Neural Network & Deep Learning

TITLE : Enhancing Communication through AI in Sign Language Translation

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Motivation :

Bridging the Communication Gap

- **Accessibility:**
  - Traditional SLT methods have limitations in availability and access, especially in remote areas or for individuals with limited resources.
  - AI-powered solutions offer on-demand and remote accessibility, overcoming geographical barriers.
- **Efficiency and Speed:**
  - AI systems can significantly speed up communication by automating the translation process.
  - Real-time translation capabilities are crucial in dynamic environments like meetings or emergency situations.
- **Scalability :**
  - The demand for SLT services is increasing, and AI offers scalable solutions to address the shortage of qualified interpreters.
  - AI-driven systems can handle large volumes of translation requests efficiently.
- **Personalization:**
  - AI algorithms can adapt to individual user preferences and learning styles, offering personalized feedback and recommendations.
  - This personalization improves user experience and learning outcomes.
- **Innovation:**
  - Investing in AI-powered SLT drives advancements in assistive technology and accessibility research.
  - Integration with AR and wearable devices can further enhance communication experiences.

Objectives:

<u>Building a Comprehensive Translation System</u>

- **Speech-to-Sign Language Translation:**
  - Develop accurate speech recognition algorithms to transcribe spoken language.
  - Utilize NLP techniques to understand the semantic meaning of the transcribed text.
  - Employ computer vision algorithms to generate corresponding sign language gestures.
- **Text-to-Sign Language Translation:**
  - Develop machine translation models to convert written text into sign language glosses or descriptions.
  - Use animation techniques to create lifelike sign language gestures from translated text.
  - Incorporate linguistic rules and cultural considerations for accurate and appropriate translations.
- **Sign Language to Speech/Text Translation:**
  - Develop robust computer vision algorithms for sign language gesture recognition.
  - Integrate natural language generation techniques to produce written text or synthesized speech.
  - Adapt to various sign language dialects and variations for broader applicability.
  - Include accessibility features like text-to-speech for spoken language output.

Problem Statement:

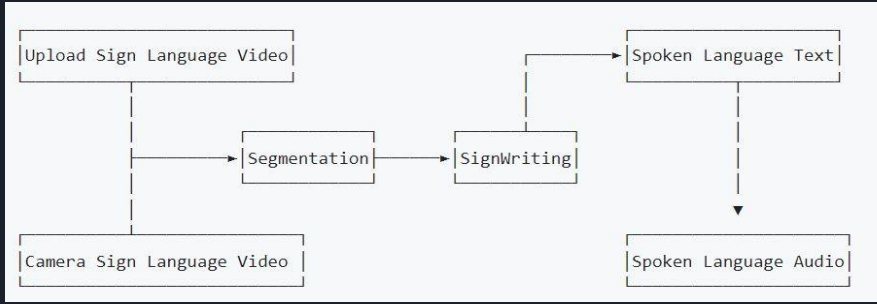
<u>Overcoming Communication Barriers and Accessibility Gaps</u>

- **Limited Accessibility of Traditional SLT Methods:** Highlight the restricted access to qualified interpreters, especially in remote areas or for specific languages.
- **Inefficiency and Time Constraints:** Emphasize the time-consuming nature of traditional translation methods, hindering real-time communication and responsiveness.
- **Scalability Issues:** Address the challenges in meeting the growing demand for sign language translation services due to limited resources and interpreter availability.
- **Lack of Personalization:** Point out the inability of traditional methods to adapt to individual learning styles and preferences, potentially hindering effective communication and learning outcomes.
- **Technological Gaps in Existing AI Solutions:** Mention the limitations of current AI-driven solutions in terms of accuracy, inclusivity, and adaptability to diverse sign languages and signing styles.

