Implement Long Short-Term Memory Recurrent Neural Network on Grammatical Facial Expression Recognition

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**Abstract.** The abstract should summarize the contents of the paper and should contain at least 70 and at most 150 words. It should be set in 9-point font size and should be inset 1.0 cm from the right and left margins. There should be two blank (10-point) lines before and after the abstract. This document is in the required format.

**Keywords:** LSTM, Recurrent Neural Network, Kinect, Grammatical Facial Expression, Deep Learning

1 Introduction

Grammatical Facial Expression (GFE), a category sign language for people with impaired hearing [1, 2]. Combination of the hardware and software solutions can make machines learn the semantic meaning of such sign language. For the hardware part, Kinect, as known as a motion sensor device produced by the Microsoft, it can capture the facial expressions [3]. For the software part, Kinect can generate facial contour landmarks (x, y and z-axis) for each frame of recording via the Face Tracking SDK [3]. The bio-inspired deep learning algorithms can be implied to these landmarks and recognize some patterns among them.

To classify a facial expression from a time-series-based recording, deep learning can help with. In deep learning field, because Recurrent Neural Network (RNN) can memories data during a sequence of time and be implemented as a multilayer feedforward network, it is a suitable architecture to train time-series based dataset [4]. In recent work, the extensions of RNN are wildly used. Long Short-Term Memory (LSTM) is an improved extension of RNN, its gradient-based approach can prevent the influence of the gradient that vanished in further steps [5].

In this paper, the dataset used in this experiment, the previous research which used the same facial landmark dataset or used the LSTM on facial expression, the training, testing and validation methods with LSTM architecture, the experiment results and further conclusion of the experiment will be explained in following sections.

2 Data

This data repository used in the following experiment is provided by the UCI website. In this repository [6], there are 9 types of facial signs of 2 signers’ (Signer A and Signer B): Affirmative, Double Question, Negative, Wh Question, Conditional, Yes/No Question, Empathies, Relative and Topic. Each facial expression consists of one data points file with timestamps and one file with binary labels (0 or 1). In the data file, the x, y and z coordinators of each landmark are listed as features (columns). The labels are listed in each row for each instance.

The quality and quantity of data are the reasons to choose this repository. For the quality part, this dataset is complete, there is no need to clean data set; these landmarks can be used to represent an expression during a time period. For the quantity, averagely, there are 2500 instances can be used in training process for each expression, the 300 attributes also make the deep learning get sufficient exploration on features.

3 Related Work

There are few recent papers used the same data repositories. Multiple Layer Perceptron architecture is firstly used by Freitas et al. [2], they did not get very high F-score on “Negative” and “Relative” expressions, most of expressions can be recognized above 0.75 (F-score). In 2016, by extracting the important facial points, Bhuvan et al [7] improved the F-score of MLP model to above 0.89. In 2017, deep learning architecture, Convolutional Neural Network (CNN) is used by Walawalkar and Devesh [1]; their model has very good performance on each facial expression, all of expressions can have over 0.94 of F-score.

There is no paper found that used the LSTM/RNN to recognize the facial expressions of this repository, but there two papers found used LSTM to train the similar facial landmarks. In Behzed and Mohammad’s research[8], they used the CNN to extract landmarks from videos, then they used LSTM to memories and train the landmarks; their final model can successfully recognize variety facial expressions from 4 data repositories. Alex et al used unidirectional LSTM for 116 facial landmarks, the final expression recognition mean error rate is 18.2 ± 0.6%.

4 Methods

4.1 Data Preprocessing

To help classifier find the patterns, each instance is reconstructed by 11 distances, 7 angles and 100 (whole) of z-coordinators, therefore, an input entry vector has 118 attributes. The distance and angles are specified in Freitas et al’s paper [2]. Since there are two signers, each signer performed 9 facial expressions, the two data files of both signers should be combined as one data file and normalized by Z-score method [1].

Each facial landmark has x, y, and z coordinators, the Euclidean distance between two landmarks uses x and y coordinators of a landmark, which are and . Thus, the Euclidean distance is calculated by [9]:

**(1)**

The Signer A and Signer B have their 1D matrixes, and , for a specified Euclidean distance. Because the Z-score can show the scaled distributions for different signers, which make the values are comparable, each distance instance of and will be calculated independently by same function, where D is a distance instance, is the mean of the 1D distance matrix and N is the number of instances in the 1D distance matrix:

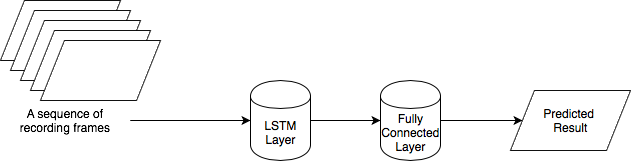
**(2)**

The angle (in cosine) between two distances ( and ) can be calculated by following function, where gets dot product, and are the norms of and respectively:

**(3)**

4.2 Deep learning Model for training

The aim of this experiment is using supervised binary classifier with LSTM architecture to classify if a frame of facial landmark belongs to a category of grammatical facial expression. As the Fig. 1 displayed, there are only two hidden layers, LSTM layer and Fully Connected (FC) layer, which will be used to connected with input layer and output layer.



**Fig. 1**

For the input layer, 5 frames of facial expression with 118 attributes will be sent to LSTM layer, since the LSTM has 10 hidden neurons, the input size is .

In the LSTM layer, there are three gates: input gate, forget gate and output gate.

4.3 Model Testing

Please check that the lines in line drawings are not interrupted and have a constant width. Grids and details within the figures must be clearly legible and may not be written one on top of the other. Line drawings should have a resolution of at least 800 dpi (preferably 1200 dpi). The lettering in figures should have a height of 2 mm (10-point type). Figures should be numbered and should have a caption which should always be positioned *under* the figures, in contrast to the caption belonging to a table, which should always appear *above* the table. Please center the captions between the margins and set them in 9-point type (Fig. 1 shows an example). The distance between text and figure should be about 8 mm, the distance between figure and caption about 6 mm.

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4.3 Model Validation

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5 Results and Discussion

The printing area is 122 mm × 193 mm. The text should be justified to occupy the full line width, so that the right margin is not ragged, with words hyphenated as appropriate. Please fill pages so that the length of the text is no less than 180 mm, if possible.

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6 Conclusion and Future Work

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Appendix: Specified Distances and Angles for Data Pre-processing

