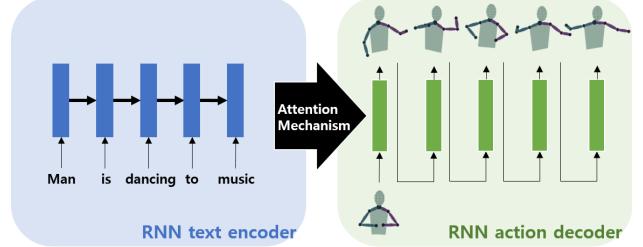


Fig. 1. An overview of the proposed generative model. It is a generative adversarial network [8] based on the sequence to sequence model [7], which consists of a text encoder and an action decoder based on recurrent neural networks [12]. When the RNN-based text encoder has processed the input sentence into a feature vector, the RNN-based action decoder converts the processed language features to corresponding human actions.

realistic data that can fool  $D$  and  $D$  tries to differentiate between the data generated by  $G$  and the real data. Based on this adversarial training method, it has been shown that GANs can synthesize realistic high-dimensional new data, which is difficult to generate through manually designed features. [9]–[11]. In addition, it has been proven that a GAN has a unique solution, in which  $G$  captures the distribution of the real data and  $D$  does not distinguish the real data from the data generated from  $G$  [8]. Thanks to these features of GANs, our experiment also shows that GANs can generate more realistic action than the previous work [5].

The proposed generative model is a GAN based on the SEQ2SEQ model. The objective of a SEQ2SEQ model is to learn the relationship between the source sequence and the target sequence, so that it can generate a sequence in the target domain corresponding to the sequence in the input domain [7]. As shown in Figure 1, the proposed model consists of a text encoder and an action decoder based on recurrent neural networks (RNNs) [12]. The text encoder converts an input sentence, a sequence of words, into a feature vector. A set of processed feature vectors is transferred to the action decoder, where actions corresponding to the input sequence are generated. When decoding processed feature vectors, we have used an attention mechanism based decoder [13].

In order to train the proposed generative network, we have chosen to use the MSR-Video to Text (MSR-VTT) dataset, which contains web video clips with annotation texts [14]. Existing datasets [2], [3] are not suitable for our purpose since videos are recorded in laboratory environments. One remaining problem is that the MSR-VTT dataset does not provide human pose information. Hence, for each video clip, we have extracted a human upper body pose sequence using the convolutional pose machine (CPM) [15]. Extracted 2D

