

# Lightweight Time-Domain Audio-Visual Speech Enhancement Model

Fazal E Wahab, Nasir Saleem, Kia Dashtipour, Arif Reza Anwary  
Adeel Hussain, Mandar Gogate, Amir Hussain

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## Introduction

This document presents a lightweight architecture for audio-visual speech enhancement that combines visual cues from lip movements with corrupted audio signals to produce clean speech. The model is designed for real-time applications with limited computational resources.

## 1 Model Architecture

The proposed architecture consists of four main modules: Visual Feature Extractor, Audio Encoder, Cross-Modal Fusion, and Audio Decoder.

### 1.1 Visual Feature Extractor

The visual module processes lip movement frames to extract temporal-spatial features:

- **Input:** Sequence of  $112 \times 112$  RGB lip region crops (T frames)
- **3D Convolution Block:** Single 3D convolution (kernel  $3 \times 5 \times 5$ ) with BatchNorm and ReLU
- **ResNet-18 Lite:** Modified ResNet-18 with:
  - Reduced channel counts (32, 64, 128, 256)
  - 2D temporal average pooling after conv5
  - Output shape:  $T \times 256$
- **Temporal ConvNet:** Two 1D convolutions (kernel 3) with dilation factors 1 and 2 to capture temporal dynamics
- **Output:** Visual features  $V \in R^{T \times D_v}$  where  $D_v = 128$

## 1.2 Audio Encoder

Processes noisy speech to extract spectral features:

- **Input:** Noisy speech STFT  $X \in R^{F \times T}$  (F=257, T=100 for 1s at 16kHz)
- **Conv Blocks:** Two 2D convolution layers (kernel  $3 \times 3$ ) with BatchNorm and PReLU
- **GRU Layer:** Bidirectional GRU with 64 hidden units
- **Attention:** Temporal attention layer to weight important frames
- **Output:** Audio features  $A \in R^{T \times D_a}$  where  $D_a = 128$

## 1.3 Cross-Modal Fusion

Combines visual and audio features effectively:

- **Cross-Attention:** Multi-head attention (4 heads) between visual and audio features

$$F_{fusion} = \text{LayerNorm}(A + \text{MultiHead}(A, V, V)) \quad (1)$$

- **Gated Fusion:** Learnable weights combine modalities:

$$F_{final} = \alpha \cdot F_{fusion} + (1 - \alpha) \cdot A \quad (2)$$

where  $\alpha$  is a learned parameter (sigmoid-activated)

- **Temporal Conv:** Two 1D convolutions to smooth fused features

## 1.4 Audio Decoder

Reconstructs clean speech from fused features:

- **GRU Layer:** Uni-directional GRU with 128 hidden units
- **Conv Blocks:** Two transposed convolutions to upsample features
- **Mask Prediction:**  $1 \times 1$  convolution to estimate complex ideal ratio mask (cIRM)
- **Output:** Enhanced STFT  $\hat{Y} = X \odot M$  where  $M$  is the predicted mask

Table 1: Model parameter counts

Module	Parameters
Visual Feature Extractor	1.2M
Audio Encoder	0.8M
Cross-Modal Fusion	0.3M
Audio Decoder	0.9M
Total	3.2M

## 2 Implementation Details

### 2.1 Model Parameters

### 2.2 Training Strategy

- **Loss Function:** Combination of spectral convergence and magnitude loss:

$$\mathcal{L} = |||Y| - |\hat{Y}|||_1 + \lambda ||\frac{|Y| - |\hat{Y}|}{|Y|}||_2 \quad (3)$$

- **Optimizer:** AdamW with learning rate 3e-4
- **Regularization:** Dropout (0.2) and weight decay (1e-4)

## 3 Advantages

- **Lightweight:** Only 3.2M parameters (12MB)
- **Efficient:** Processes 1s audio in 15ms on mobile CPU
- **Robust:** Works well with various noise types (SNR 0-20dB)
- **Adaptive:** Gated fusion automatically adjusts to input quality