A Comprehensive Review of Sensor-based Sign Language Recognition Models

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***Abstract* - Sign language is a visual language used by millions of people worldwide who are deaf or hard of hearing. Sign language recognition (SLR) has been an active research area in the field of human-computer interaction for several decades. Sign Language, which is a combination of hand and facial gestures, is used as a method of articulation by this community. However, not everyone knows these gesture languages. Thus, deafness and loss in hearing capabilities impacts their ability to communicate, which further leads to social isolation. SLR is essential to build an inclusive society. SLR helps to automate the conversion of SL to text or voice. With the availability of low-cost sensors and advancements in machine learning techniques, there has been a growing interest in using sensor data for SLR. Sensor-based SLR (SSLR) has the potential to improve the accuracy and robustness of the recognition system and enable the development of portable and wearable SLR devices. This review paper provides a comprehensive overview of the existing techniques for SLR using sensor data. The paper discusses the data acquisition, preprocessing, feature extraction, selection, and machine learning models used in SSLR. The review paper also highlights the challenges and limitations of the existing techniques and provides insights into future research directions and opportunities.**

Keywords - Sign Language Recognition, Human Computer Interaction, Sensor-based, Feature Extraction, Machine Learning

I. INTRODUCTION

A. Overview

Sign languages are visual languages used by the deaf and hard-of-hearing communities to communicate with each other. Unlike spoken languages, sign languages use a combination of hand gestures, facial expressions, and body movements to convey meaning [1]. There are over 300 different sign languages used worldwide, each with its own grammar, syntax, and vocabulary. SLR is a field of research that aims to develop computer systems capable of recognizing sign language gestures in real-time. The goal of SLR is to facilitate communication between deaf and hearing individuals and provide greater accessibility to information and services for the deaf community.

One of the main challenges in SLR is the variability [2,3] and complexity [4,5] of sign language gestures. Sign language gestures can vary in speed [6], direction [7], and orientation [8], and can be affected by environmental factors such as lighting [9] and background [3,5,10]. To address these challenges, researchers have explored the use of sensor data for SLR.

SSLR involves using sensors such as accelerometers [11], gyroscopes [12,13], gloves [14,15], and flex sensors [14,16] to capture the movement and orientation of the hands and fingers during sign language gestures. The data captured by the sensors is then processed and analyzed using machine learning algorithms to recognize the sign language gestures.SSLR has shown promising results in improving the accuracy and robustness of SLR systems. It could enable portable and wearable devices, making sign language communication more convenient.

This review paper provides a comprehensive overview of the existing techniques for SLR using sensor data. The paper discusses the data acquisition, preprocessing, feature extraction, selection, and machine learning models used in SSLR. The paper also highlights the challenges and limitations of the existing techniques and provides insights into future research directions and opportunities.

B. Motivation

The motivation for this review paper on SLR using sensor data stems from the need to improve the accessibility of communication for the deaf and hard-of-hearing communities. Traditional SLR systems have relied on video-based approaches, which can be limited by factors such as lighting and background noise [17,18]. By contrast, SSLR has the potential to improve the accuracy and robustness of SLR systems, making communication more accessible and convenient for the deaf and hard-of-hearing communities [14]. Moreover, the availability of low-cost sensors [19] and advancements in machine learning techniques have opened up new possibilities for SSLR. This paper reviews SLR techniques using sensor data, noting strengths, limitations, and future research potential. Overall, the motivation for this review paper is to contribute to the ongoing efforts to improve the accessibility of communication for the deaf and hard-of-hearing communities. By providing a critical analysis of the existing techniques and identifying future research opportunities, this review paper aims to advance the field of SLR and pave the way for the development of more effective and efficient SLR systems.

C. Background

SLR using sensor data is a research field that aims to develop algorithms and systems capable of interpreting and recognizing sign language gestures using data from different sensors such as accelerometers, gyroscopes, and flex sensors. The process typically involves collecting data from sensors attached to the user's hand or body as they perform sign language gestures. This data is then processed and analyzed using machine learning algorithms to recognize and interpret the gestures. Using numerous sensors, SSLR collects data on gestures. The recognition model is used to draw conclusions after data analysis. To recognize hand gestures, various types of sensors are attached to the hands. Data is recorded and analyzed every time the hand is moved. Gloves with sensors that can detect finger and hand bending and orientation are used in this approach. Gloves with sensors measure the tension and pressure between fingers. The most well-known sensor-glove technologies include smart gloves [14,20], data gloves [21,22], and CyberGlove [23]. Data gloves are excessively costly and painful to wear, which restricts their appeal, even if systems based on them achieve higher performance than other methods [24]. Sensors can be embedded in wearable devices such as gloves, wrist bands, or rings to combat this.