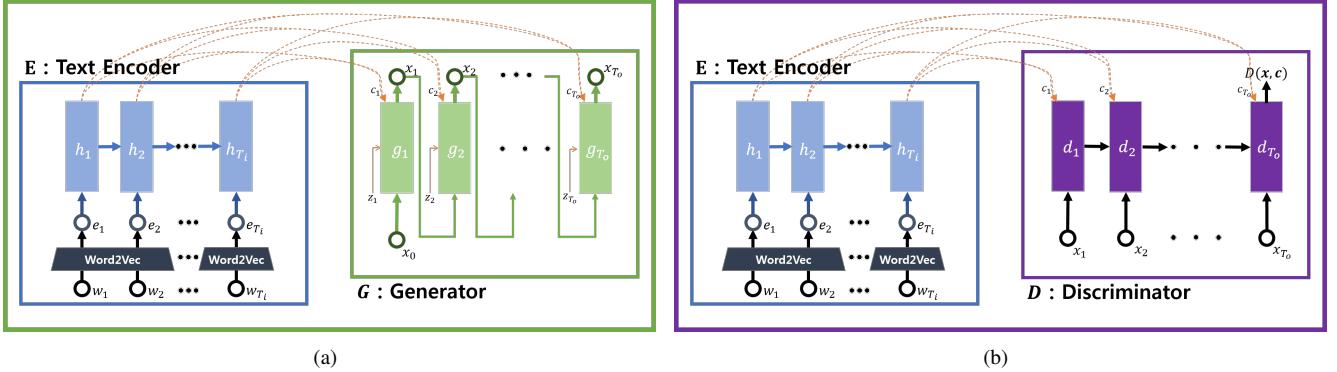


Fig. 2. The text encoder  $E$ , the generator  $G$ , and the discriminator  $D$  constituting the proposed generative model. The pair of  $E$  and  $G$ , and the pair of  $E$  and  $D$  are SEQ2SEQ model composed of the RNN-based encoder and decoder. Each rectangular denotes the LSTM cell of the RNN. (a) The text encoder  $E$  processes the set of word embedding vectors  $e = \{e_1, \dots, e_{T_i}\}$  into its hidden states  $\mathbf{h} = \{h_1, \dots, h_{T_i}\}$ . The generator  $G$  takes  $\mathbf{h}$  and decodes it into the set of feature vectors  $\mathbf{c}$  and samples the set of random noise vectors  $\mathbf{z} = \{z_1, \dots, z_{T_o}\}$ . It receives  $\mathbf{c}$  and  $\mathbf{z}$  as inputs and generates the human action sequence  $\mathbf{x} = \{x_1, \dots, x_{T_o}\}$ . (b) After the text encoder  $E$  encodes the input sentence information into its hidden states  $\mathbf{h}$ , the discriminator  $D$  also takes  $\mathbf{h}$  and decodes it into the set of feature vectors  $\mathbf{c}$ . By taking  $\mathbf{c}$  and  $\mathbf{x}$  as inputs,  $D$  identifies whether  $\mathbf{x}$  is real or fake.

poses are converted to 3D poses and used as our dataset [16]. We have gathered 29,770 pairs of sentence descriptions and action sequences, containing 3,052 descriptions and 2,211 actions.

The remaining of the paper is constructed as follows. The proposed Text2Action network is given in Section II. Section III describes the structure of the proposed generative model and implementation details. Section IV shows various 3D human like action sequences obtained from the proposed generative network and discusses the result. In addition, we demonstrate that a Baxter robot can generate the action based on a provided sentence.

## II. TEXT2ACTION NETWORK

Let  $\mathbf{w} = \{w_1, \dots, w_{T_i}\}$  denote an input sentence composed of  $T_i$  words. Here,  $w_t \in \mathbb{R}^d$  is the one-hot vector representation of the  $t$ th word, where  $d$  is the size of vocabulary. We encode  $\mathbf{w}$  into  $e = \{e_1, \dots, e_{T_i}\}$ , the word embedding vectors for the sentence, based on the word2vec model [17]. Here,  $e_t \in \mathbb{R}^{n_e}$  is the word embedding representation of  $w_t$  where  $n_e$  is dimension of the word embedding vector, and we have pretrained the word2vec model with our dataset based on the method presented in [17].

The proposed network is a GAN, which consists of a generator  $G$  and a discriminator  $D$  as shown in Figure 2. A proper human action sequence corresponding to the input embedding sentence representation  $e$  is generated by  $G$ , and  $D$  differentiates the real actions from fake actions considering the given sentence  $e$ . A text encoder  $E$  encodes  $e$  into its hidden states  $\mathbf{h} = \{h_1, \dots, h_{T_i}\}$ , such that  $\mathbf{h}$  contains the processed information of  $e$ . Here,  $h_t \in \mathbb{R}^n$  and  $n$  is the dimension of the hidden state.

Let  $\mathbf{x} = \{x_1, \dots, x_{T_o}\}$  denote an action sequence with  $T_o$  poses. Here,  $x_t \in \mathbb{R}^{n_x}$  denotes the  $t$ th human pose vector and  $n_x$  denotes its dimension. The pair of  $E$  and  $G$  is a SEQ2SEQ model, which converts  $e$  into the target human pose sequence  $\mathbf{x}$ . In order to generate  $\mathbf{x}$ ,  $G$  decodes the hidden states  $\mathbf{h}$  of  $E$  into a set of language feature vectors

$\mathbf{c} = \{c_1 \dots c_{T_o}\}$  based on the attention mechanism [13]. Here,  $c_t \in \mathbb{R}^n$  denotes a feature vector for generating the  $t$ th human pose  $x_t$  and  $n$  is the dimension of the feature vector  $c_t$ , which is the same as the dimension of  $h_t$ .

