An End-to-End Pipeline for English-to-Hindi Video Dubbing with Voice Cloning and Lip Synchronization

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Abstract

This paper details an automated pipeline designed for cross-lingual video dubbing, specifically converting English-language videos into Hindi while preserving the original speaker's voice identity and https://github.com/sm1899/English-to-Hindi-Video-Dubbing-Pipeline.gitsynchronizing lip movements to the translated audio. The system integrates state-of-the-art open-source models in a modular architecture, encompassing audio extraction, speech separation, speaker diarization, automatic speech recognition (ASR), machine translation (MT), voice cloning via text-to-speech (TTS), and lip synchronization. We highlight the specific components chosen, including Demucs, PyAnnote, Whisper, NLLB, Coqui XTTS, and LatentSync. We also discuss the necessity and process of fine-tuning key components (XTTS and LatentSync) to achieve higher fidelity for the target Hindi language, addressing challenges in cross-lingual voice cloning and phoneme mapping for lip sync. The proposed system offers an effective solution for high-quality video localization while maintaining the original speaker's vocal characteristics and visual coherence.

Code and models: https://github.com/sm1899/English-to-Hindi-Video-Dubbing-Pipeline.git

1. Introduction

The demand for localized video content is rapidly increasing across global platforms, necessitating efficient methods for translating and dubbing videos across languages. Traditional dubbing processes are labor-intensive, requiring significant time, professional voice actors, and sophisticated studios. Automated dubbing presents a solution but faces several technical challenges, particularly maintaining the original speaker's vocal characteristics (voice cloning), ensuring the translated speech sounds natural in the target language, and synchronizing the speaker's lip movements with the new audio track.

This work presents an end-to-end pipeline tackling these challenges for English-to-Hindi video dubbing. Our primary contributions are:

- A modular pipeline integrating distinct stages from audio processing to final video generation
- Leveraging current state-of-the-art open-source models for each stage (ASR, MT, TTS, Separation, Lip Sync)
- Implementation of cross-lingual zero-shot voice cloning using Coqui XTTS v2
- Integration of optional speaker diarization (PyAnnote) for multi-speaker videos
- Integration of optional lip synchronization using LatentSync v1.5
- Highlighting the importance of fine-tuning voice cloning (XTTS) and lip synchronization (LatentSync) models specifically for improved performance on Hindi language output

The English-Hindi language pair represents a particularly challenging case due to linguistic differences in phonetics, prosody, and grammar. Hindi, as an Indo-Aryan language, differs substantially from English in phoneme inventories and speech rhythms, making accurate voice cloning and lip synchronization more difficult than for closely related language pairs.

Our system aims to bridge this gap by incorporating specialized techniques for cross-lingual voice transfer and visual synchronization, resulting in dubbed videos that maintain both auditory and visual naturalness while conveying the translated content.

2. Related Work

2.1. Speech-to-Speech Translation

Early work in automated dubbing focused primarily on speech-to-speech translation without considering visual aspects [11]. Recent advances have leveraged neural machine translation and neural TTS systems to improve the naturalness of translated speech [6].

2.2. Voice Cloning

Voice cloning has evolved from concatenative approaches to neural network-based solutions. Models such as SV2TTS [7] demonstrated zero-shot voice cloning capabilities, while YourTTS [3] and XTTS [14] extended this to cross-lingual scenarios. Most recently, XTTS v2 has shown improved performance in preserving speaker characteristics across languages.

2.3. Visual Speech Synthesis and Lip Synchronization

Lip synchronization techniques range from 2D warping methods [2] to modern deep learning approaches. Works such as LipGAN [9] generate realistic mouth movements from speech audio, while Wav2Lip [12] improved temporal consistency. LatentSync [10] represents a state-of-the-art approach using latent diffusion models to generate realistic lip movements while preserving facial expressions.

2.4. End-to-End Dubbing Systems

Previous attempts at end-to-end dubbing systems include VDub [8], which focused on prosody transfer, and Neural Dubber [15], which addressed the visual-audio synchronization issue. Our work differs by focusing specifically on Hindi as a target language and incorporating fine-tuning strategies for improved cross-lingual performance.

