
Generating Animated Videos of Human Activities from Natural Language Descriptions

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Abstract

Generating realistic character animations is of great importance in computer graphics and related domains. Existing approaches for this application involve a significant amount of human interaction. In this paper, we introduce a system that maps a natural language description to an animation of a humanoid skeleton. Our system is a sequence-to-sequence model that is pretrained with an autoencoder objective and then trained end-to-end.

1 Introduction

Developing automatic tools to generate visual content is a fundamental problem in computer graphics. The primary way artists currently create CGI animation sequences is by specifying a series of key frames for the characters. A key frame is a character pose at a particular point in time. This is a time-consuming and tedious process since each key frame is specified by manually moving the character into the desired position. This paper presents a method for automatically mapping a natural language (NL) description of a human activity to an animated video, specifically a sequence of 3D human skeletal poses that can be used to animate a CGI character. This allows the generation of animations with minimal user effort. Human-provided NL descriptions of human activities for which motion-capture (mocap) data is available [29] is used to train the system.

The problem of mapping between language and other modalities such as images and videos has attracted significant recent attention. In particular, there has been considerable work on deep neural networks for mapping videos to NL descriptions [25, 40, 45]; however, there is very little work on the inverse problem of text-to-video. The small amount of work on generating images and videos from text [21, 26, 33, 34, 47] generates pixel-level images that are sometimes low-quality, rather than concise 3D models that can be flexibly rendered into a variety of high-definition visual content using standard computer graphics techniques. The small amount of work on generating 3D graphics models from text [5–8, 36] focuses on static scenes rather than animations. There have been a few prior projects on mapping natural language descriptions of human activities to motion sequences using mocap data [30, 44], however, they do not specifically focus on generating animated videos for graphics applications and do not evaluate the quality of the generated animations using human judges.

Text-to-video is inherently harder than video-to-text since it requires generating long, real-valued, high-dimensional sequences from short, discrete ones, instead of the other way around. Also, language is inherently ambiguous, so there may be many animations that fit the same description. In addition, the amount of labeled mocap data is limited compared to images and videos. Mocap

Note: () denotes co-first authorship

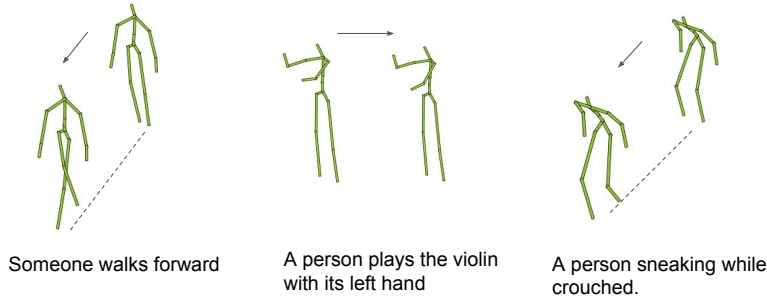


Figure 1: Examples of gold-standard description-animation pairs. The dotted lines show movement through space and the arrows show movement through time.

systems are expensive to setup and existing datasets do not use the same joint markers on the actors, making the resulting animations incompatible with each other. Finally, there is a large imbalance in the number of videos for different types of action in the dataset – there are many more videos of walking compared to dancing. Examples from the dataset are shown in Figure 1.

Due to these complexities, our initial attempts to use standard recurrent neural network (RNN) sequence-to-sequence (seq2seq) models [37] used for video-to-text met with limited success. To address these problems, we use a neural autoencoder to learn a compact representation of human motions by training on mocap data without NL descriptions, and then use an RNN to map descriptions into this motion representation.

The remainder of the paper describes the details of our method and presents a detailed evaluation of the animations generated for held-out test examples by comparing them to gold-standard animations, and by asking crowd-sourced human judges to evaluate their faithfulness to the given descriptions.

2 Related Work

Video Captioning There has been a growing amount of recent work on generating NL descriptions of videos. Venugopalan et al. [40] developed a seq2seq model for video captioning using convolutional neural nets (CNNs) to encode the frames and RNNs to map the sequence of frames to a sequence of words. Subsequent works [2, 25, 41] have improved this model using language models, pretrained word embeddings, attention, and hierarchical modelling.

