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A SURVEY ON SIGN LANGUAGE RECOGNITION USING MACHINE INTELLIGENCE FOR HEARING IMPAIRED PERSONS

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ABSTRACT

Sign language serves as the main communication method for millions of individuals with hearing impairments across the globe. Nonetheless, a significant communication gap persists between those who use sign language and the broader population. Machine intelligence-based sign language recognition (SLR) systems have surfaced as effective solutions for overcoming this challenge [1], [2]. This survey paper examines the various existing SLR methods, with an emphasis on machine learning and deep learning techniques, datasets, tools, challenges, and applications [3], [4]. It also explores future avenues for improving accuracy, robustness, and the implementation of real-time solutions [5]. In addition, the survey highlights integration with wearable devices, cross-lingual sign translation, and mobile-based recognition systems, which are gaining momentum in real-world accessibility solutions [6].

1. INTRODUCTION

The World Health Organization (WHO) reports that over 430 million individuals worldwide suffer from disabling hearing loss, for whom sign language serves as an indispensable medium of communication. However, limited proficiency in sign language among the hearing population creates a significant communication barrier. Automatic Sign Language Recognition (SLR) systems aim to mitigate this challenge by translating signs into text or speech, thus enabling more effective interaction between hearing-impaired and hearing individuals [5].

Early SLR systems relied heavily on sensor-based gloves and handcrafted feature engineering [6], [7]. While effective to some extent, these methods were costly and impractical for daily use. The advent of machine intelligence—particularly deep learning—has brought remarkable progress in recognition performance [1], [3]. Modern architectures such as Convolutional Neural Networks (CNNs) and Transformers, supported by large-scale multilingual datasets, have made real-time SLR systems increasingly feasible [4], [8]. This survey provides an overview of contemporary approaches, tools, and datasets in SLR while highlighting ongoing challenges and future directions.

2. OVERVIEW OF SIGN LANGUAGE RECOGNITION

Sign languages are natural and complete languages, each with distinct grammatical structures and syntactic rules [5]. Widely recognized examples include American Sign Language (ASL), Indian Sign Language (ISL), British Sign Language (BSL), and German Sign Language (DGS). Recognition remains a complex task due to inter- and intra-signer variability, variations in hand gestures, facial expressions, signing speed, and environmental conditions such as lighting [6].

Initial research in SLR was dominated by glove-based and sensor-driven approaches, which offered high accuracy but lacked practicality for real-world applications [6]. Subsequently, vision-based systems employing cameras became the standard, enabling recognition without wearable devices [7]. With advancements in deep learning, modern SLR systems now leverage pose estimation frameworks such as MediaPipe and OpenPose, which enhance precision in detecting detailed hand, body, and facial movements [4], [5].

3. MACHINE INTELLIGENCE TECHNIQUES IN SLR

3.1 Machine Learning Approaches

Support Vector Machines (SVMs): Widely applied for static gesture recognition by classifying extracted visual features [2].

Hidden Markov Models (HMMs): Frequently used to model sequential data, making them suitable for continuous sign language recognition [2], [7].

Random Forests & k-Nearest Neighbors (KNN): Effective for small-scale datasets, but less efficient when scaling to large vocabularies [6].

3.2 Deep Learning Approaches

Convolutional Neural Networks (CNNs): Capture spatial information effectively, making them particularly suitable for static hand gesture recognition [3].

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Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM): Address temporal dependencies in continuous signing by modeling gesture sequences [2], [8].

Transformers and 3D CNNs: Recently introduced to handle longer video sequences, achieving state-of-the-art performance in continuous SLR tasks [4], [5].

3.3 Hybrid Approaches

Hybrid frameworks, such as CNN-LSTM and CNN-HMM, integrate spatial and temporal learning capabilities. These combinations have shown superior results in real-time SLR applications by simultaneously extracting visual patterns and sequence dependencies [1], [8].

4. DATASETS AND TOOLS

Popular Datasets:

- **RWTH-PHOENIX-Weather 2014** – German sign language, continuous signing dataset [2].
- **ASL Lexicon Video Dataset** – Covers static and dynamic ASL gestures [3].
- **Indian Sign Language Dataset** – Provides gesture images for ISL [5].
- **Chalearn IsoGD Dataset** – Contains over 40,000 RGB and depth gestures [4].
- **WLASL (Word-Level ASL Dataset):** Large-scale dataset with 21,000 videos of 2,000 signs [6].
- **MS-ASL Dataset:** Includes thousands of labeled ASL signs for large-scale deep learning experiments [7].

Tools and Frameworks:

- **Deep Learning:** TensorFlow, PyTorch, Keras [3], [5].
- **Computer Vision:** OpenCV, MediaPipe, OpenPose.
- **Traditional ML:** MATLAB, scikit-learn.
- **Annotation Tools:** ELAN and VIA for labeling sign language videos [5].

5. COMPARATIVE ANALYSIS

- **CNN models** consistently achieve >90% accuracy on static gesture datasets [3].
- **CNN + LSTM networks** perform better in continuous recognition tasks such as RWTH-PHOENIX [2].
- **Transformers** outperform RNNs on large datasets but are computationally intensive [4], [5].
- **Hybrid approaches** show the best balance between accuracy and efficiency [1].

Despite these successes, major challenges remain:

- **Signer-independence:** Models trained on one signer may fail on unseen individuals.
- **Resource-intensiveness:** Large datasets and GPUs are required.
- **Contextual understanding:** Most systems still cannot fully integrate hand gestures with facial expressions and body postures [5], [6].

6. CHALLENGES IN SLR

1. **Variability in signing styles** – Different regions and individuals use varied gestures.
2. **Limited datasets** – Most datasets are small, domain-specific, and lack diversity [6].
3. **Real-time performance** – Achieving high accuracy with low latency is still difficult [5].
4. **Multilingual recognition** – Few systems can handle multiple sign languages simultaneously [7].
5. **Integration of non-manual features** – Facial expressions and body postures remain underutilized in recognition models [8]

7. FUTURE DIRECTIONS

- **Multimodal Learning:** Combining gesture recognition with **facial expression and lip movement analysis**.
- **Cross-Lingual SLR:** Developing models that can generalize across ASL, ISL, BSL, and other sign languages [6].
- **Edge & Mobile Computing:** Lightweight models for deployment on smartphones and AR/VR devices.
- **Wearable Devices:** Integration with smart gloves, AR glasses, and IoT devices for seamless accessibility [7].
- **Sign-to-Speech Translation:** End-to-end systems that directly convert gestures into speech for real-time communication [1], [5].

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8. CONCLUSION

The field of sign language recognition has advanced from glove-based systems to camera-based machine intelligence models [6], [7]. CNNs, LSTMs, and transformers have significantly improved recognition accuracy [3], [4]. However, signer-independence, limited datasets, and high computational costs remain open challenges [5]. Future research must focus on **real-time, multilingual, and multimodal SLR systems** that integrate facial, body, and gesture recognition. Such advancements will provide inclusive solutions for bridging the communication gap between hearing and hearing-impaired communities [1], [8]

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