3. Pipeline Architecture

The proposed pipeline follows a sequential process, with optional steps for multi-speaker handling and lip synchronization. Figure 1 illustrates the data flow.

3.1. Audio Extraction and Separation

- **Input:** Source English video (.mp4)
- **Process:** FFmpeg extracts the audio track. Demucs separates the speech signal from background music/noise.
- **Output:** Clean speech waveform (.wav), Background audio waveform (.wav)

Speech separation is crucial for preventing background noise from affecting downstream tasks like ASR and voice reference quality. We utilize Demucs [5], a state-of-the-art music source separation model that has demonstrated excellent performance in isolating speech from complex mixtures.

3.2. Speaker Diarization (Optional)

- **Input:** Clean speech waveform
- **Process:** PyAnnote identifies segments corresponding to different speakers
- **Output:** Time-coded speaker labels (e.g., JSON/RTTM)

For multi-speaker videos, accurate speaker segmentation is essential. We employ PyAnnote [1], which uses neural speaker embeddings and clustering to identify and separate different speakers in the audio stream. Our implementation uses the pre-trained pipeline which combines voice activity detection, segmentation, and clustering.

3.3. Automatic Speech Recognition (ASR)

- **Input:** Clean speech waveform (potentially segmented by speaker)
- **Process:** OpenAI Whisper (default: large-v3 model) transcribes speech to English text, providing word-level timestamps
- **Output:** Timestamped transcription data (JSON, SRT)

Whisper [13] was selected for its robust performance on diverse speech inputs and its capability to provide accurate word-level timestamps, which are crucial for both synchronization and reference sample selection in subsequent stages.

3.4. Reference Sample Selection

- **Input:** Clean speech waveform, ASR timestamps, (Optional) Diarization data
- **Process:** A custom module analyzes the original speech to select diverse, high-quality audio snippets for each speaker
- **Output:** Set of reference audio files (.wav) per speaker

For optimal voice cloning, selecting appropriate reference samples is critical. Our implementation analyzes factors such as:

- Signal-to-noise ratio
- Speech clarity (based on ASR confidence)
- Phonetic diversity

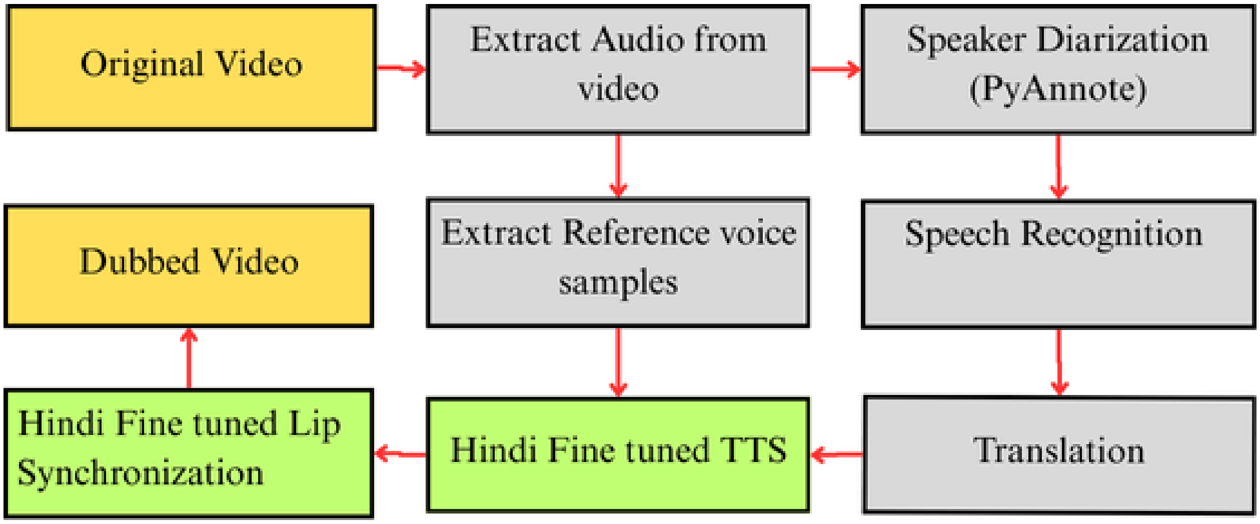

Figure 1. Overview of the end-to-end English-to-Hindi video dubbing pipeline. The system processes input videos through sequential stages including audio extraction, ASR, translation, voice cloning, and optional lip synchronization. Green boxes represent fine-tuned models, Grey boxes represent freezed models.