Animation Synthesis from Text There has been some recent work on generating animations from text, however they use a data representation [39] where the hip position of the character has a fixed 3D location, therefore the character moves in place rather than along the floor. Plappert et al. [30] propose a seq2seq model for mapping text to a series of Gaussian distributions representing the joint angles of the character. Yamada et al. [44] use an autoencoder for text and an autoencoder for animations with a shared latent space to generate animations from text. These models are incomplete as the descriptions of the motions often include information about how the character moves in the global coordinate frame as well as how the character moves in the local coordinate frame.

Direct Animation Synthesis Since collecting motion capture data is expensive, generating new animation sequences from existing data has a long history in the computer graphics community [18, 31, 43]. Recently, researchers have used deep learning techniques to tackle this problem. One line of work has been on synthesizing animations under user constraints such as foot placement locations and times [13–15]. There have also been several works on synthesizing the continuation of an animation sequence given a few frames at the beginning of the animation [12, 22, 23]. In contrast to our problem setting, the input and output domain are the same in these methods, therefore their networks only need to model the uncertainty and wide range of futures, rather than also modeling the gap between the text and animation domains.

Motion Controllers In addition to methods that directly synthesize animations, there have been methods that learn policies for controlling simulated characters. The motivation for this approach is that animated characters should obey the physics of their world, thus the training procedure should include the complexity of the environment. One classical approach for generating animations is by

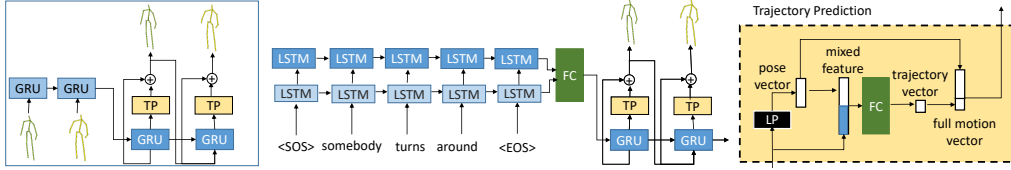


Figure 2: Our network architecture. (Left) Autoencoder architecture for the animation. (Middle) Network architecture for our full pipeline. (Right) Network architecture for the trajectory prediction module. LP indicates the linear projection layer and FC indicates the fully connected layer.

modeling the body using physics models [20, 48]. Another approach to this problem is to learn a policy for executing different actions using reinforcement learning. Some of these methods learn policies from scratch [38, 46] while others try to mimic the behavior in examples [3, 24, 27, 28, 42].

3 Approach

In the same spirit as other seq2seq modeling tasks (e.g., machine translation [32] and video captioning [40]), we design an end-to-end neural network f_θ , where θ encodes the network parameters, by combining a module for encoding the input NL description, a module for decoding the result into the output skeleton animation, and an intermediate module for connecting these two modules (See Figure 2). The encoder is a standard two layer stacked LSTM [11] and the decoder architecture is based on the GRU [9] with residual connections proposed by Martinez et al. [23]. We use the data representation proposed by Holden et al. [14], which factors out the skeleton animation as the combination of the character’s pose as represented by the joint positions of the character with respect to the local coordinate frame and the character’s trajectory of movement in the global coordinate frame. Drawing inspiration from the network architecture proposed by Agrawal et al. [1], we separated the pose prediction and trajectory prediction so that the trajectory prediction is conditioned on the pose prediction in addition to the GRU output.

Network training. Since the animation representation is higher dimensional compared to the NL descriptions, we first pretrain the decoder with an autoencoder loss. This is similar to the pretraining step for the task of machine translation. For the autoencoder pretraining step, we use a combination of the KIT Motion-Language Dataset [29] and the Human3.6M dataset [4, 16]. We then use the paired NL-mocap data from the KIT Motion-Language Dataset [29] and additional paired data that we collected on Amazon Mechanical Turk (AMT) using a video segmentation and annotation tool designed for dense video event captioning [19] to train the entire network. The loss function for both training steps is the L2 distance between the pose and trajectory of the gold-standard animation and predicted animation. We train the model until convergence using Adam [17].

4 Experimental Results

This section presents experiments that use both an automatic metric and crowd-sourced human judgments to evaluate our generated animations and compare them to several baselines.

Baseline Methods

1. Nearest Neighbor (NN) Our simplest baseline is a standard TF-IDF bag-of-words nearest neighbor method. First, we vectorize all sentences using TfidfVectorizer in Scikit-learn (*scikit-learn.org*). Then, to generate a video for a test description, we find the closest vectorized description in the training set using cosine similarity and return the corresponding animation.

