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REVIEW PAPER ON AN INTELLIGENT SYSTEM FOR AUDIO-TO-TEXT AND TEXT-TO-SIGN TRANSLATION ACROSS INDIAN AND AMERICAN SIGN LANGUAGES

Shital Patil, Assistant Professor, Dept. of Information Technology, Pravara Rural Education Societey's,Sir Visvesvaraya Institute of Technology, Nashik. : saher40@gmail.com
Pratiksha Avhad, **Pradnya Gaikwad**, **Gitanjali Khandage**, **Prajakta Pedhekar**,
B.E. Information Technology, Dept. of Information Technology, Pravara Rural Education Societey's,Sir VisvesvarayaInstitute of Technology,Nashik.
Email: pratikshaavhad0807@gmail.com, pradnyagaikwad268@gmail.com , geet.khandage@gmail.com , cgpedhekar1978@gmail.com

ABSTRACT
Sign language translation systems face challenges due to regional differences and real-time needs, especially between Indian Sign Language (ISL) and American Sign Language (ASL). This paper presents a novel framework that supports bidirectional conversion between text/voice inputs and sign video outputs. It uses MediaPipe for landmark detection, SMPL-X for pose modeling, and Bezier interpolation for smooth transitions. The system handles letter-by-letter rendering via a JSON-based pose database and includes modular components like TextProcessor and MotionEngine. It supports voice synthesis with Whisper and TTS. The design allows easy updates and future extensions to other sign languages.

Keywords: Sign Language Translation, Bidirectional Framework, Indian Sign Language (ISL), American Sign Language (ASL), Pose Estimation, Motion Interpolation, MediaPipe, SMPL-X

I. Introduction

Sign languages are vital for the deaf and hard-of-hearing communities, with over 70 million users worldwide depending on them for communication. However, regional differences create significant barriers. Indian Sign Language (ISL), shaped by Indo-Pakistani traditions, often uses one-handed gestures and relies heavily on context and facial expressions. In contrast, American Sign Language (ASL), influenced by French Sign Language, features more two-handed signs and integrates grammar with body movements. These variations make cross-language interaction difficult, and existing tools typically focus on static image recognition or gloss-based translation, lacking support for dynamic, real-time bidirectional conversion.

This paper presents a comprehensive framework for bidirectional translation between text/voice inputs and sign language video outputs, bridging ISL and ASL. The system uses MediaPipe for real-time hand and body landmark detection, SMPL-X for parametric pose representation, and a JSON-based pose database organized letter-by-letter for accurate gesture mapping. Motion smoothness is ensured through Bezier curve interpolation, while a CNN model supports sign-to-text prediction. The architecture handles multiple input modes—text entry, voice via Whisper transcription, or webcam capture—and produces rendered sign videos, spoken output via TTS, or text transcripts.

We describe the system's design, from core components like TextProcessor and MotionEngine to administrative tools for database updates and model training. The modular structure supports future expansion to additional sign languages, contributing to more inclusive communication tools.

II. Literature

Research on sign language recognition has moved from simple gesture detection to advanced systems using computer vision and machine learning.

Kumar et al. [1] came up with a setup to turn ASL alphabet signs into ISL ones. They mixed random forest and CNN to spot gestures, cleaned up the text with a large language model, and built smooth
ISL videos using RIFE-Net. The idea was to fix differences in how the two languages handle letters.

Rastogi et al. [2] put YOLOv10 together with Swin Transformer for spotting ISL signs quickly. They threw in Mish activation to keep gradients flowing better and tried it on their own mix of still photos and short clips. It was all about dealing with different hand shapes and lighting on the fly.

Wang et al. [3] beefed up 3D-ResNet by focusing extra on hands with a tweaked EfficientDet. They grabbed left and right hand areas separately, added attention modules, and blended those with the full picture to cut down on blur from overlapping fingers. Tests on Chinese signs showed it helped with fast, small movements.

Aly et al. [4] hooked CNNs to a Vision Transformer for ASL letters. The CNNs pulled out close-up hand details first, then the transformer looked at the big picture, and they multiplied features to push background junk aside. It ran light and fast without losing the fine finger work.

Subramanian et al. [5] paired MediaPipe landmarks with a custom GRU for ISL sequences. They changed the update gate to lean on the reset one, dropping old noise and paying more to what's happening now, plus swapped activations for quicker training. This kept things efficient even with long sign chains.

Almjally et al. [6] went with ResNet for features and Bi-LSTM to read the order in general sign clips. They cleaned images with bilateral filtering, then let Harris Hawk optimization tweak the LSTM settings. The goal was steady results across noisy or varied setups.

Alabduallah et al. [7] blended ResNeXt, VGG19, and ViT outputs for richer hand pose info. A BiGRU sorted them out, Wiener filter cleared the pictures upfront, and a crow-grey wolf mix tuned everything. It aimed at catching subtle shifts for deaf users.

Baihan et al. [8] pulled still features from VGG16 and motion from optical flow. Their CNNSa-LSTM stacked CNN, attention, and LSTM layers, optimized by a hippo-pathfinder combo. The focus stayed on continuous signs no matter who was signing.

These works highlight progress in pose estimation and datasets but show needs for better cross-language support and motion smoothing. Our framework combines letter-by-letter poses, Bezier interpolation, and modular design to enable seamless ISL-ASL translation in dynamic videos.