In addition,  $\mathbf{z} = \{z_1, \dots, z_{T_o}\}$  is provided to  $G$ , where  $z_t \in \mathbb{R}^{n_z}$  is a random noise vector from the zero-mean Gaussian distribution with a unit variance and  $n_z$  is the dimension of a random noise vector. With  $\mathbf{c}$  and  $\mathbf{z}$ ,  $G$  synthesizes a corresponding human action sequence  $\mathbf{x}$ , such that  $G(\mathbf{z}, \mathbf{c}) = \mathbf{x}$  (see Figure 2(a)). Here, the first human pose input  $x_0$  is set to the mean pose of all first human poses in the training dataset.

The discriminator  $D$  differentiates  $\mathbf{x}$  generated from  $G$  and the real human action data  $\mathbf{x}$ . As shown in Figure 2(b), it also decodes the hidden state  $\mathbf{h}$  of  $E$  into the set of language feature vectors  $\mathbf{c}$  based on the attention mechanism [13]. With  $\mathbf{c}$  and  $\mathbf{x}$  as inputs,  $D$  determines whether  $\mathbf{x}$  is fake or real considering  $\mathbf{c}$ . The output from its last RNN cell is the result of the discriminator such that  $D(\mathbf{x}, \mathbf{c}) \in [0, 1]$  (see Figure 2(b)). It returns 1 if the  $\mathbf{x}$  is identified as real.

In order to train  $G$  and  $D$ , we use the value function defined as follows [8]:

$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{data}(\mathbf{x})} [\log D(\mathbf{x}, \mathbf{c})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z}, \mathbf{c}), \mathbf{c}))] \quad (1)$$

$G$  and  $D$  play a two-player minimax game on the value function  $V(D, G)$ , such that  $G$  tries to create more realistic data that can fool  $D$  and  $D$  tries to differentiate between the data generated by  $G$  and the real data.

## III. NETWORK STRUCTURE

### A. RNN-Based Text Encoder

The RNN-based text encoder  $E$  shown in Figure 2 encodes the input information  $e$  into its hidden states of the LSTM cell [12]. Let us denote the hidden states of the text encoder  $E$  as  $\mathbf{h} = \{h_1, \dots, h_{T_i}\}$ , where

$$h_t = q_t(e_t, h_{t-1}) \in \mathbb{R}^n. \quad (2)$$

Here,  $n$  is the dimension of the hidden state  $h_t$ , and  $q_t$  is the nonlinear function operating in a LSTM cell. Interested readers are encouraged to read [12].

### B. Generator

The generator  $G$  decodes  $\mathbf{h}$  into the set of feature vectors  $\mathbf{c} = \{c_1, \dots, c_{T_o}\}$  based on the attention mechanism [13], where  $c_t \in \mathbb{R}^n$  is calculated as follows:

$$c_t = \sum_{i=1}^{T_o} \alpha_{ti} h_i. \quad (3)$$

The weight  $\alpha_{ti}$  of each feature  $h_i$  is computed as

$$\alpha_{ti} = \frac{\exp(\beta_{ti})}{\sum_{k=1}^{T_o} \exp(\beta_{tk})}, \quad (4)$$

where

$$\beta_{ti} = a[g_{t-1}, h_i] = v_a^\top \tanh[W_a g_{t-1} + U_a h_i + b_a]. \quad (5)$$

Here, the dimensions of matrices and vectors are as follows:  $W_a, U_a \in \mathbb{R}^{n \times n}$ ,  $v_a, b_a \in \mathbb{R}^n$ .

With the language feature  $\mathbf{c}$  and a set of random noise vectors  $\mathbf{z}$ ,  $G$  synthesizes a corresponding human action sequence  $\mathbf{x}$  such that  $G(\mathbf{z}, \mathbf{c}) = \mathbf{x}$ . Let  $\mathbf{g} = \{g_1, \dots, g_{T_o}\}$  denote the hidden states of the LSTM cells composing  $G$ . Each hidden state of the LSTM cell  $g_t \in \mathbb{R}^n$ , where  $n$  is the dimension of the hidden state, is computed as follows:

$$\begin{aligned} g_t &= \gamma_t[g_{t-1}, x_{t-1}, c_t, z_t] \\ &= W_g(o'_t \circ C'_t) + U_g c_t + H_s z_t + b_g \end{aligned} \quad (6)$$