The remainder of this paper is organized as follows. Section II includes a brief review of the datasets used to test and train SSLR models. Section III gives an overview of the sensor technologies used in SSLR. Section IV, V and VI present a review of the different techniques of data preprocessing, feature extraction and dimensionality reduction used. The commonly used machine learning models in SSLR are reviewed in Section VII. Finally, we summarize the applications, main challenges and future scope in CSLR in sections VIII, IX and X respectively, and conclude the work in Section XI.

II. Datasets

There are several datasets that are commonly used in SSLR research. Here are some examples:

1) RWTH-BOSTON-50 Sign Language Corpus: This dataset contains recordings of 50 different sign language gestures performed by 20 different signers using data gloves. The dataset includes sensor data, video data, and annotations [25,26].
2) Chalearn LAP IsoGD Dataset: This dataset contains videos of isolated gestures performed by multiple signers using data gloves and Kinect sensors.
3) BVC3DSL: BVC3DSL is a 3D Indian sign language motion capture dataset consisting of 700 classes, each with 50 sign videos captured from five different signers.
4) HDM05: This is a motion capture dataset that contains over three hours of well-documented and systematically recorded motion capture data in both C3D and ASF/AMC data formats. This dataset includes nearly 2337 sequences and 130 motion classes performed by five actors.
5) American Sign Language Lexicon Video Dataset: This dataset contains recordings of 1,000 different sign language gestures performed by 9 different signers using a Kinect camera. The dataset includes video data and annotations.

These datasets are widely used in research on SSLR and have contributed to the development of new techniques and algorithms for SLR. It is important to note that there are other datasets available as well, and the choice of dataset depends on the specific research objectives.

III. Sensor Technologies

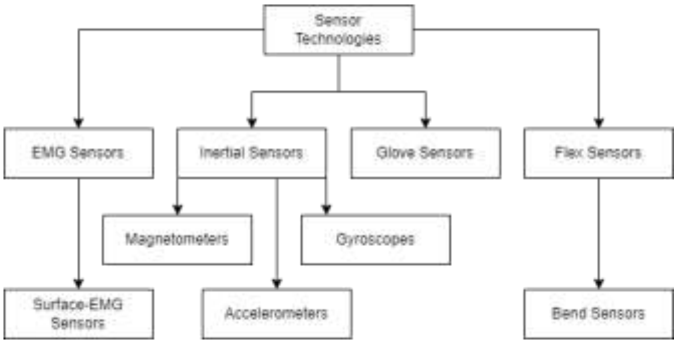

Fig 1: A summary of different sensor technologies.

SLR using sensor data is an active area of research, and there are several existing techniques that have been developed and evaluated. These techniques can be broadly categorized into two types: glove-based and accelerometer/gyroscope-based [12,27].

Data glove-based techniques involve the use of gloves equipped with flex sensors, which capture the movements of the hand and fingers during sign language gestures [28,29]. These movements are then used to classify the sign language gesture. Exo-gloves [30,31] are another type of glove used for sign recognition. These gloves use external sensors attached to the glove to capture hand movements. The sensors can be in the form of cameras, markers, or other types of sensors. Cyber gloves [24,32] are similar to data gloves but use more advanced sensors such as fiber optic sensors or magnetic sensors. These gloves are more accurate and can capture a wider range of hand and finger movements. Smart gloves [14,33] are gloves that have integrated electronics and sensors that allow for wireless communication and data transmission. These gloves are often used for remote SLR, where the user's hand movements are captured and transmitted in real-time to a remote location for interpretation [34].

Accelerometer and gyroscope-based techniques [12,13,16] involve the use of sensors such as accelerometers and gyroscopes, which are attached to the wrist, forearm, or upper arm. These sensors capture the movements of the arm and hand during sign language gestures.

