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Sign Language Recognition and Application Based on Graph Neural Networks: Innovative Integration in TV News Sign Language

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Abstract: With the rapid development of information technology, sign language recognition plays an extremely important role in the communication among people with hearing impairments. Especially in the context of television news, the real-time and accuracy of sign language translation are very important. Traditional sign language translation technology faces challenges such as low accuracy of gesture recognition and poor real-time performance, which makes it difficult to meet the translation needs of daily complex news content. This paper proposes a sign language recognition method based on graph neural network (GNN). By constructing a graph structure of gesture nodes and joint connections, GNN can capture the relationship between gestures and efficiently transfer learning information. Through comparative experiments with traditional convolutional neural networks (CNN), the advantages of GNN in sign language recognition are proved, especially in the application of news broadcasting, which significantly improves the real-time and accuracy of sign language translation. Future research will focus on optimizing the generalization ability of the model and broadening its applicability to more languages and scenarios.

Keywords: Graph Neural Networks (GNN), Sign Language Recognition, Television News, Real-time Translation, Automation.

Disciplines: Artificial Intelligence and Intelligence. **Subjects:** Machine Learning.

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1 INTRODUCTION

With the rapid development of modern technology, sign language, as the primary means of communication for the hearing-impaired, has received increasing attention. Particularly in the context of TV news, ensuring the real-time accuracy of sign language interpretation is crucial. Traditional sign language translation typically relies on human interpreters, but this method has limitations such as low translation efficiency and limited human resources. Graph Neural Networks (GNN), as an emerging machine learning model, provide new technological means for the automation of sign language translation. This paper will explore how GNN technology can be integrated with sign language translation, especially in the application of TV news sign language translation. [3]

2 LIMITATIONS OF TRADITIONAL SIGN LANGUAGE TRANSLATION TECHNOLOGY: PRACTICAL CASES IN TV NEWS

Traditional sign language translation technology mainly relies on video capture and gesture recognition. Cameras capture hand movements, and through feature extraction methods, recognize the corresponding language. While this technology aids in the translation of sign language, it still faces issues such as lack of real-time performance and low accuracy in gesture recognition. [4]

Traditional sign language translation is widely used in TV news, but as the complexity of news content increases and the demands for sign language interpretation grow, traditional technologies gradually reveal certain limitations. The following are several practical cases demonstrating the constraints of traditional sign language translation in TV news. [2] E.g, in TV news, real-time performance is one of the most critical requirements. Sign language interpreters need to complete the sign language expression of news content in a very short time. [5] However, relying on traditional sign language recognition technologies and human interpretation, delays often occur, especially when news content changes rapidly or contains highly specialized vocabulary. In a live broadcast covering a "natural disaster emergency," for instance, the interpreter needs to handle a large number of technical terms such as "typhoon path," "wind speed," and "precipitation." [1] Due to the complexity of these terms and the limitations in the interpreter's reaction time, the sign language translation often fails to keep up with the pace of the news broadcast.[6]"Low accuracy in gesture recognition" – traditional sign language recognition technologies depend on image recognition and gesture matching algorithms. However, the hand movements in sign language are often complex and diverse, and the same gesture can express different meanings depending on the context. [7] In a "health news" broadcast, for example, the term "heart disease" was discussed. Traditional gesture recognition systems failed to accurately distinguish subtle differences in sign language, often confusing "heart disease" with other similar medical terms, leading to translation errors. This issue is particularly common when dealing with more abstract or specialized content.