$$o'_t = \sigma[W_{o'} x'_t + U_{o'} g_{t-1} + b_{o'}] \quad (7)$$

$$x'_t = W_{x'} x_{t-1} + U_{x'} c_t + H_{x'} z_t + b_{x'} \quad (8)$$

$$C'_t = f'_t \circ C'_{t-1} + i'_t \circ \sigma[W_{c'} x'_t + U_{c'} g_{t-1} + b_{c'}] \quad (9)$$

$$f'_t = \sigma[W_{f'} x'_t + U_{f'} g_{t-1} + b_{f'}] \quad (10)$$

$$i'_t = \sigma[W_{i'} x'_t + U_{i'} g_{t-1} + b_{i'}] \quad (11)$$

and the output pose at time  $t$ , is computed as

$$x_t = W_x g_t + b_x \quad (12)$$

The dimensions of matrices and vectors are as follows:  $W_g, W_{o'}, W_{c'}, W_{f'}, W_{i'}, U_g, U_{o'}, U_{x'}, U_{c'}, U_{f'}, U_{i'} \in \mathbb{R}^{n \times n}$ ,  $W_{x'} \in \mathbb{R}^{n \times n_x}$ ,  $W_x \in \mathbb{R}^{n_x \times n}$ ,  $H_s, H_{x'} \in \mathbb{R}^{n \times n_z}$ ,  $b_g, b_{o'}, b_{x'}, b_{c'}, b_{f'}, b_{i'} \in \mathbb{R}^n$ , and  $b_x \in \mathbb{R}^{n_x}$ .  $\gamma_t$  is the nonlinear function constructed based on the attention mechanism presented in [13].

### C. Discriminator

The discriminator  $D$  takes  $\mathbf{c}$  and  $\mathbf{x}$  as inputs and generates the result  $D(\mathbf{x}, \mathbf{c}) \in [0, 1]$  (see Figure 2(b)). It returns 1 if the input  $\mathbf{x}$  has been determined as the real data. Let  $\mathbf{d} = \{d_1, \dots, d_{T_o}\}$  denote the hidden states of the LSTM cell composing  $D$ , where  $d_t \in \mathbb{R}^n$  and  $n$  is the dimension of the hidden state  $d_t$  which is same as the one of  $g_t$ . The output of  $D$  is calculated from its last hidden state as follows:

$$D(\mathbf{x}, \mathbf{c}) = \sigma[W_d d_{T_o} + b_d],$$

where  $W_d \in \mathbb{R}^{1 \times n}$ ,  $b_d \in \mathbb{R}$ . The hidden state of  $D$  is computed as  $d_t = \gamma_t[d_{t-1}, x_t, c_t, w_t]$  as similar in (6)-(11), where  $w_t \in \mathbb{R}^{n_z}$  is the zero vector instead of the random vector  $z_t$ .

### D. Implementation Details

The desired performance was not obtained properly when we tried to train the entire network end-to-end. Therefore, we pretrain the RNN-text encoder  $E$  first. Regarding this,  $E$  is trained by training an autoencoder which learns the relationship between the natural language and the human action as shown in Figure 3. This autoencoder consists of the text-to-action encoder that maps the natural language to the human action, and the action-to-text decoder which reconstructs the human action back to the natural language description. Both the text-to-action encoder and the action-to-text decoder are SEQ2SEQ models based on the attention mechanism [13].

The encoding part of the text-to-action encoder corresponds to  $E$ . Based on  $\mathbf{c}$  (see (3)-(5)), the hidden states of its decoder  $\mathbf{s} = \{s_1, \dots, s_{T_o}\}$  is calculated as  $s_t = \gamma_t[s_{t-1}, x_{t-1}, c_t, w_t]$  (see (6)-(11)), and  $\mathbf{x}$  is generated (see (12)). Here,  $w_t \in \mathbb{R}^{n_z}$  is the zero vector instead of random vector. The action-to-text decoder works similar as the text-to-action encoder. After the information of  $\mathbf{x}$  is encoded into  $\mathbf{s} = \{s_1, \dots, s_{T_o}\}$  (see Figure 3), its decoding part decodes  $\mathbf{s}$  into the set of feature vectors  $\mathbf{c}'$  (see (3)-(5)). Based on  $\mathbf{c}'$ , the hidden states of its decoder  $\mathbf{h}' = \{h'_1, \dots, h'_{T_i}\}$ , is calculated as  $h'_t = \gamma_t[h'_{t-1}, e'_{t-1}, c'_t, w_t]$ . (see (6)-(11)). From the set of hidden states  $\mathbf{h}'$ , the word embedding representation of the sentence  $\mathbf{e}$  is reconstructed as  $\mathbf{e}' = \{e'_1, \dots, e'_{T_i}\}$  (see (12)).