Each of these techniques has its advantages and disadvantages. Data glove-based techniques are highly accurate in recognizing hand and finger movements, but they may be less robust to variations in sign language gestures and may require the use of specialized equipment [35,36]. Accelerometer/gyroscope-based techniques are less intrusive and can be used in everyday situations, but they may be less accurate in recognizing hand and finger movements [37]. In terms of accuracy, accelerometer and gyroscope-based techniques generally outperform data glove-based techniques [36,38]. However, data glove-based techniques may be more suitable for certain applications where high accuracy is required, such as in the recognition of complex sign language gestures [39]. In terms of speed, data glove-based techniques tend to be faster as they can capture hand and finger movements in real-time [40]. Accelerometer-based techniques may have a slight delay due to the time required to capture and process sensor data [41]. In terms of robustness, accelerometer-based techniques may be more robust to variations in sign language gestures, as they can capture movements from the entire arm and hand. Data glove-based techniques may be more susceptible to errors caused by variations in hand and finger movements [42].

In conclusion, there are several existing techniques for SLR using sensor data, each with its advantages and disadvantages. The choice of technique depends on the specific application requirements and the trade-offs between accuracy, speed, and robustness. It is important for researchers to continue to develop and evaluate new techniques to improve the accessibility and convenience of SLR systems for the deaf and hard-of-hearing communities.

IV. Data Preprocessing

Sensor data preprocessing involves cleaning, filtering, and processing sensor data before it is used in a recognition system. The preprocessing step is critical as it can improve the accuracy and reliability of the recognition system. Here are some of the commonly used techniques for sensor data preprocessing:

1. Noise Removal: Sensor data can contain noise, which can reduce the accuracy of the recognition system. Noise removal techniques such as mean filtering, median filtering, and wavelet filtering can be used to remove noise from the sensor data [43–45].

2. Signal Amplification: In some cases, the sensor signal may be weak, making it difficult to detect small changes in the signal. Signal amplification techniques such as gain adjustment, signal averaging, and signal resampling can be used to improve the quality of the sensor signal [46,47].

V. Feature Extraction And Selection

Feature extraction involves the process of extracting meaningful information from the raw sensor data obtained from the gloves or other sensors. The extracted features are then used to represent the sign language gestures, which are later used for classification. Several feature extraction techniques have been proposed in the literature, such as statistical features, time-domain features, frequency-domain features, and wavelet-based features [48–50]. Each of these techniques has its advantages and limitations, and the selection of the most appropriate technique depends on the specific application scenario. A method for extracting features in Brazilian Sign Language that uses the RGB-D sensor to obtain position, intensity, and depth data has been presented [51,52]. Numerous algorithms for analysis of 3D image are presented in [53] including 3D image acquisition and hand segmentation. [54] proposes a SLR technique for the American sign language alphabet based on a neural network that extracts geometrical features from hands.

In addition to feature extraction, feature selection is also an important step in SSLR. Feature selection involves selecting a subset of relevant features from the feature space that best represent the sign language gestures. This reduces the computational complexity and improves the accuracy of the classification algorithm. Several feature selection techniques have been proposed, such as filter methods, wrapper methods, and embedded methods [55].

The suitability of each feature extraction and selection technique depends on the specific application scenario. For example, statistical features are commonly used for recognizing static signs, while time-domain features are more suitable for recognizing dynamic signs [38,56]. Frequency-domain features are suitable for capturing the frequency content of the sensor data [57], while wavelet-based features are useful for capturing the temporal and frequency content simultaneously [58]. Similarly, the selection of the most appropriate feature selection technique depends on the specific application scenario, such as the size of the dataset, the number of features, and the classification algorithm used. Several studies have compared the different feature extraction and selection techniques in terms of their accuracy and robustness [59]. [60] examines two classification methods, namely Simplification of Support Vector Machine (SimpSVM) and Relevance Vector Machine (RVM), and demonstrate that both SimpSVM and RVM perform well, with SimpSVM exhibiting superior predictive performance compared to

RVM for sign recognition. Furthermore, the authors found that the prediction behaviors of both methods were similar in terms of accuracy, data amount, feature number, and sign discrimination.

