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 (adding 3 gates) can prevent the influence of the gradient that vanished or exploded 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.

1.1 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.

1.2 Related Work

There are few recent papers used the same data repository as this paper. Multiple Layer Perceptron (MLP) architecture is firstly implemented on this repository by Freitas et al. [2, 7], 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 [8] improved the F-score of MLP model to above 0.89. In 2017, a 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 this repository, but there are two papers found used LSTM to train the similar facial landmarks. In Behzed and Mohammad’s research[9], 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 [10] used unidirectional LSTM for 116 facial landmarks, the final expression recognition mean error rate is 18.2 ± 0.6%.

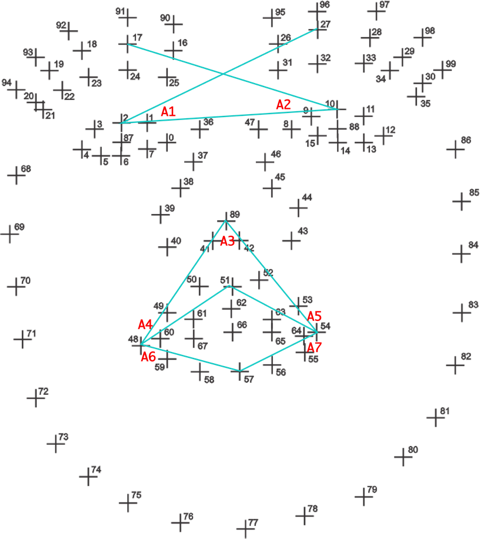
2 Methods

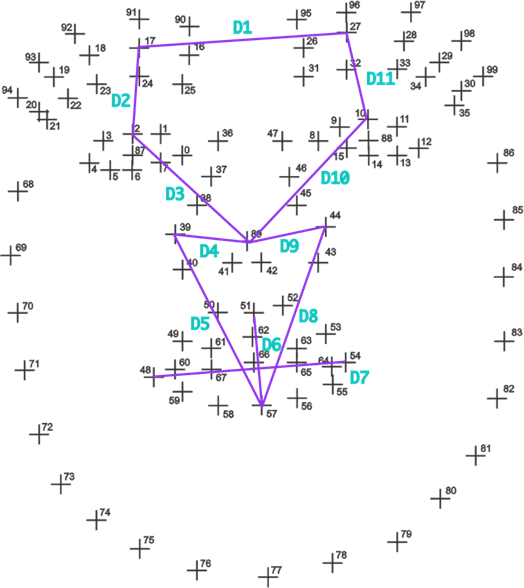
2.1 Data Preprocessing

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 for deep learning model has 118 attributes with 1 dimension. The distance and angles showed in Table 1 and Figure 1 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].

**Table. 1** Summary of accuracies from three experiments

|  |  |  |  |
| --- | --- | --- | --- |
| **A1** | **A2** | **A3** | **A4** |
| {27,2,10} | {17,10,2} | {48,89,54} | {89,48,51} |
| **A5** | **A6** | **A7** |  |
| {89,54,51} | {51,48,57} | {51,54,57} |
| **D1** | **D2** | **D3** | **D4** | **D5** | **D6** | **D7** |
| {17,27} | {17,2} | {2,89} | {89,39} | {39,57} | {51,57} | {48,54} |
| **D8** | **D9** | **D10** | **D11** |  | | |
| {44,57} | {44,89} | {89,10} | {10,27} |





**Fig. 1** Top image: 7 angles; Bottom image: 11 distances

Each facial landmark has x, y, and z coordinators, the Euclidean distance between two landmarks uses x and y coordinators of two landmarks, which are and . Thus, the Euclidean distance is calculated by [11]:

**(1)**

The Signer A and Signer B have their 1D matrixes, and , for one of specified Euclidean distances. Because the Z-score [1] 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:

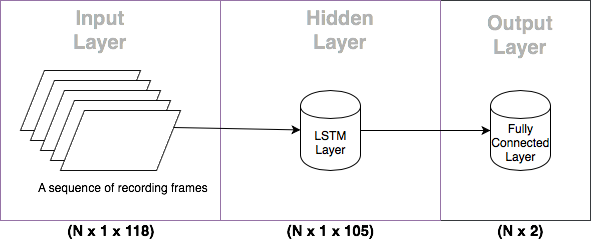
**(3)**

The input vector for neural network will be 1D, it has 118 attributes: 11 distances, 7 angles, all Z coordinators (100), each input vector represents one frame of recording:

(**4**)

2.2 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 one hidden layer, LSTM layer. Fully Connected (FC) layer is used as an output layer.



**Fig. 2** Training Model Architecture

For the input layer, since each instance vector has a related target label, the total N frames (training data) of 1D input entry vector with 118 attributes which given by the section 4.1, will be sent to LSTM layer. For the hidden layer, there are 3 gates and 2 memory cells used for this gradient-based approach of LSTM, which are input gate (), forget gate (), output gate (), new memory cell () and final memory cell () [5]; In the following formulas [9], the “t” means a timestamp, “” is the sigmoid function, “” is the input, “h” is the output, “b” is the parameter vector, “W” means the parameter matrix.

**(5)**

**(6)**

**(7)**

**(8)**

**(9)**

**(10)**

In this experiment, 105 of hidden neurons were found as the best choice, the output size of LSTM is .