In order to train this autoencoder network, we have used a loss function  $\mathcal{L}_a$  defined as follows:

$$\mathcal{L}_a(\mathbf{x}, \mathbf{e}) = \frac{a_1}{T_o} \sum_{t=1}^{T_o} \|x_t - \hat{x}_t\|_2^2 + \frac{a_2}{T_i} \sum_{t=1}^{T_i} \|e_t - \hat{e}_t\|_2^2 \quad (13)$$

where  $\hat{x}_t$  denotes the resulted estimation of  $x_t$ . The constants  $a_1$  and  $a_2$  are used to control how much the estimation loss of the action sequence  $\mathbf{x}$  and the reconstruction loss of the word embedding vector sequence  $\mathbf{e}$  should be reduced.

After training the autoencoder network, the part of  $E$  is extracted and passed to  $G$  and  $D$ . In addition, in order to make the training of  $G$  more stable, the weight matrices and bias vectors of  $G$  that are shared with the autoencoder are initialized to trained values. When training  $G$  and  $D$  with the GAN value function shown in equation (1), we do not train the text encoder  $E$ . It is to prevent the pretrained encoded language information from being corrupted while training the network with the GAN value function. Regarding training the generator  $G$ , we choose to maximize  $\log D(G(\mathbf{z}, \mathbf{c}), \mathbf{c})$  rather than minimizing  $1 - \log D(G(\mathbf{z}, \mathbf{c}), \mathbf{c})$  since it has been shown to be more effective in practice from many cases [8], [9]. For more details, we recommend the readers to refer the longer version [18] and the released code.<sup>1</sup>

