Highly-accurate gesture recognition based on ResNet with low-budget data gloves

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ABSTRACT

Gesture recognition has been widely used in various fields such as virtual reality (VR), human-computer interaction, and clinical medicine. Traditionally, gesture recognition requires expensive sensors to obtain high-precision data, but some applications—such as VR games—do not require high accuracy and users prefer a lower cost instead. Thus some researchers began to use Convolutional Neural Networks (CNN) to recognize gestures directly without other calibration equipment. However, using CNN encounters the degradation phenomenon of the neural network. In this paper, we propose a highly-accurate gesture recognition method for low-precision glove data based on Residual neural Networks (ResNet). Our method combines 1D convolution with 2D convolution and adopts a sliding window for sample size constraint to achieve data enhancement. Evaluation results indicate that compared to the CNN method, our method improves the classification accuracy rate from 94.4% to 99.2%.

CCS CONCEPTS

• **Computing methodologies** → **Model development and analysis; Modeling methodologies.**

KEYWORDS

gesture recognition; low-budget data glove; VR games; ResNet

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1 INTRODUCTION

Nowadays, gesture recognition has a pivotal role in various fields such as human-computer interaction [20], robotics [19], self-driving [13], smart wearable device [25] and virtual reality [24]. Seokwon et al. [15] describe the application of data gloves in VR games. In VR games, many things that are difficult to accomplish in real life can be easily achieved. You can play the piano, ski, and even save the world like the protagonist of a Marvel movie. All of this just requires one compact VR equipment. However, the cost is a classic problem in the application of VR equipment. Good-quality and inexpensive equipment is one of the necessary conditions for the promotion of VR games. VR games are mainly composed of interactive and action simulation which need a lot of motion recognition. It has been observed that compared with wireless controllers, vision-based gesture recognition lacks the sense of vibration feedback. Also, it is impossible to achieve satisfactory sensitivity and accuracy by relying on computer vision alone. Fortunately, low-budget data gloves can overcome these shortcomings. At present, gesture recognition with data gloves can be used for some common operations, such as aiming, selecting, moving, rotating, zooming, etc. Virtual objects can be directly touched with users' hands, and data gloves can provide users with tactile feedback.

In addition, gesture recognition with data gloves does not require placing hands in a specific position to track and identify. In many complex game scenarios, we also need to do different actions in different places. Data gloves are not restricted by light, camera angle of view, distance, and other factors. Compared with other devices, VR devices with data gloves can provide a better immersive experience. Data gloves can expand the application scenarios of VR, especially those that require finger details, such as teaching experiments. Ognjan et al. [18] have also researched low-budget data gloves, but in his work, the type of gestures is very limited.

Quam et al. [22] have researched that gesture recognition can be accomplished by the data gloves with flex sensors. Then some researchers use neural networks [27] to study gesture recognition. In terms of classification, neural networks are being increasingly adopted by researchers. In theory, neural networks can fit any continuous function and have powerful feature extraction capabilities. Gesture recognition with data gloves has been widely researched via a neural network like Convolutional Neural Network (CNN) [17] and Recurrent neural network(RNN) [10]. Weissmann et al. [29] propose a gesture recognition method based on neural networks used in VR applications. Emmanuel et al. [3] use the CNN classification with a weft knit data glove on grasp recognition and achieve the mean accuracy of up to 86.27%. Sai et al. [11] propose a Fully-Connected Neural Network (FCNN) classifier which could learn hand gestures from data with 98% accuracy but only a few grasp movements are evaluated. The more complex the neural network is, the more parameters there are. For example, GPT-3 [4] has hundreds of billions of parameters. It is infeasible to deploy it on a portable device like a glove. Convolutional neural networks are more suitable for data gloves than other neural networks because of shared weights. In this work, we refer to ResNet [9] and link the CNN across layers to recognize gestures and make the comparison with machine learning algorithms.

On the one hand, this paper reveals that it is possible to recognize different common gestures accurately from inertial sensor data with a pair of low-budget data gloves. Using a residual neural network instead of CNN to classify gestures generates fresh insight that inexpensive data gloves can help us experience VR. On the other hand, we evaluate the performance of the classification method based on ResNet in the relatively small data set, which proves that our method generates good results.

In summary, the following contributions are made in this paper:

- Motivated by ResNet, we design a new deep learning model which combines 1D convolution with 2D convolution.
- Due to the limitation of sample size, we adopt a sliding window method to achieve data enhancement.
- We demonstrate that our approach significantly improves the maximum accuracy of common gesture recognition up to 99.2%, while the accuracy of CNN is only 94.4% under the same conditions.

2 METHOD

2.1 Dataset

In this paper, we designed a pair of data gloves to collect the corresponding data from subjects. The gestures are given by the Ninapro [2] which is famous for EMG databases. The data gloves we designed consist of 6 inertial sensors and each sensor contains an MPU-6050 gyroscope. The sensor can record the joint angle information of the fingers. It is driven by an ARM architecture Micro Controller Unit (MCU). The data glove is pretty cheap and convenient.