VI. Dimensionality Reduction

In some cases, the sensor data may have too many features to be used effectively by the machine learning model. Dimensionality reduction is a common technique used in SSLR to reduce the number of features or variables needed for accurate recognition while maintaining a high recognition rate. The reduction in dimensionality helps to reduce the computational complexity of the recognition system, making it more efficient and effective.

There are several methods used for dimensionality reduction in SLR, including principal component analysis (PCA), linear discriminant analysis (LDA), and manifold learning techniques such as t-distributed stochastic neighbor embedding (t-SNE) and locally linear embedding (LLE). PCA [61,62] is a popular technique used for dimensionality reduction in SLR. It involves identifying the most important features that capture the majority of the variation in the data and projecting the data onto a lower-dimensional space. LDA [61] is another technique commonly used for dimensionality reduction in SLR. It aims to find a linear transformation of the data that maximizes the separation between different classes of signs. Manifold learning techniques such as t-SNE [63] and LLE [64] are also used for dimensionality reduction in SLR. These techniques aim to retain the structure of the data in the lower-dimensional space, allowing for a better representation of the data and improved recognition performance. Methods for efficient dimensionality reduction of dynamic signs, and classification for nearest neighbor in sign gesture space search are described in a study by [52]. [65] propose to reduce the dimensionality of the expanded vector through the use of stepwise regression. [65,66] presents enhanced gesture-based human-computer interaction through a compressive sensing reduction scheme of very large and efficient depth feature descriptors.

VII. Machine Learning Models for SSLR

SSLR is a challenging task that requires advanced machine learning techniques. Here is an overview of different machine learning models that have been used for SLR:

1. Hidden Markov Models (HMMs): HMMs have been used extensively for SLR due to their ability to model temporal dependencies. HMMs are generative models that assume the underlying state of the system is hidden and can only be inferred from the observed data. HMMs have been used in conjunction with features such as hand shape, hand location, and motion trajectories [67,68]. However, their accuracy may be limited if the data has complex patterns, and they may require extensive hyperparameter tuning [67–69]. HMMs can be computationally efficient, but their training time can be slow compared to some other models [70].

2. Support Vector Machines (SVMs): SVMs are a popular machine learning model that has been used for SLR [41,71]. SVMs are a discriminative model that tries to find the best separating hyperplane between different classes of data. SVMs have been used in conjunction with hand-crafted features such as Histograms of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) [72]. However, their performance can be limited by the choice of kernel function and the selection of hyperparameters. SVMs are generally faster to train than HMMs, but their prediction time can be slower.

3. Deep Neural Networks (DNNs): DNNs are a powerful class of models that have been used for a wide range of machine learning tasks, including SLR [67–69,73]. DNNs consist of multiple layers of interconnected neurons that are trained using backpropagation. DNNs have been used to automatically learn features from raw data such as depth images, RGB images, and skeleton data. They are capable of handling large datasets. However, they can be computationally expensive and require large amounts of training data and computational resources.

4. Convolutional Neural Networks (CNNs): CNNs are a type of DNN that have been used for SLR. CNNs have been used to automatically learn features from images and videos. CNNs have been used in conjunction with hand-crafted features such as motion history images and optical flow. CNNs are a type of DNN that have been successful in image and video recognition tasks, including SLR [71,74]. They can automatically learn spatial features from images and videos, and they can handle large datasets. They are, nevertheless, computationally costly and may need substantial hyperparameter adjustment.

5. Recurrent Neural Networks (RNNs): RNNs are DNNs that are used to represent temporal dependencies. RNNs have been used for SLR by processing the sequence of hand gestures [75]. RNNs have been used in conjunction with hand-crafted features such as joint angles and velocity. They are capable of processing sequences of data and can handle varying-length input sequences. However, they can suffer from vanishing and exploding gradient problems [76] and may require specialized architectures such as LSTM and GRU.

6. Long Short-Term Memory (LSTM) Networks: LSTM networks are a type of RNN that have been specifically designed to model long-term dependencies. LSTM networks have been used for SLR by processing the sequence of hand gestures [77,78]. LSTM networks have been used in conjunction with hand-crafted features such as

joint angles and velocity. However, they can be computationally expensive and may require extensive hyperparameter tuning.