<sup>1</sup><https://github.com/hiddenmaze/Text2Action>

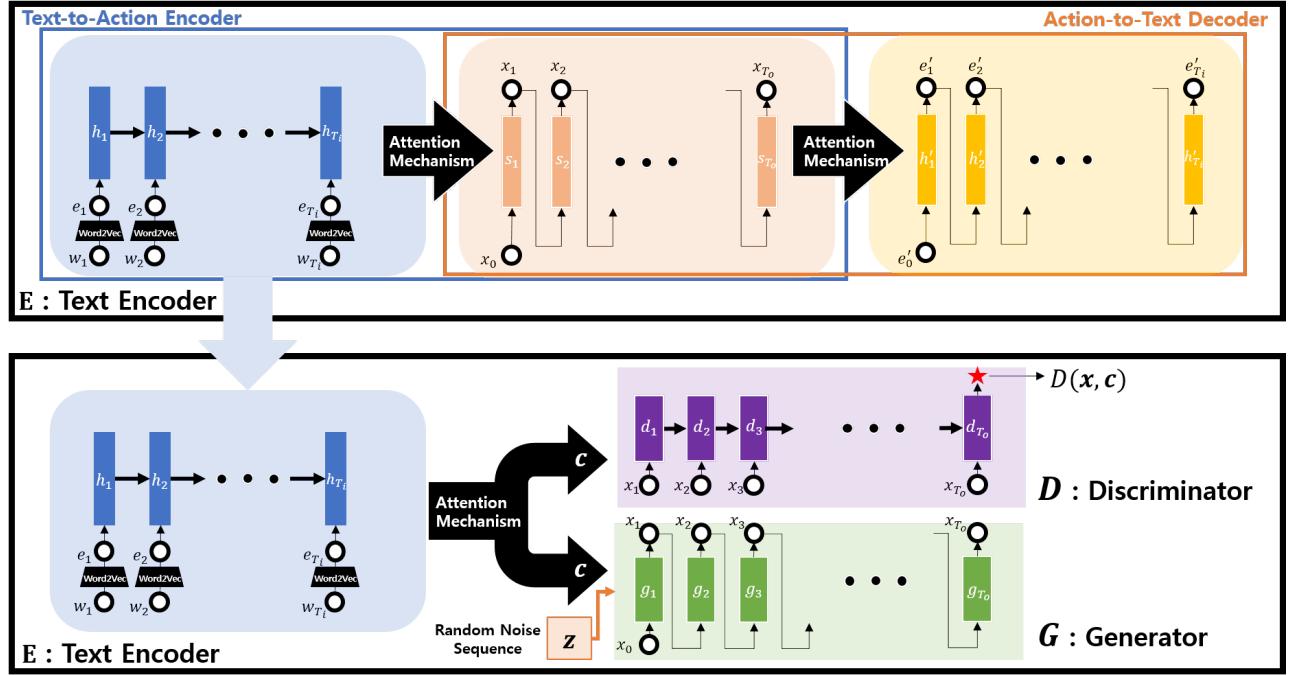


Fig. 3. The overall structure of proposed network. First, we train an autoencoder which maps between the natural language and the human motion. Its encoder maps the natural language to the human action, and decoder maps the human action to the natural language. After training this autoencoder, only the encoder part is extracted to generate the conditional information related to the input sentence so that  $G$  and  $D$  can use.

#### IV. EXPERIMENT

##### A. Dataset

In order to train the proposed generative network, we use a MSR-VTT dataset which provides Youtube video clips and sentence annotations [14]. As shown in Figure 4, we have extracted the upper body 2D pose of the person in the video through CPM [15]. Extracted 2D poses are converted to 3D poses and used as our dataset [16]<sup>1</sup>. Each extracted upper body pose is a 24-dimensional vector such that  $x_t \in \mathbb{R}^{24}$ . The 3D position of the human neck, and other 3D vectors of seven other joints compose the pose vector data  $x_t$  (see Figure 5). Since sizes of detected human poses are different, we have normalized the joint vectors such that  $\|v_i\|_2 = 1$  for  $i = 1, \dots, 7$ . Each action sequence is 3.2 seconds long, and the frame rate is 10 fps, making a total of 32 frames for an action sequence. In total, we have gathered 29,770 pairs of sentence descriptions and action sequences, which consists of 3,052 descriptions and 2,211 actions. The number of words included in the sentence description data is 21,505, and the size of vocabulary which makes up the data is 1,627.

##### B. 3D Action Generation

We first examine how action sequences are generated when a fixed sentence input and a different random noise vector inputs are given to the trained network. Figure 6 shows three actions generated with one sentence input and three differently sampled random noise vector sequences. The input sentence description is ‘A girl is dancing to the hip

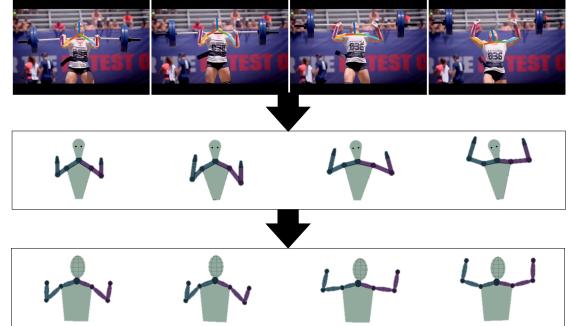


Fig. 4. The example dataset for the description ‘A woman is lifting weights’. From the video of the MSR-VTT dataset, we extract the 2D human pose based on the CPM [15]. Extracted 2D human poses are converted to 3D poses based on the code from [16] and used to train the proposed network.

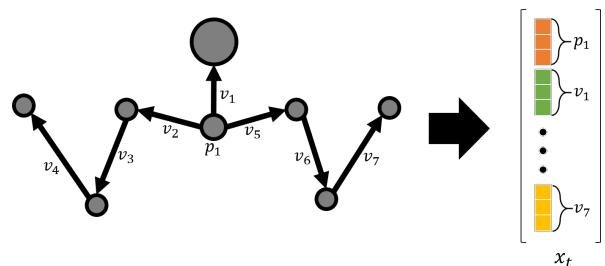


Fig. 5. The illustration of how the extracted 3D human pose constructs the pose vector data  $x_t \in \mathbb{R}^{24}$ .