Grasping movement is as common as sign languages in our daily lives. Thus we selected 13 kinds of common gestures including sign languages and grasping movements. When collecting data, we always keep the palm in the vertical direction. Then we use a data glove to directly record relevant joint signals at a frequency of 30 hertz by the 6 sensors. For each gesture, we will record 500 values

per sensor. The raw hand gesture data will be used as the input data of the neural network after the sliding window. Figure 2 shows all the common gestures in this experiment. It's important to note that our method does not need to map from sensor values to actual joint angles. It means that a complex calibration is not necessary. So our method can quickly recognize common human hand gestures. The appearance of the data glove is shown in Figure 1.

Figure 1: Low-budget data glove used in the experiments.

2.2 Data preprocessing

Most research uses the original data as input directly without considering data preprocessing. If the collected raw data is directly input into the neural network, the final result will likely be affected by factors such as noise. We must preprocess the data. Inspired by previous bio-signal processing methods[7] [5], we adopt a sliding window method to process the raw gesture data. The joint angle data of each gesture we collected is a series of continuous signals. The collected signal can be represented as following:

$$A = \{a_1, a_2, \dots, a_n\}.$$

Traditional approach is to combine a single vector a_k , we adopt a sliding window to intercept the collected data, the result is represented as:

$$B_1 = \{a_1, a_2, \dots, a_t\}, t < n.$$

Like the convolution kernel in the convolution neural network, the data is intercepted by moving the window according to the given step size s , the next result can be presented as:

$$B_2 = \{a_{1+s}, a_{2+s}, \dots, a_{t+s}\}, t < n.$$

The data processed by the sliding window will be as input to the neural network. It not only enhances the original data but also the generalization performance of the network. The principle of the sliding window is shown in Figure 3.

2.3 Traditional algorithms

Traditional methods on gesture recognition such as decision trees [6], random forests, and linear regression have made significant

Figure 2: Different gestures used in the experiments.

contributions to gesture recognition. Each of them has its advantages and disadvantages. We will introduce these common gesture recognition algorithms as follows:

- Linear regression (LR) is simple and easy to understand. It can process numerical data and predict that the target data is continuous. Gesture data is just a kind of continuous data. So lots of researchers have been studied gesture recognition with linear regression. LR can be calculated as follows:

$$f(x) = w^T x + b.$$

We can directly see the degree of influence of each feature on the result from the weight w . However, there are still

Figure 3: Schematic diagram of the sliding window.

some limits. For example, not all models are linear and LR cannot handle non-linear models effectively. Unfortunately, this is one of the inevitable situations in the research.

- Decision tree (TR) is a very classic machine learning method. In many classification problems, especially when the amount of data is relatively small, decision trees usually perform very well than any other machine learning method. Decision tree training requires fewer data and is highly interpretable and that is why we chose it as the method of comparison. But TR is prone to produce an overly complex model, resulting in poor generalization performance. At the same time, learning an optimal decision tree is usually an NP-hard problem.
- Random forest (RF) is a classifier built haphazardly and contains multiple decision trees. It can handle very high-dimensional data without feature selection. In the training process, the mutual influence between features can be detected and after training, it can give out which features are more important. When RF solves the regression problem, it does not perform as well as it does in classification. This is because it does not give a continuous output. These machine learning methods have limitations in the field of gesture recognition.
- Convolutional neural networks are widely used in the field of deep learning, and many classification problems can be easily solved through it. Compared with other neural networks, CNN can automatically perform feature extraction, and sharing weights. It means that the number of parameters will be relatively small, which helps us deploy neural networks on devices with low computing power such as gloves. However, if the network level is too deep, the gradient disappears or explodes. Therefore, there is still room for improvement in many related studies.

2.4 The framework of the proposed gesture recognition

After the neural network was proposed, many scholars have been trying to deepen the number of layers of the network. From the

initial three-layer fully connected neural network to AlexNet [14], VGG16 [26], etc., the number of neural networks is increasing. But the researchers soon discovered that when the number of layers was increased to a certain number of layers, the accuracy began to drop. The emergence of a Residual neural network (ResNet) solves this problem. ResNet has been widely used in deep learning algorithms and make a breakthrough. If we only use CNN to classify gestures, we usually need a multi-layer neural network. However, the experimental results will not increase with the depth of the neural network, and the accuracy rate will start to decline after the neural network exceeds a certain depth. Compared with previous deep learning algorithms, ResNet can effectively avoid the gradient disappearance or gradient explosion, which is especially important when the neural network is deep. We decide to change the original convolutional neural network structure and added a residual block. Figure 4 shows our design of the residual block.

Figure 4: Residual block.

We conduct the experiments on the PyTorch [12] platform and scikit-learn package [21]. Our algorithm flow chart is shown in Figure 5. After we collected data through the data glove, then we process the gesture data by sliding window. Next, the data will be sent to the neural network for classification. Our network has a total of 14 layers, including 4 residual modules. We choose the cross-entropy as a loss function and use the Adam optimizer. For multi-class problems, the softmax function is one of the best choices. It can be calculated as follow:

$$\text{Soft max}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}.$$

3 RESULT

The results of different classification methods are illustrated in Figure 6. It can be seen that on average, gesture recognition method based on ResNet has higher accuracy than any other method. From

Figure 5: The architecture of the proposed model.