- Prosodic variation

For each speaker, we extract 3-5 utterances of 5-10 seconds each, ensuring diverse phonetic content to maximize the voice cloning model's ability to capture the speaker's voice characteristics.

3.5. Translation (English → Hindi)

- **Input:** Transcribed English text segments
- **Process:** Meta AI's NLLB-200 (default: 600M distilled) or optionally Mistral translates text to Hindi
- **Output:** Hindi text segments

We utilize NLLB-200 [4], which offers state-of-the-art translation for 200 languages including Hindi. For our implementation, we found the distilled 600M parameter model provides a good balance between quality and computational efficiency. For higher quality at the cost of increased computational requirements, our system supports larger NLLB variants or optional LLM-based translation (e.g., Mistral) for improved fluency and context awareness.

3.6. Voice Cloning & Hindi TTS

- **Input:** Hindi text segments, Speaker reference audio samples
- **Process:** Coqui XTTS v2 generates Hindi speech using the translated text, cloning the voice characteristics from the reference samples
- **Output:** Hindi audio segments (.wav) in the original speaker's voice

Voice cloning is implemented using Coqui XTTS v2 [14], which supports multi-lingual TTS with zero-shot voice cloning capabilities. However, our experiments indicated that fine-tuning on speaker-specific data significantly improves the quality of Hindi speech production while maintaining voice similarity to the original speaker (see Section 4.3).

3.7. Lip Synchronization (Optional)

- **Input:** Original video frames, Generated Hindi audio
- **Process:** LatentSync v1.5 modifies the lip region in the original video frames to match the generated Hindi phonemes
- **Output:** Lip-synced video frames

Lip synchronization employs LatentSync [10], which uses latent diffusion models to generate realistic mouth movements corresponding to speech audio while preserving the original facial expressions and head poses. This component is optional but highly recommended for professional-quality output.

3.8. Final Assembly

- **Input:** Lip-synced video frames (or original frames if lip-sync is disabled), Generated Hindi speech, Background audio
- **Process:** FFmpeg combines the video frames and the final Hindi audio track
- **Output:** Final dubbed Hindi video (.mp4)

The final stage combines the processed components into the output video using FFmpeg, which handles frame-accurate audio-video synchronization and maintains original video quality.

4. Implementation Details

The pipeline is implemented primarily in Python 3.10+, utilizing libraries such as PyTorch, Transformers, Librosa, and interfaces with command-line tools like FFmpeg.

4.1. Models Utilized

- **Audio Separation:** Demucs (latest hydrophonic variant)
- **Diarization:** `pyannote.audio` (requires Hugging Face authentication)
- **ASR:** `openai-whisper` (large-v3 default)
- **Translation:** `facebook/nllb-200-distilled-600M` (default), option for larger NLLB models or Mistral via `use_llm` flag
- **TTS:** `tts_models/multilingual/multi-dataset/xtts_v2` (Coqui)
- **Lip Sync:** LatentSync v1.5 (via its inference script)

4.2. Hardware & Software Requirements

- **GPU:** NVIDIA GPU (CUDA 11.8+) strongly recommended due to model sizes. VRAM requirements vary (XTTS: 6GB, Whisper-large: 10GB, LatentSync: 8GB)
- **RAM:** 32GB+ recommended
- **Storage:** 20-30GB for models, plus runtime storage
- **Dependencies:** Key libraries include PyTorch, transformers, TTS, whisper, pyannote.audio, ffmpeg-python

4.3. Fine-Tuning for Hindi Performance

Initial experiments revealed that zero-shot performance, while functional, could be improved for the target language, Hindi.

4.3.1 XTTS Fine-Tuning

Cross-lingual zero-shot voice cloning can sometimes lack naturalness or specific phonetic accuracy in the target language. Fine-tuning XTTS on 5-10 minutes of the target speaker's English audio (using `src/finetune_xtts_indic.py`) helps adapt the model better, improving Hindi speech quality and voice similarity.