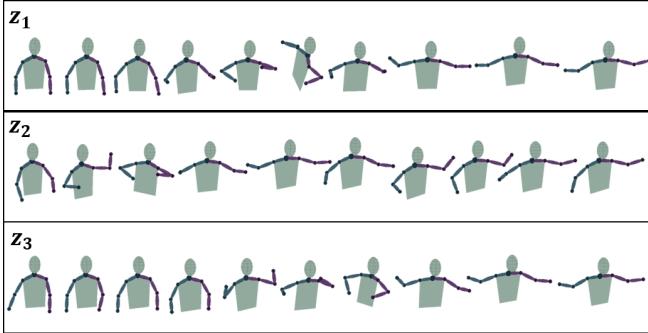


Fig. 6. Generated various actions for ‘A girl is dancing to the hip hop beat’.  $z_1$ ,  $z_2$ , and  $z_3$  denote the differently sampled random noise vector sequences.

hop beat’, which is not included in the training dataset. In this figure, human poses in a rectangle represent the one action sequence, listed in time order from left to right. The time interval between the each pose is 0.5 second. It is interesting to note that varied human actions are generated if the random vectors are different. In addition, it is observed that generated motions are all taking the action like dancing.

We also examine how the action sequence is generated when the input random noise vector sequence  $z$  is fixed and the sentence input information  $c$  varies. Figure 7 shows three actions generated based on the one fixed random noise vector sequence and three different sentence inputs. The time interval between the each pose is 0.5 second. Input sentences are ‘A woman drinks a coffee’, ‘A muscular man exercises in the gym’, and ‘A chef is cooking a meal in the kitchen’. The first result in Figure 7 shows the action sequence as if a human is lifting right hand and getting close to the mouth as when drinking something (see the 5th frame). The second result shows the action sequence like a human moving with a dumbbell in both hands. The last result shows the action sequence as if a chef is cooking food in the kitchen and trying a sample.

### C. Comparison with [5]

In order to see the difference between our proposed network and the network of [5], we have implemented the network presented in [5] based on the Tensorflow and trained it with our dataset. First, we compare generated actions when the sentence ‘Woman dancing ballet with man’, which is included in the training dataset, is given as an input to the each network. The result of the comparison is shown in Figure 8. The time interval between the each pose is 0.4 second. In this figure, results from both networks are compared to the human action that matches to the input sentence in the training dataset. Although the network presented in [5] also generates the action as the ballet player with both arms open, it is shown that the action sequence synthesized by our network is more natural and similar to the data.

In addition, we give the sentence which is not included in the training dataset as an input to each network. The result

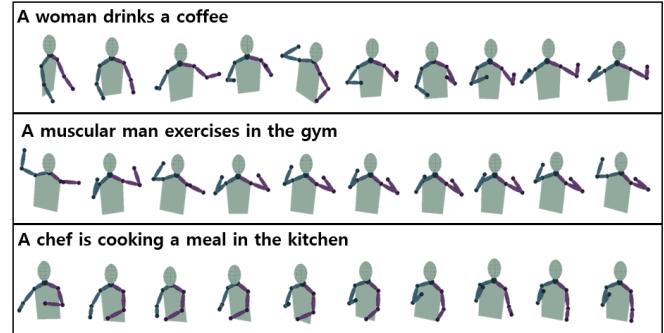


Fig. 7. Generated actions when different input sentence is given as input. When generating these actions, the random noise vector sequence  $z$  is fixed.

of the comparison is shown in Figure 9. The time interval between the each pose is 0.4 second. The given sentence is ‘A drunk woman is stumbling while lifting heavy weights’. It is a combinations of two sentences included in the training dataset, which are ‘A drunk woman stumbling’ and ‘Woman is lifting heavy weights’. The action sequence generated from our network is like a drunk woman staggering and lifting the weights, while the action sequence generated from the network in [5] is just like a person lifting weights.

It is shown that the method suggested in [5] also produces the human action sequence that seems somewhat corresponding to the input sentence, however, the generated behaviors are all symmetric and not as dynamic as the data. It is because their loss function is designed to maximize the likelihood of the data, whereas the data contains asymmetric pose to the left or right. As an example of the ballet movement shown in Figure 8, our training data may have a left arm lifting action and a right arm lifting action to the same sentence ‘Woman dancing ballet with man’. But with the network that is trained to maximize the likelihood of the entire data, a symmetric pose to lift both arms has a higher likelihood and eventually become a solution of the network. On the other hand, our network which is trained based on the GAN value function (1) manages to generate various human action sequences that look close to the training data.