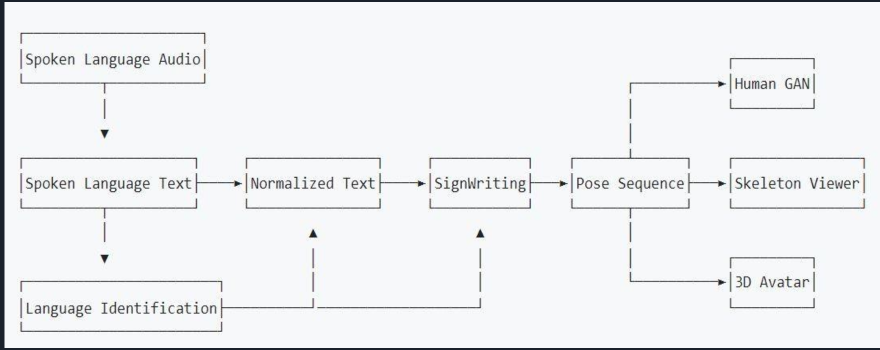
Related work:

Learning from Existing Research

- Sign Language Segmentation:
  - Explain current segmentation methods and challenges due to the simultaneous nature of sign language gestures.
  - Stress the importance of understanding sign language structure for improved segmentation techniques.



- Sign Language Recognition, Translation, and Production:
  - Discuss previous work on isolated sign recognition and continuous signing sequence recognition.
  - Highlight the advancements and limitations of existing sign language translation and production systems.



Opensourced Datasets :

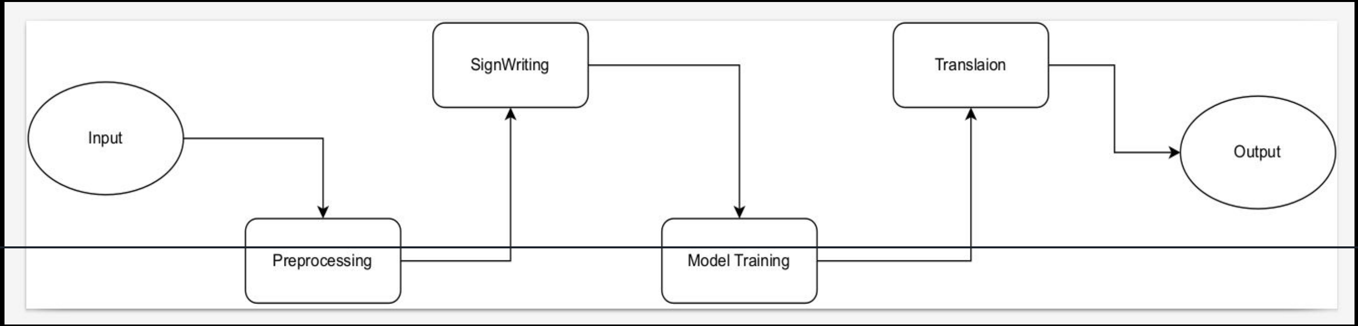
Dataset	Videos	Poses	Versions
aslg_pc12	N/A	N/A	0.0.1
asl-lex	No		2.0.0
rwth_phoenix2014_t	Yes	Holistic	3.0.0
autsl	Yes	OpenPose, Holistic	1.0.0
dgs_corpus	Yes	OpenPose, Holistic	3.0.0
dgs_types	Yes		3.0.0
how2sign	Yes	OpenPose	1.0.0
sign2mint	Yes		1.0.0
signtyp	Links		1.0.0
swojs_glossario	Yes		1.0.0
SignBank	N/A		1.0.0
wlasl	Failed	OpenPose	None
wmtslt	Yes	OpenPose, Holistic	1.2.0
signsuisse	Yes		1.0.0
msasl			None
Video-Based CSL			None
RVL-SLLL ASL			None
ngt_corpus	Yes		3.0.0
bsl_corpus	No	No	3.0.0

Table 1: *Summary of signed language datasets*

Several publicly available datasets can be leveraged for training sign language translation models. Below are datasets selected to evaluate the models used in our project

- Speech-to-Sign Language Translation
- Text-to-Sign Language Translation
- Sign Language-to-Text/Speech Translation

Proposed Solution:



Key Components:

- **Data Acquisition & Preprocessing**
- **SignWriting Representation**
- **Machine Translation Models**
- **API Server**

Experimentation:

- **Bilingual ASL-to-English Translation :**

  Model: "baseline transformer spm factor sign+"

  Dataset: SignBank

  Framework: Joey NMT

  Evaluation Metric: BLEU score

  Results: BLEU score exceeding 30, indicating strong performance in translating ASL to English.

- **Comparison with Alternative Approaches:**

  1. Direct comparisons were challenging due to variations in data, evaluation methods, and methodologies.

  2. The SignWriting-based approach appears competitive, potentially offering more accurate and nuanced translations compared to systems relying on glosses or other intermediate representations.

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Thank you :)