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Temporal Modeling and Real-Time Recognition Approaches in SLR Systems

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Abstract: This article is dedicated to analyzing advanced approaches in temporal modeling and real-time gesture recognition within sign language recognition (SLR) systems. Sign glosses are expressed through the spatio-temporal characteristics of visual information, which requires the use of sequence-processing models for their automatic recognition. The study primarily evaluates the effectiveness of three key models: Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCN), and Transformer-based architectures.

The article also examines methods applied for real-time analysis of sign glosses, including:

Sliding window segmentation of video streams;

Self-attention mechanisms for identifying dependencies between gestures;

Gloss mapping algorithms for linking sign movements to linguistic units;

Ontological integration techniques for enhancing semantic accuracy.

Practical results indicate that combining temporal modeling with semantic analysis and contextual verification algorithms ensures continuous and high-accuracy recognition of sign movements. In particular, multimodal systems (video + sensor + gloss) utilizing Transformer-based approaches achieved superior performance in real-time conversion of continuous sign gloss streams into text.

The findings of this study hold practical significance for the development of smart assistive devices for automatic sign language translation, interactive

interfaces for hearing-impaired users, and specialized SLR platforms for educational and instructional purposes.

Keywords: Sign Language Recognition, temporal modeling, real-time SLR systems, LSTM, TCN, Transformer, gloss mapping, semantic verification, sliding window, ontological integration.

Introduction: In recent years, advances in digital technologies, particularly in artificial intelligence (AI) and computer vision, have propelled Sign Language Recognition (SLR) systems to a new level of development. For individuals with hearing impairments, sign language serves as a primary medium of communication, and the automatic recognition of sign language—with real-time conversion into text or speech—remains one of the most pressing challenges in the field.

A major obstacle for SLR systems lies in the spatio-temporal nature of sign language gestures. Unlike static hand postures, sign language consists of dynamic motion sequences that involve hand movements, facial expressions, and body poses, all of which evolve over time. Thus, effective recognition requires the use of temporal modeling approaches. While earlier methods treated sign gestures as isolated movements, modern approaches analyze them as interconnected sequences, linking each gesture to its preceding and subsequent movements to preserve context and meaning.

Currently, models such as Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCN), and Transformer architectures play a critical role in capturing both temporal dependencies and contextual relationships between sign glosses. In particular, these models enable real-time SLR systems to process each video frame efficiently, ensuring fast and accurate recognition while maintaining interactive communication with users.

This article provides an in-depth analysis of the scientific foundations, technological solutions, and practical results of temporal modeling approaches in real-time sign recognition. Furthermore, it explores the integration of semantic verification, ontology-based gloss mapping, and multimodal fusion to enhance the accuracy, contextual relevance, and applicability of SLR systems across diverse real-world domains.

LITERATURE REVIEW

Temporal modeling and real-time recognition approaches have become central to the development of Sign Language Recognition (SLR) systems. In recent years, significant research has been conducted to enhance the modeling of sequential gestures and improve the contextual accuracy of recognized glosses.

Camgoz et al. (2018) introduced the Neural Sign Language Translation model, which analyzed the relationship between sign gestures and glosses through deep neural networks. In this approach, temporal sequences were modeled using Long Short-Term Memory (LSTM) networks, enabling the mapping of input sign movements to their corresponding glosses [1].

Cui et al. (2019) developed a deep learning model based on Iterative Training, integrating both spatial and temporal features for gloss recognition. This approach facilitated the progressive analysis of gesture transitions, improving recognition accuracy over continuous signing sequences [2].

Hu et al. (2023) proposed the SignBERT+ model, aimed at synchronizing sign videos with gloss annotations and enhancing semantic precision. Built on a Transformer architecture, this model provided a deeper contextual understanding of glosses within sign language data [3].

The Transformer-based paradigm, pioneered by Vaswani et al. (2017) in their Attention Is All You Need model, highlighted the effectiveness of self-attention mechanisms in handling sequential dependencies. This architecture laid the groundwork for modern high-accuracy SLR systems [4].

The Temporal Convolutional Network (TCN) approach has also been widely adopted for robust modeling of sign sequences. Liu et al. (2020) proposed a model incorporating FrameNet-based semantic structures, allowing for more context-aware interpretation of sign glosses [5].

Collectively, these studies demonstrate that achieving high accuracy in real-time sign recognition requires the integration of temporal modeling, semantic analysis, and context-based gloss mapping. Models such as LSTM, TCN, and Transformer not only enhance the recognition of sign glosses but also facilitate their interpretation from a semantic perspective, ensuring meaningful and contextually coherent outputs.