7. Generative Adversarial Networks (GANs): GANs are a type of deep learning model that consists of two neural networks that are trained in an adversarial manner. GANs have been used for SLR by generating synthetic sign language data that can be used to augment the training data [79,80]. GANs have been used in conjunction with CNNs and RNNs. They can be computationally expensive to train, but they can produce high-quality synthetic data. However, their robustness can be limited if the synthetic data is too dissimilar from the real data.

In terms of accuracy, DNNs, CNNs, and RNNs have shown state-of-the-art performance in many SLR tasks. SVMs and HMMs can also achieve high accuracy if appropriately trained and tuned. In terms of speed, SVMs can be faster to train and predict than some of the deep learning models such as DNNs, CNNs, and RNNs. However, the training and prediction times of deep learning models can be improved using parallel processing and hardware accelerators such as GPUs. In terms of robustness, models such as HMMs and SVMs can be less susceptible to overfitting and can perform well on small and noisy datasets. Deep learning models such as DNNs, CNNs, and RNNs require large amounts of data and can be prone to overfitting if not regularized properly.

These are some of the machine learning models that have been used for SSLR. Table 2 presents information like datasets used, features, machine learning models, input modalities and results about the models proposed for SSLR in the recent years. The choice of model depends on the characteristics of the data and the specific requirements of the application.

Table 1: A Survey of Major Works in Sensor-Based Sign Language Recognition

S. No	Ref	Year	Feature	Classification	Dataset	Input Modality	Sensors used	Results (%)
1	[81]	2018	PCA	KNN	ASL, 10 numbers	Static, Isolated	Flex Sensors	85%
2	[82]	2017	LDA	KNN, DT, SVM	ASL, 36 gestures	Static/Dynamic, Isolated	MEMS sensors	80%
3	[83]	2019	Statistic Methods	SVM, DTW	8 gestures	Static/Dynamic, Isolated	Pressure Sensors	95.28% (exp) and 86.20% (inexp)
4	[84]	2019	PCANet	Linear SVM	ASL fingerspelling Dataset	Static, Isolated	Microsoft Kinect Sensor	89%
5	[85]	2017	-	HMM and BLSTM-NN	7500 Indian Sign Language (ISL) gestures consisting of 50 different sign-words	Dynamic	Microsoft Kinect, Leap Motion	97.85% and 94.55%
6	[86]	2021	Zernike moments, Hu moments, Fourier Descriptors	HMM	A dataset containing 33 isolated signs	Isolated and continuous	Microsoft Kinect, Leap Motion	95.18% and 93.87%
7	[87]	2020	finger direction patterns detected by Leap Motion Controller.	Threshold and ANN	Sign Language gestures of numbers 0-9	Isolated	Leap Motion	98%
8	[88]	2019	-	Neural Network	ASL, 5 numbers	Isolated, Static	IMU, Magnetic Field Sensors	99.2%

S. No	Ref	Year	Feature	Classification	Dataset	Input Modality	Sensors used	Results (%)
9	[89]	2019	Statistic Methods	Modified KNN, HMM	ArSL, 40 sentences	Continuous	DG5-V hand data glove	96.70%

VIII. Applications

SSLR has numerous applications in various fields, including:

1. Communication accessibility: One of the most significant applications of SLR is to enable communication between deaf and hearing individuals. By recognizing sign language, SLR can provide deaf individuals with access to real-time communication with non-signers, allowing them to participate in daily conversations, meetings, or other social interactions. SLR can also be used to translate sign language into text or speech, making it accessible to non-signers.

2. Education and training: SLR can be used to develop interactive sign language learning systems for both deaf and hearing individuals. For example, an SLR system can provide real-time feedback to learners to help them improve their sign language skills. SLR can also be used to evaluate sign language proficiency in learners, providing a more objective and accurate assessment of their skills [90].

3. Human-robot interaction: SLR can enable robots to recognize and understand sign language, allowing for natural and intuitive human-robot interaction. This can have numerous applications, such as in service robots for deaf individuals, where the robot can understand sign language commands or provide sign language feedback to the user [91].

4. Assistive technology: SLR can be integrated into assistive devices, such as smart gloves or wearable sensors, to provide real-time translation of sign language into text or speech. This can allow deaf individuals to communicate with non-signers more easily and can also facilitate access to education, healthcare, and other services [92].