### D. Generated Action for a Baxter Robot

We enable a Baxter robot to execute the give action trajectory defined in a 3D Cartesian coordinate system by referring the code from [19]. Since the maximum speed at which a Baxter robot can move its joint is limited, we slow down the given action trajectory and apply it to the robot. Figure 10 shows how the Baxter robot executes the given 3D action trajectory corresponding to the input sentence ‘A man is throwing something out’. Here, the time difference between frames capturing the Baxter’s pose is about two seconds. We can see that the generated 3D action takes the action as throwing something forward.

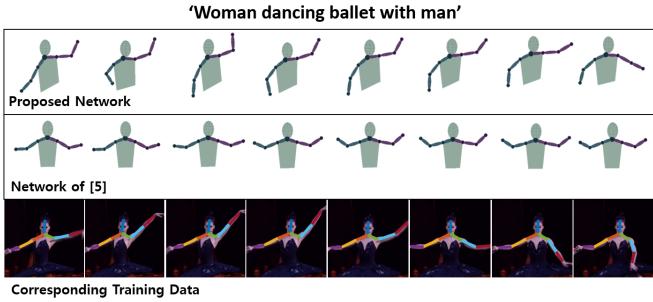


Fig. 8. The result of comparison when the input sentence is ‘Woman dancing ballet with man’, which is included in the dataset. Each result is compared with the human action data that corresponds to the input sentence in the training dataset.

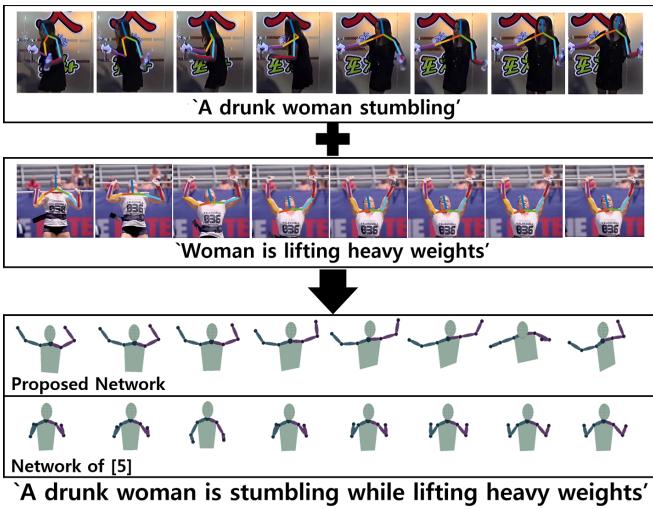


Fig. 9. The result of comparison when the input sentence is ‘A drunk woman is stumbling while lifting heavy weights’, which is not included in the dataset. The result shows that our proposed network generates the human action sequence corresponds to the proper combinations of the two training data.

## V. CONCLUSION

In this paper, we have proposed a generative model based on the SEQ2SEQ model [7] and generative adversarial network (GAN) [8], for enabling a robot to execute various actions corresponding to an input language description. It is interesting to note that our generative model, which is different from other existing related works in terms of utilizing the advantages of the GAN, is able to generate diverse behaviors when the input random vector sequence changes. In addition, results show that our network can generate an action sequence that is more dynamic and closer to the actual data than the network presented in [5]. The proposed generative model, which understands the relationship between the human language and the action, generates an action corresponding to the input language. We believe that the proposed method can make actions by robots more understandable to their users.

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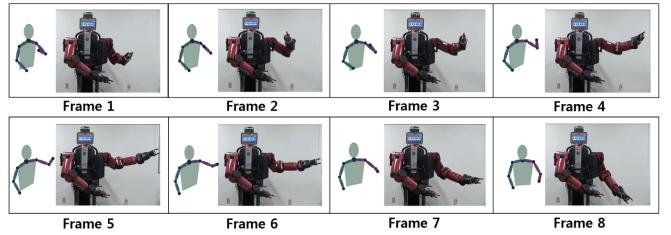


Fig. 10. Results of applying generated action sequence to the Baxter robot based on the Baxter-teleoperation code from [19]. The time difference between frames capturing Baxter’s pose is about two seconds.

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