2. Plappert et al. [30] (P) This is one of the aforementioned algorithms that also maps NL descriptions to mocap sequences. We modified their code to incorporate our new data while keeping everything else intact and trained their model using the hyperparameter settings listed in their paper.

Evaluation Metrics

Dynamic Time Warped Mean Absolute Error (DTW-MAE) We compare an animation generated for a description to the gold-standard (GS) animation and compute the mean absolute error. To compare animations of different lengths, we use a dynamic time warping algorithm [35] to stretch

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|------|-----------------|-----------------|-------------|-------------|-------------|
| | DTW-MAE | DTW-MAE-T | M1 vs. M2 | M1 Win Rate | M2 Win Rate |
| NN | 9.80 \pm 5.79 | 9.76 \pm 5.77 | P vs. GS | 0.105 | 0.895 |
| P | N/A | 8.44 \pm 3.99 | Ours vs. GS | 0.196 | 0.804 |
| Ours | 9.74 \pm 4.34 | 9.71 \pm 4.32 | Ours vs. P | 0.790 | 0.210 |

Table 1: Results on the test set. For DTW-MAE, lower is better. For the win rate, higher is better.

the shorter animation to the length of the longer animation. We then compute the mean absolute error between all of the corresponding poses and trajectories, averaging across animation frames. We computed this metric on all 805 gold-standard description-animation pairs in the test set. Plappert et al. [30]’s method only considers the pose of the animation, therefore we also present the DTW-MAE without the trajectory information (DTW-MAE-T) on the nearest neighbors baseline and our method for a fairer comparison.

Human Evaluation Since many different animations can be a good depiction of the described activity, similarity in the joint position space may not correlate with the overall quality of the generated result. Therefore, we also conduct a crowd-sourced human evaluation of the generated animations using AMT. We evaluate the generated animations for faithfulness, analogous to machine translation evaluations of fidelity. Our Human Intelligence Task (HIT) presents AMT workers with two videos for the same description, randomly chosen from: gold-standard, our method, and Plappert et al.’s method, along with the description. The AMT worker is then asked to select the animation that is a better depiction of the activity described in the text. The win rate is defined as the number of comparisons won by the method (M) divided by the total number of comparisons for a particular pair of methods.

In each HIT, we have workers rate three pairs of videos. For quality control, one of the pairs is a “verification” test to determine if the worker is paying attention. We generate a pool of 20 verification tasks from the validation set videos by randomly pairing a gold-standard description-animation pair with a gold-standard animation from a different pair. We manually check that the selected distractor animation does not depict the described activity. For each HIT, we include a randomly selected verification pair and discard data from the HIT if it is answered incorrectly. We selected a subset of 200 gold-standard description-animation pairs from the test set for the human evaluation experiment. 17 percent of the evaluations were thrown out due to failure on the verification task.

Discussion As we can see from Table 1, our method outperforms Plappert et al. [30]’s method in the human evaluation study. This may not be a fair comparison for Plappert et al. [30]’s method as many descriptions describe movement in the global coordinate frame and cannot be acted out while standing in place, e.g., “A person walking in a circle to the left.” The gold-standard animations greatly outperforms both models, showing that there is still more room for improvement for automatic methods. In a preliminary human evaluation study, we found that the nearest neighbor baseline is surprisingly strong for this task. This may be due to the fact that there are different actors performing the same activity in the dataset. We do not use the activity information when determining the dataset split, therefore animations of the same activity may be in both the training set and the test set. The main failure cases of our model are producing animations that fail to depict the description for less well-represented activities or producing animations that are physically impossible, e.g., the human figure glides along the floor instead of taking distinct steps.

The automatic evaluation metric, DTW-MAE, does not agree well with human judgment of animation quality. This demonstrates the need for human evaluation on graphics tasks and better automatic metrics that capture semantic meaning [10]. Martinez et al. [23] found that predicting the average pose at every time step is a strong baseline when comparing animations using mean absolute error of joint angles. Upon visual inspection of results produced by Plappert et al. [30], we found that the human figure is static in many of the animations, which may cause the mean absolute error to be low.

5 Conclusions and Future Work

We present an end-to-end sequence-to-sequence model for generating human motion animations from natural language descriptions. In the future, we plan to improve our model by improving our loss function to capture more semantic meaning and explore physically-based controller approaches to generate more realistic animations.

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