The fully connected layer which helps map data, the input size is (). As a standard logistic function, sigmoid function can only result in 0 or 1 when the input is not 0. Thus, it can be used to indicate the target facial expression quickly.

In order to keep the balance between training and testing sets, 80% of data will be used in the training process. However, LSTM needs time series data sequences, the input data will be in time stamp order. After several times of the experiments, as Table 2 displayed, this paper chooses the parameters make high final accuracy.

**Table. 2** Summary of parameters in Training

|  |  |
| --- | --- |
| **Hyperparameter** | **Value** |
| Number of features(attributes) | 118 |
| Output Classes | 2 |
| Number of Hidden Neurons | 105 |
| Learning Rate | 0.0099 |
| Number of Epoch | 30 |
| Optimizer | Adam |
| Loss Function | Cross-Entropy |

Adam [12] as a first-order-gradient-based optimizer, it can achieve fast convergence and perform well in deep learning, thus by using it, less epoch will be needed [13]. Following Cross-Entropy [14] which combined with the SoftMax is used as the loss function to calculate the differences between the output values of model and the actual target value; then the gradient of cross-entropy will be calculated through backpropagation and fed to the Adam optimizer:

**(11)**

There are n classes. The x is the output given by the deep learning model, the class is the target output.

2.3 Model Testing and Validation

This paper adopts hold-out validation method [15], which means that validation and testing use the same data set, which is 20% of data. The reason of using hold-out is it can have simpler implementation than other validation approaches (e.g. 10-folder cross validation) and avoid using the duplicated data from the training set [15]. By using the hold-out, the loss values of testing/validation and training after each epoch can be stored in the middle of process, thus, these loss values can draw a loss graph to display if a model is overfitting or underfitting. The beginning epoch was set to 1500, after several testing the epoch was corrected to 30.

To evaluate the model, the accuracy is calculated by F1-score [16], where “tp” means all prediction and actual values are negative, “fn” means prediction is positive while actual value is negative, “fp” has opposite meaning of “fn”:

**(12)**

**(13)**

**(14)**

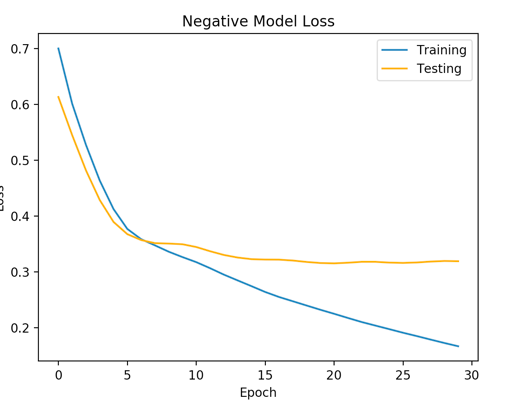
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3 Results

3.1 Analysis of the LSTM model

Except using hold-out, the learning rate and optimizer function are helpful on reducing time of training by using less epochs.

The final loss graphs of 9 grammatical facial expressions, show that the training and testing loss values decrease in the same trend. Because all 9 facial expressions use the same model, the loss changes are varied among of them. For “Negative” expression (Figure 3), it always has significant overfitting after 5 epochs, for other expressions, training line is a little below the testing line at the last epoch, the overfitting is not significant after correction of epoch by hold-out [15].



**Fig. 3** Loss for “Negative” facial expression

3.2 Comparison of Results

As the Table 3 showed, there are 3 columns of accuracies. “Accuracy A” has the accuracies from the Freitas et al’s most recent work [7], “Accuracy B” shows the accuracies produced by LSTM of this paper. “Affirmative” and “Wh Question” have the both highest accuracies compared to values of “Accuracy A”. The other expressions cannot have better recognition while using the LSTM of this paper. The average accuracy of using LSTM is less about 4% of Accuracy A.

**Table. 3** Summary of accuracies (F1-scores) from 2 experiments

|  |  |  |
| --- | --- | --- |
| **Grammatical Facial Expressions** | **Accuracy A**  **(MLP)** | **Accuracy B**  **(LSTM)** |
| Affirmative | 0.8773 | 0.9022 |
| Conditional | 0.9534 | 0.8784 |
| Doubt Question | 0.9700 | 0.9416 |
| Emphasis | - | 0.8696 |
| Negative | 0.9582 | 0.8816 |
| Relative | 0.9759 | 0.9339 |
| Topic | 0.9544 | 0.9246 |
| Wh Question | 0.8988 | 0.9211 |
| Yes/No Question | 0.9412 | 0.9222 |
| **Average Accuracy** | 0.9412 | 0.9084 |

Signer needs to move the head from up to down several times to perform “Affirmative”. To perform “Wh Question”, signer’s forehead needs to fold. Since these two expressions need a sequence of movement to be identified, the higher accuracies in LSTM than in MLP model [7] are reasonable.

The accuracies of “Conditional”, “Emphasis” and “Negative” are below the average accuracy. In the MLP mode [7], the accuracies of “Conditional” and “Negative” are similar and high. It may show the LSTM model hardly recognizes these two expressions; memorizing a sequence of these types of instances can reduce the model accuracy. Although the “Negative” also involves moving head, but it has more changes of other facial landmarks than “Affirmative”, handling variety changes may cause low accuracy.

In both MLP [7] and LSTM model, the final accuracies of “Doubt Question” are very high among the 9 facial expressions. The results may mean this expression has significant changes by comparing to other neutral frames while training the model.

4 Conclusion and Future Work

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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