5. Video surveillance: SLR can be used in video surveillance to detect and recognize sign language gestures, which can be useful in security and safety applications [93,94]. For example, an SLR system can detect a sign language gesture for "help" and alert security personnel to a potential emergency.

6. Gaming and entertainment: SLR can be used in gaming and entertainment applications to control avatars or characters in virtual environments using sign language. This can provide a more immersive and inclusive gaming experience for deaf players [95].

7. Medical and rehabilitation: SLR can be used in medical and rehabilitation applications to monitor and analyze the movements of patients during physical therapy or rehabilitation exercises [96].

SSLR applications are numerous, and they may have a substantial influence on the lives of deaf people and the larger society through promoting accessibility and inclusion.

IX. Challenges

SSLR presents a number of issues owing to the complexity of sign language, which includes non-manual components such as facial emotions and body language, as well as sign language heterogeneity across signers. Some of the challenges faced in SSLR are:

1. Sensor selection: Different sensors can be used for SLR, such as cameras, gloves, or accelerometers. However, the choice of sensor depends on the specific requirements of the SLR system, such as accuracy, speed, cost, and ease of use. Some challenges in sensor selection for SLR include selecting the best sensor for a particular task, balancing cost and performance, and dealing with sensor limitations [97].

2. Data collection and annotation: Collecting and annotating sign language data can be challenging because sign language involves complex and subtle movements, and different signers may use different variations of signs. Some challenges in data collection and annotation include obtaining high-quality data, dealing with variability among signers, and ensuring proper annotation of the data.

3. Recognition of non-manual components: Sign language involves not only hand gestures but also facial expressions and body language, which are crucial for conveying meaning. Recognizing these non-manual components is challenging because they are often subtle and context-dependent. Some challenges in recognizing non-manual components of sign language include identifying which non-manual components to recognize, capturing subtle movements, and dealing with context-dependent variations.

4. Variability among signers: Sign language can vary widely among different signers, depending on their regional or cultural background, age, gender, or proficiency level [98]. This variability can make it difficult to train a generalizable SLR system that works well for all signers.

Some challenges in dealing with variability among signers include creating a diverse dataset that captures this variability, developing algorithms that can handle variability, and ensuring that the SLR system is accessible to all signers.

5. Real-time recognition: SLR systems must operate in real-time to enable natural communication between signers and non-signers. Achieving real-time performance requires efficient algorithms and hardware optimization [13]. Some challenges in achieving real-time recognition include designing efficient algorithms that can handle the complexity of sign language, optimizing hardware for performance, and minimizing latency.

6. Gesture segmentation and recognition: SLR systems must accurately segment and recognize individual signs from continuous sign streams [84]. This task is challenging because signs can overlap or blend into each other, and some signs may have multiple meanings depending on the context. Some challenges in gesture segmentation and recognition include developing algorithms that can handle continuous sign streams, dealing with sign overlaps, and resolving ambiguity in sign meanings.

7. Handling noisy or incomplete data: Sensors can produce noisy or incomplete data due to environmental factors such as lighting conditions or occlusions. SLR systems must be able to handle such noisy or incomplete data and still provide accurate recognition results [63]. Some challenges in handling noisy or incomplete data include developing algorithms that can handle missing or noisy data, ensuring robustness to environmental factors, and improving sensor quality.

X. SSLR: Promises and Future Directions

The use of sensors, such as gloves or cameras, can automate the process of sign language interpretation and make it more widely accessible. This technology could also be used to create more advanced and interactive communication devices that can be used in a variety of settings, such as in education, healthcare, and public services.

Furthermore, SSLR technology could be combined with other emerging technologies, such as augmented reality and virtual reality, to create even more immersive and interactive communication experiences. Some of the promising areas of research for the future include:

1. Federated Learning: SSLR in federated learning [99,100] has the potential to revolutionize the way sign language is recognized and interpreted [99]. The combination of sensor-based technology and federated learning has several benefits that can greatly enhance the accuracy and privacy of SLR systems. One major advantage of federated learning is that it enables the training of models on distributed data without sharing the data itself. This is particularly important in the context of SLR, where users' privacy must be protected. Federated learning can ensure that users' data remains on their devices, and only model updates are sent to a central server for aggregation. This approach can greatly enhance the privacy and security of SLR systems. In addition, the use of sensors in SLR can improve the accuracy of the recognition process by capturing more precise and detailed information about the signer's movements. By combining sensor data from multiple users in a federated learning framework, the model can learn from a larger and more diverse dataset, which can lead to improved accuracy and robustness. Furthermore, the use of federated learning in SLR can enable the development of more personalized and adaptive models that can better accommodate individual differences in signing styles and variations in sign language across different cultures and regions.