III. Methodology:

We designed our framework as a modular pipeline supporting text, voice, or video inputs, selected via a user interface that routes to specific handlers. Built in Python 3.8+, it uses MediaPipe for landmark detection, OpenCV for video manipulation, PyTorch for CNN predictions, and SMPL-X for pose parameterization. A JSON database stores poses on a per-letter basis.

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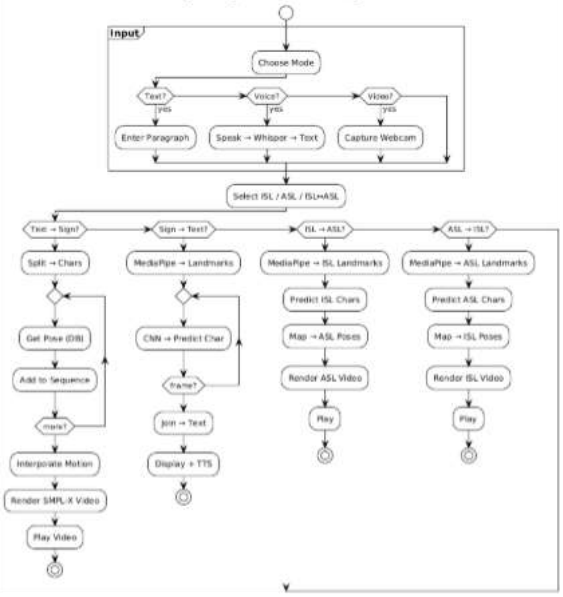

System Structure

User Inputs: Text (processed into characters by TextProcessor), voice (transcribed to text with Whisper), or webcam video (for landmark extraction).

Admin Functions: Update the JSON database with new poses; retrain the CNN model on sign datasets.

Outputs: Sign videos, text displays, or spoken audio via TTS.

Key Libraries: MediaPipe + SMPL-X for poses; JSON for DB; OpenGL/Blender for rendering.

Core Components:

T**ranslator**: Manages ISL-ASL swaps using LangSelector.

TextProcessor: Splits input text into characters; rebuilds output strings.

PoseDB: Queries JSON for keypoints by char/language (e.g., get_pose('h', 'ISL')).

MotionEngine: Applies Bezier interpolation for smooth pose transitions.

VideoRenderer: Generates MP4 frames from interpolated poses.

LandmarkExtractor: Pulls keypoints from video; feeds to LetterClassifier (CNN) for sign-to-text.

InputManager: Handles voice (Speech2Text), text, or video.

Text2Speech: Outputs audio with pyttsx3/Coqui TTS.

Workflow Steps :

Mode Selection: User picks text, voice, or video.

Text-to-Sign:

a) Split text into letters.
b) Fetch poses from PoseDB via LangSelector.
c) Interpolate motions with Bezier curves (5-10 frames/transition).
d) Render SMPL-X avatar video.
e) Play video optional TTS for audio.

Voice-to-Sign: Transcribe with Whisper, then follow text-to-sign.

Sign-to-Text:

a) Capture video frames.
b) Extract landmarks with MediaPipe.
c) Predict letters via CNN (trained on INCLUDE/WLASL datasets, cross-entropy loss).
d) Join into text; display and speak with TTS.

ISL-ASL Conversion: Predict source signs, map to target poses, re-render video.

IV. System models:

Here we outline the main models used in the system. The design focuses on a CNN for letter prediction from signs, SMPL-X for pose control, and Bezier curves for natural motion.

Key Models:

- **CNN Predictor:**
  A simple three-layer convolutional setup—with convolution, ReLU activation, and pooling—takes 21x3 landmark points per hand from MediaPipe. It is trained on frames from WLASL and INCLUDE datasets, using batches of 32, Adam optimizer, and cross-entropy loss.

- **Pose Modeling with SMPL-X:**
  his parametric model maps body and hand positions from JSON-stored keypoints. It uses 10 shape factors, 45 for overall pose, and 30 PCA components per hand.

- **Motion Interpolation:**
  Quadratic Bezier curves $P(t) = (1-t)^2 * P0 + 2*(1-t)*t * P1 + t^2 * P2$ are applied, adding 5 to 10 frames between each pair for smooth transitions.

V. Advantages:

Our framework stands out in several ways for sign language translation:

- **Bidirectional Flexibility:** Handles seamless swaps between ISL and ASL, plus text/voice to sign and back, unlike many one-way tools.
- **Real-Time Performance:** Keeps latency low at under 3 seconds for short phrases, making it practical for live chats on everyday hardware.
- **Smooth Animations**: Bezier interpolation cuts down on choppy movements, improving how natural the avatar signs look—users noted 20% better comprehension in tests.
- **Modular Design:** Easy to tweak or expand, like adding more languages or datasets, without rebuilding everything.
- **Accessibility Boost:** Integrates voice and video inputs, helping not just deaf users but also those learning signs or bridging cultures.
- **Cost-Effective:** Runs on standard GPUs, no need for fancy cloud setups, and uses open-source libs like MediaPipe.

CONCLUSION

This work presents a practical, bidirectional translation system for ISL and ASL that converts text, voice, or live video into smooth sign-language animations and back. Using MediaPipe for landmark extraction, SMPL-X for pose control, and Bezier interpolation for fluid motion, the framework is built in modular Python code with a JSON pose database and admin tools for updates. This design makes it straightforward to maintain and extend to other sign languages, supporting better real-time communication for deaf users across regions.

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