3 APPLICATION OF GRAPH NEURAL NETWORKS IN SIGN LANGUAGE RECOGNITION

3.1 Basics of Graph Neural Networks

Graph Neural Networks (GNNs) are deep learning models capable of processing graph-structured data. In GNNs, nodes represent entities, and edges represent relationships between nodes. [8] In sign language, hand gestures, facial expressions, and body movements can be modeled in the form of graphs. The joints of fingers can be considered as nodes, and the connections between joints can be considered as edges. This representation enables GNNs to capture the complex interrelationships between gestures, thereby improving the accuracy of sign language translation. [9]

3.2 Graph Neural Networks in Gesture Recognition

Gesture recognition is the foundation of sign language translation. By treating fingers and joints as nodes in a graph, GNNs can capture the spatiotemporal relationships of hand movements. For instance, a hand gesture can be represented as a graph $G = (V, E)$, where V represents the joints of the hand and E represents the connections between these joints. By learning from the graph, GNNs can recognize the specific semantics that the gesture represents.[10] Let the position of a node in a gesture at time t be $P_t = (x_t, y_t, z_t)$, where x_t, y_t, and z_t represent the coordinates of the node in three-dimensional space. By processing this graph structure with a GNN, it is possible to predict the meaning of the gesture. Here, W_t represents the edge weights in the graph, and b_t represents the bias term. So we can get the final equation $P_t = f(GNN(W_t, b_t))$.

3.3 Experimental Data and Results of Graph Neural Networks in Sign Language Recognition

In an experiment based on a TV news broadcast, we used a dataset containing 5,000 different sign language gestures, each representing various news-related vocabulary such as "climate change," "typhoon," "pandemic," etc. To evaluate the performance of Graph Neural Network (GNN) technology, we conducted a comparative experiment with traditional Convolutional Neural Networks (CNN), focusing on the performance in the following three aspects:

- Recognition Accuracy: This measures the accuracy of the system in recognizing the sign language gestures.
- Real-time Performance: The translation speed of the system, measured in frames processed per second (FPS). We optimize real-time processing by adhering to the real-time data processing framework
- Error Rate: This shows the rate of translation errors occurring during the process.

In this experiment, we compared a GNN-based model with a traditional CNN model, both using the same sign language dataset· [11] In each experiment, 1,000 test samples were introduced to evaluate the system's real-time performance and recognition accuracy. The specific experimental setup is as follows:

- Hardware: Intel i9 processor, NVIDIA RTX 3090 GPU.
- Software: TensorFlow framework, Python programming language.
- Dataset: A custom news dataset containing 5,000 sign language gestures.

Model Type	Recognition accuracy	Average real-time processing speed (FPS)	Error rate
Traditional CNN model	85.4%	22 FPS	14.6%
GNN Model	94.2%	28 FPS	5.8%

Experimental results show that the performance of the graph neural network model in sign language recognition is significantly better than that of the traditional CNN model: Recognition accuracy: The recognition accuracy of GNN is as high as 94.2%, which is much higher than the 85.4% of traditional CNN, indicating that GNN can better capture the complex relationship between sign language gestures. Real-time: The average processing speed of the GNN model is 28 FPS, compared with the 22 FPS of the traditional CNN model, indicating that GNN has advantages in dealing with scenarios with high real-time requirements such as live news. [12] Error rate: The error rate of GNN is only 5.8%, while the error rate of the traditional CNN model is 14.6%, which significantly reduces translation errors. [13] The above experimental results are made into a visual chart to more intuitively show the comparison results of the two models:

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3.4 Real-World Case of Graph Neural Networks in Sign Language Recognition Applications

The application of Graph Neural Networks (GNN) in sign language recognition has demonstrated significant advantages in terms of real-time performance and recognition accuracy. [14] The following is a specific case of GNN applied to TV news sign language translation, illustrating how GNN enhances the effectiveness of sign language recognition. [15]

During a live news broadcast covering the "Global Climate Change Conference," the news involved a large number of technical terms such as "climate change," "global warming," "carbon emissions," and "renewable energy." [16] Traditional sign language interpreters struggled to keep up with the rapid emergence of these specialized terms, while a sign language recognition system based on GNN was able to quickly process these complex gestures.

In the practical operation process, the "node and edge representation" depicts each finger joint as a node in the graph, and the joint movements as the connecting edges. For instance, in the sign for "global warming," the hand gradually opens to simulate the rising temperature, and the changing positions of the finger joints are captured and analyzed by the GNN. [17]

The "application of graph convolution layers" shows how the system processes gesture data through graph convolution layers, identifying the relationships between nodes. For example, the GNN model is able to analyze the complex interactions between the arm and fingers in the sign for "climate change" and convert it into specific translated text. Compared to traditional gesture recognition algorithms, GNNs can capture more complex spatiotemporal dependencies between gestures, greatly improving translation accuracy.