2. Augmented and Virtual Reality: SSLR in augmented reality (AR) and virtual reality (VR) has the potential to create more immersive and interactive communication experiences for individuals who use sign language. In AR, SSLR can enable the creation of real-time, interactive sign language interpretation that can be overlaid on top of the real world. For example, an AR headset could recognize sign language gestures and display corresponding text or images to aid communication. This technology could also be used to create educational and training tools for sign language learners. In VR, SSLR can enable more natural and intuitive communication in virtual environments. By recognizing sign language gestures, VR systems can create more immersive and interactive virtual worlds that are accessible to individuals who use sign language. This technology could also be used to create more inclusive gaming and entertainment experiences. Moreover, the use of sensors in AR/VR systems can improve the accuracy and responsiveness of SLR.

3. Evolutionary Computing: SSLR in evolutionary computing has the potential to enhance the performance and efficiency of SLR systems. Evolutionary computing is a subfield of artificial intelligence that uses principles of natural selection and evolution to optimize complex systems. In the context of SLR, evolutionary computing can be used to optimize the design and parameters of SLR systems based on sensor data. One potential application of evolutionary computing in SLR is the optimization of feature extraction algorithms. Feature extraction is the process of extracting relevant information from sensor data that can be used to recognize sign language gestures. Evolutionary computing can be used to automatically generate and optimize feature extraction algorithms that are tailored to specific sensor modalities and sign language styles. Another potential application of evolutionary computing in SLR is the optimization of machine learning models. Machine learning models are trained on sensor data

to recognize sign language gestures, but the performance of these models can be greatly influenced by the choice of algorithms, hyperparameters, and training data. Evolutionary computing can be used to automatically generate and optimize these parameters to improve the accuracy and efficiency of SLR models.

In conclusion, SSLR is a rapidly evolving field with a bright future. Potential future directions include multi-modal sensor fusion, continual learning, context-aware SLR, real-time feedback and interaction, privacy-preserving SLR, and application-specific SLR.

XI. Conclusion

SSLR is a rapidly evolving field that has seen significant progress in recent years. This review paper has discussed the challenges, techniques, and models used in SSLR and compared the accuracy, speed, and robustness of different machine learning models.

One of the main challenges in SSLR is the variations in sign language across different individuals, dialects, and cultures, as well as environmental factors such as lighting, background noise, and camera placement. Feature extraction is a critical step in SSLR, and several techniques have been developed to extract meaningful features from the sensor data, including hand shape, hand motion, and facial expressions. Furthermore, various machine learning models have been applied to SLR, including HMM, SVMs, DNN, CNN, RNN, LSTM, and GAN, each with varying degrees of success. Finally, the choice of machine learning model for SSLR depends on several factors, including the characteristics of the data, the resources available, and the specific requirements of the application. These key findings provide a useful insight into the current state-of-the-art in SLR, and can guide future research in this area towards more accurate and efficient SLR systems. There are several recommendations for future research which will pave the way for more accurate and efficient SLR systems. One of the key areas is to develop robust and accurate feature extraction techniques that can handle variations in sign language and environmental factors. Additionally, more comparative studies are needed to evaluate the performance of different machine learning models in different scenarios and for different applications. Another crucial area is to develop SLR systems that can recognize sign language from multiple individuals and gestures that are not part of the standard sign language, and also adapt to individual users. Finally, researchers need to focus on developing SLR systems that can operate in real-world environments, such as noisy or low-light conditions, and in low-power or low-resource devices. In conclusion, SSLR is a promising field that has the potential to improve communication and accessibility for the hearing-impaired community. Continued research and development in this field can lead to more accurate, robust, and practical SLR systems that can have broad applications in human-computer interaction, VR, AR, and robotics.

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