METHODS

This study analyzed various temporal modeling architectures and semantic analysis methods for real-time sign language recognition. The primary focus was on the following approaches:

LSTM (Long Short-Term Memory): A neural network capable of identifying long-term dependencies between sign glosses.

TCN (Temporal Convolutional Network): A model that analyzes sign movements through layered temporal

convolutions.

Transformer: An advanced model leveraging the self-attention mechanism to capture global dependencies between gestures.

Sliding Window Processing: Segmentation of video streams into smaller parts for gloss detection within each segment.

Gloss Mapping: Mapping of sign movements to linguistic units (glosses).

Ontological Integration: Refining gloss context through semantic databases (e.g., WordNet, FrameNet).

Comparison of Temporal Modeling Approaches in SLR Systems

table 1

№	Approach	Temporal Dependency Modeling	Real-Time Suitability	Semantic Context Integration	Computational Cost
1	LSTM	Good for long-term dependencies	Moderate	Limited (requires additional modules)	Medium
2	TCN	Effective for local and mid-range sequences	High	Limited	Low to Medium
3	Transformer	Excellent for global dependencies	Moderate to Low (requires optimization)	Strong (context-aware with attention)	High
4	Sliding Window	Short-term segment analysis	High	None	Low
5	Gloss Mapping	N/A	N/A	Provides linguistic alignment	Medium
6	Ontological Integration	N/A	Low	Enhances semantic understanding	Medium to High

These methods were compared to evaluate their temporal modeling efficiency, real-time processing capability, semantic integration, and computational requirements.

DISCUSSION

The study findings highlight the critical role of combining temporal modeling and semantic analysis methods in achieving accurate real-time recognition of sign glosses. Both LSTM and Transformer architectures demonstrated high efficiency in identifying long-term and contextual dependencies between glosses. In particular, Transformer-based approaches significantly improved the understanding of the global semantic context of sign gestures, achieving an accuracy rate of 93.1%.

On the other hand, the TCN model, being optimized for faster processing, proved essential for real-time systems, although it was less effective than LSTM or Transformer in deep semantic interpretation. The Sliding Window approach provided temporal segmentation of sign gestures, facilitating sequential analysis; however, it lacked the ability to ensure comprehensive semantic coherence across segments.

Gloss mapping methods were effective in aligning gestures with their linguistic units, though challenges remained in capturing their meaning within broader contextual frames. This limitation was largely mitigated by ontological integration, where semantic networks such as WordNet and ConceptNet were leveraged to identify conceptual relationships between glosses,

enhancing interpretative depth.

The discussion further emphasizes that for real-time systems, factors such as computational complexity, recognition speed, semantic consistency, and user interface design must be carefully balanced. While Transformer-based models provide superior accuracy, their high computational demands limit their feasibility for deployment on resource-constrained real-time devices. Therefore, future research should focus on developing Transformer-Lite architectures or layer-optimized models to reduce resource usage without compromising performance.

Additionally, the integration of multimodal data sources—including video streams, skeletal keypoints, gloss annotations, and textual descriptions—offers a solid foundation for building robust and comprehensive real-time SLR systems, ensuring both high accuracy and contextual relevance.

CONCLUSION

This study analyzed temporal modeling and real-time recognition approaches in sign language recognition (SLR) systems, leading to the following key conclusions:

Temporal modeling is one of the main factors determining the effectiveness of SLR systems. In particular, models such as LSTM and Transformer demonstrated superior performance for consistent analysis of sequential sign gestures.

The Transformer architecture achieved the highest accuracy (93.1%) by evaluating sign glosses in a global context, while LSTM proved effective for long-term dependencies, and TCN stood out for its high processing speed.

Sliding Window and Gloss Mapping approaches are applicable in real-time analysis but require integration with methods that enhance semantic accuracy.

Ontological integration significantly improved recognition by clarifying the semantic position of glosses within conceptual networks, thereby increasing accuracy and interpretability.

Multimodal approaches—combining gesture data, skeletal keypoints, gloss annotations, and textual descriptions—enable more comprehensive interpretation of sign glosses.

For real-time SLR systems, achieving an optimal balance between accuracy, processing speed, semantic consistency, and computational efficiency is crucial when selecting models.

The study's findings provide a solid scientific and practical foundation for developing real-time SLR systems capable of delivering accurate, contextually meaningful, and user-friendly recognition of sign glosses.

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