The "real-time translation" capability of the GNN model allows it to output translation results in real time during the news broadcast, ensuring that the sign language interpreter can quickly convey important information from the news to the hearing-impaired audience. When processing the sign for "global warming," the GNN not only captured the dynamic changes in the gesture but also learned the subtle movements through multiple layers of convolution.

4 4. CASE STUDY: SIGN LANGUAGE TRANSLATION IN TELEVISION NEWS

4.1 Background Introduction

Sign language translation in television news typically demands high efficiency, real-time performance, and extreme accuracy. During live news broadcasts, sign language interpreters need to convey information to hearing-impaired audiences in real time, placing significant demands on their response speed and precision. [18] Given the limited human resources and the intensity of interpreters' work, the automation of sign language translation has become an urgent issue that needs to be addressed.

4.2 Case Analysis: Sign Language Translation for Global Climate Change News

"The issue of global climate change is becoming increasingly serious, and global warming caused by the greenhouse effect is intensifying. [19] Countries must take measures to reduce carbon emissions and mitigate climate issues." In this news segment, the keywords "climate change," "greenhouse effect," "global warming," and "carbon emissions" are crucial sign language content that needs to be conveyed. [20] Examples of the keywords and their corresponding sign language gestures are as follows:

Climate Change: The gesture depicts changes in the sky, using arm movements to simulate different layers of climate variation. [21]

Greenhouse Effect: The hands form the shape of a transparent "house," followed by gestures mimicking air movement, simulating the rise in heat within a greenhouse.

Carbon Emissions: The hands imitate chimneys expelling gas upwards, representing the release of carbon.

Global Warming: The palm gradually opens, signifying the rise in temperature, accompanied by changes in facial expressions to convey the sense of warming climate. [22]

Using a Graph Neural Network (GNN), each gesture is first broken down into multiple key points, with gesture nodes representing fingers, palms, and joints. [23] In the GNN, nodes represent key points in the gesture, while edges signify the connections between joints in the movement. The specific GNN translation process involves:

Node Representation: This represents each finger, palm, and joint as nodes in the graph.

Edge Connections: The joint movements in the gesture serve as the edges.

Graph Convolution Operation: The GNN applies multiple layers of graph convolution operations to extract key features from the gesture structure. [24]

Translation Output: The trained model can then recognize sign language gestures like "climate change" and "greenhouse effect" in real time and generate the corresponding text. [25]

By training on graph structures, we can capture the complex relationship between gestures and language, allowing sign language movements to be translated into specific text in real time. The figure below will visualize the nodes and edges of sign language gestures and demonstrate how these gestures are processed and translated through the GNN. [26] It will illustrate how the GNN handles nodes, edges, and information propagation during the sign language translation of the "global climate change" news.

In this case, we utilize the propagation mechanism of Graph Neural Networks (GNN) to enable each node (joint) to receive information from its neighboring nodes. [27] Then, through a series of graph convolution layers, the model gradually learns the meaning of each gesture action and ultimately generates the translated text. The strength of GNN lies in its ability to efficiently propagate information between multiple nodes and perform exceptionally well when handling data with complex dependencies. The diagram below will vividly visualize the nodes and edges of the sign language gestures, illustrating how these gestures are processed and translated by the GNN.

5 CONCLUSION

By introducing Graph Neural Network (GNN) technology into the field of sign language translation, especially in the application of television news, the automation of sign language translation has been significantly enhanced. GNNs are capable of effectively handling the complex gestures and facial expressions in sign language, offering higher accuracy and real-time performance compared to traditional methods. Future research should focus on further optimizing the model's real-time capabilities and generalization, as well as expanding its applicability to more sign languages and diverse scenarios. [28]

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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