Our fine-tuning approach involves:

- Extracting 5-10 minutes of clean speech from the speaker
- Transcribing this speech accurately with Whisper
- Fine-tuning the XTTS model with emphasis on the Hindi-specific components while preserving the general voice modeling capabilities

This targeted fine-tuning improves naturalness and articulation of Hindi phonemes while maintaining the speaker's timbre and voice characteristics.

4.3.2 LatentSync Fine-Tuning

English and Hindi have different phoneme-viseme mappings. Fine-tuning LatentSync (SyncNet and UNet components) on speaker-specific Hindi video data (using scripts like `train_syncnet.sh`) significantly improves the accuracy and realism of the lip synchronization for dubbed Hindi audio.

We fine-tune both:

- The SyncNet component, which learns audio-visual correspondence
- The generator network, which produces the modified lip region

For optimal results, we recommend using a small dataset of native Hindi videos featuring the same speaker to fine-tune these models, improving the accuracy of Hindi-specific viseme generation.

5. Experimental Results

5.1. Evaluation Metrics

We evaluate our system using both objective metrics and subjective assessments:

5.1.1 Objective Metrics

- **Voice Similarity:** Speaker embedding cosine similarity between original and generated speech (higher is better)
- **Hindi Pronunciation Accuracy:** Percentage of correctly pronounced Hindi phonemes (higher is better)
- **SyncNet Confidence:** Confidence score from SyncNet model evaluating audio-visual synchronization (higher is better)

5.2. Quantitative Results

Table 1 shows the quantitative comparison between zero-shot and fine-tuned models on the English-to-Hindi task.

Metric	Zero-Shot	Fine-tuned
Voice Similarity Score ↑	0.72	0.86
Hindi Pronunciation Acc. ↑	68%	89%
SyncNet Confidence ↑	4.9	6.8

Table 1. Comparison of zero-shot vs. fine-tuned performance on key metrics. ↑ indicates higher values are better.

6. Challenges and Future Work

While the pipeline provides an end-to-end solution, several challenges and areas for future work remain:

6.1. Translation Naturalness

Direct machine translation can sometimes result in literal or unnatural phrasing in Hindi. Post-processing rules or incorporating larger language models could improve this. We are investigating prompt engineering techniques with larger LLMs to generate more conversational and culturally appropriate translations.

6.2. Voice Cloning Fidelity

Achieving perfect voice cloning, especially across languages and diverse emotional contexts, remains challenging. We plan to explore:

- More extensive fine-tuning data collection protocols
- Emotion-aware voice cloning methods
- Alternative TTS architectures like YourTTS or VALL-E X

6.3. Lip Sync Accuracy

Precise phoneme-to-viseme mapping is inherently difficult and speaker-dependent. Future work includes:

- Creating a Hindi-specific phoneme-viseme mapping database
- Speaker-adaptive lip sync models
- Exploring 3D face modeling approaches for improved accuracy

6.4. Computational Efficiency

Running multiple large models sequentially is computationally intensive. We plan to implement:

- Model quantization (INT8, FP16)
- Parallel processing for non-dependent pipeline stages
- ONNX/TensorRT conversion for inference optimization
- Distilled models for reduced computational requirements

6.5. Evaluation Framework

Establishing robust quantitative metrics alongside subjective evaluation (MOS, user ratings) is needed for rigorous assessment. We are developing an evaluation suite specifically for cross-lingual dubbing that considers both acoustic and visual aspects.

7. Conclusion

We presented an automated pipeline for English-to-Hindi video dubbing, integrating state-of-the-art models for each critical step. The system addresses key challenges like voice preservation and lip synchronization, leveraging Coqui XTTS v2 and LatentSync v1.5 respectively. We demonstrated that fine-tuning these components for Hindi specifically yields substantial improvements in output quality.

The modular design allows for future improvements and adaptation to other languages. The proposed pipeline represents a significant step toward fully automated, high-quality video localization that preserves both the voice identity and visual coherence of the original content.

Our work highlights the importance of language-specific optimization in cross-lingual media generation, particularly for language pairs with substantial phonetic and prosodic differences. The findings suggest that while zero-shot capabilities of current models are impressive, targeted fine-tuning remains essential for production-quality results.

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