Figure 6, we can easily observe that the results based on ResNet and random forest (RF) [1] both achieve promising results in terms of precision. Decision tree (TR) performs worst in general because decision tree has a high risk of over-fitting. We also note that the CNN model shows worse performance than the based on the ResNet model as well. We argue this may be caused by the fact that the input data size is relatively small. Compared with random forest (RF), linear logistic regression (LR) [8], and other machine learning methods, the CNN model is not adequate. In summary, we have proved that gesture recognition based on ResNet could recognize different common gestures accurately from initial inertial sensor input with a pair of low-budget data gloves. Further classification results could be observed through the confusion matrix.

Figure 6: The results of different classification methods, where the x-axis represents the method and the y-axis denotes the accuracy.

The confusion matrix [28] which stands for estimation accuracy with each gesture is shown in Figure 7. From the confusion matrix, we find that sign languages are easier to identify than grasp movement. Due to the relatively large amount of data, it is not intuitive to draw the confusion matrix directly. Therefore, after normalizing the data, we keep two decimal places and use the sklearn package to draw the confusion matrix. From Figure 7, we can observe the classification results. Because we always wear the data glove and keep the palm in the vertical direction to acquire data, so the gestures of label 1 and label 12 are very similar. The same is true for label 5, label 9, and label 10 gestures. A very small number of data with labels 0 and label 6 is not classified by neural networks. For these similar gestures, our model based on the ResNet is still able to reach at least 96% accuracy. This proved that ResNet has high estimation accuracy in gesture recognition even if there are extremely similar gestures. For those gestures with big differences, the model based on the ResNet makes few mistakes.

Figure 7: The confusion matrix

4 DISCUSSION

Gesture recognition has been widely used in daily lives. Using a pair of low-budget data gloves could easily realize gesture recognition. Data gloves can help us complete many tasks in human-computer interaction scenarios. Correctly and quickly recognizing the users' gestures can help us judge their motivation which plays an important role in VR games [23] and other scenarios. In this study, we researched hand gesture recognition based on ResNet and compare it with traditional machine learning methods.

Generally speaking, the volume of data collected by data glove is not large. The most exciting finding was that CNN sometimes is not effective compared with random forest, linear logistic regression, and other machine learning methods. Machine learning algorithms also have a good performance when the data set is relatively small and is superior to lots of neural network classification algorithms. Thus, in this research, we choose to improve the original CNN model and combine the residual block and the result turns out that the improved model is more suitable than CNN. For similar gestures,

CNN needs to deepen the number of layers to distinguish due to small data, but worsening the number of network layers will cause the gradient to disappear or the gradient to explode. Combined with ResNet can overcome these shortcomings so our deep learning model combined 1D convolution with 2D convolution not only can the training time of the multilayer neural network be reduced, but also a very high accuracy rate can be achieved.

However, there are still some shortcomings in the work we have done. Firstly, we do not acquire continuous motion gesture data and this is will be one of our works. The gesture data is basic functionality without complex gesture data. And continuous motion gesture is necessary for gesture recognition. Only the continuous motion gesture can be accurately estimated, low-budget data gloves can play an irreplaceable role in VR games, human-computer interaction, and other scenarios. In terms of gesture recognition with data gloves, continuous motion gesture estimation is a trend [16]. Secondly, the amount of gesture data acquired in our work is not big enough. We should consider different subjects in terms of gender, age and health.

To some extent, gesture data is a type of EMG. This means it is also a type of time series data. For this kind of data, we can also use recurrent neural networks (RNN) to process. In this field, few people currently use RNN alone to recognize continuous motion gesture data with a pair of data gloves. For continuous motion gesture data, long short-term memory (LSTM) neural network may be a solution [30].

As discussed above, our future work will focus on continuous motion gestures on various subjects. We will try to do continuous motion gesture recognition based on LSTM.

5 CONCLUSION

The purpose of this paper is to determine whether ResNet could classify gesture data in the case that the amount of data is relatively small. The result is in line with our expectations. This is of great significance to the promotion of VR. Deploying a neural network with a relatively small amount of parameters on the chip can quickly and accurately identify various gestures. At the same time, low-cost gloves can be widely used in many human-computer interaction scenarios as wearable devices.

The paper has argued that low-budget data gloves could recognize gestures easily and effectively. In terms of some applications, especially in VR games, the lower cost is vital. In this paper, we propose a method based on ResNet via a sliding window to recognize the gesture. The model architecture is not extremely complex but the result is very promising. Simple neural networks can be deployed on low-end chips and this is meaningful. We experimented with CNN, RF, LR, and TR classifiers to identify which one is the most suitable for gesture recognition. Our method achieves the best prediction gesture result with 99.2% accuracy on the test data. In the future, We plan to increase the number of gestures including gestures to cover the general gestures in VR games based on our low-budget data-glove. Although the classification accuracy of our algorithm has achieved 99.2%, it is still limited in the object seen scenarios and there is no continuous dynamic gesture. Future work will involve continuous dynamic gesture and gesture recognition in unseen scenarios.

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