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Audio-Visual Speech Enhancement with Pace-Synchronized Fusion and Dynamic Modality Balancing

Ivana Pereira, Sakura Tanaka, Anton Connie

Faculty of Science, University of Helsinki, Helsinki, Finland

Abstract.

Speech enhancement in noisy environments remains a formidable challenge in computational audition, particularly when relying solely on acoustic signals. While the integration of visual modalities, such as lip movements, has demonstrated substantial potential in mitigating background noise, existing audio-visual speech enhancement systems frequently struggle with asynchronous temporal dynamics and suboptimal modality weighting. This paper introduces a comprehensive framework termed Audio-Visual Speech Enhancement with Pace-Synchronized Fusion and Dynamic Modality Balancing. The proposed system addresses the fundamental temporal mismatch between audio and visual streams caused by varying frame rates and natural human articulation inconsistencies. By employing a pace-synchronized fusion mechanism, the architecture temporally aligns cross-modal feature representations before integration. Furthermore, a dynamic modality balancing module is introduced to continuously evaluate the reliability of each modality in real-time, assigning adaptive fusion weights based on the instantaneous signal-to-noise ratio and visual occlusion metrics. Extensive evaluations across multiple standardized datasets demonstrate that this approach significantly outperforms conventional audio-only and static audio-visual models, particularly in highly dynamic, non-stationary noise environments. The findings indicate a paradigm shift in how multimodal features should be aligned and weighted, paving the way for more robust and perceptually accurate speech processing systems.

Keywords: *Speech Enhancement, Modality Fusion, Pace Synchronization, Dynamic Balancing.*

1.INTRODUCTION

1.1 Background And Motivation

The ability to isolate and understand a single speaker in a noisy environment, commonly referred to as the cocktail party problem, has been a central focus of speech processing research for decades. Human perception naturally leverages multiple sensory inputs to parse complex scenes [1]. In particular, when auditory conditions degrade due to overlapping speech or environmental noise, human listeners instinctively direct their visual attention to the speakers mouth and facial

expressions. This visual information provides critical phonetic cues, such as the place of articulation, which are highly robust to acoustic interference. Early computational models primarily focused on audio-only speech enhancement, utilizing sophisticated signal processing techniques and, more recently, deep learning architectures to map noisy audio segments to clean speech targets [2]. However, the fundamental limitation of unimodal acoustic models is their susceptibility to masking, where the target speech and background noise share overlapping frequency bands, making perfect separation theoretically impossible without additional prior information.

The integration of visual data into speech enhancement frameworks has emerged as a promising solution to overcome the limitations of unimodal approaches. Visual cues are inherently immune to acoustic noise, providing a stable reference that can guide the auditory feature extraction process [3]. The concept of audio-visual speech enhancement builds upon the biological phenomenon known as the McGurk effect, which illustrates the inextricable link between what we hear and what we see during speech perception. In computational terms, the visual modality serves as a strong conditioning signal that helps neural networks distinguish between target speech and background interference [4]. Despite the theoretical advantages, practical implementations of audio-visual speech enhancement encounter significant hurdles, primarily concerning the temporal alignment of the two modalities and the determination of their relative importance under varying environmental conditions.

1.2 Problem Statement

Current state-of-the-art audio-visual speech enhancement models generally assume a fixed, synchronous relationship between the audio and visual streams. They typically up-sample the low-frame-rate video features to match the high-resolution audio frames or employ recurrent structures that assume strict frame-to-frame correspondence [5]. In reality, however, the pace of speech generation involves complex physiological processes where lip movements often precede or lag behind the actual acoustic emission. Furthermore, different hardware recording systems introduce inherent temporal jitter and synchronization offsets. When strict alignment is assumed but not present, the cross-modal fusion process can introduce artifacts, misleading the enhancement network and degrading the final audio quality rather than improving it.

Beyond synchronization, a secondary but equally critical issue is modality dominance and the lack of dynamic balancing. In many existing architectures, the fusion weights assigned to the audio and visual branches are learned during the training phase and remain static during inference [6]. This static approach fails to account for the highly dynamic nature of real-world environments. For instance, in a scenario where the visual feed is suddenly obscured by a passing object, or the speaker turns their head away from the camera, a statically balanced model will continue to rely on the degraded visual features, leading to a catastrophic drop in enhancement performance. Conversely, in a completely silent environment, relying heavily on visual cues is unnecessary and computationally wasteful. Therefore, there is a critical need for a system that can not only align the modalities in time but also dynamically assess their reliability and adjust their influence on the enhancement process accordingly.

1.3 Contributions

This paper proposes a novel framework designed to tackle the dual challenges of temporal mismatch and static modality weighting in audio-visual speech enhancement. The primary contributions of this research are manifold. First, we introduce a pace-synchronized fusion mechanism that actively models the temporal lag and lead between auditory and visual features.

This mechanism utilizes cross-domain attention to establish soft alignments, allowing the network to synchronize features dynamically based on phonetic content rather than strict timestamps. Second, we present a dynamic modality balancing module that calculates instantaneous reliability scores for both the audio and visual streams. This module dictates the information flow into the final enhancement layers, ensuring that the system relies on visual cues when acoustic noise is high and defaults to audio dominance when the visual signal is compromised. Finally, we provide a comprehensive empirical analysis of the proposed framework, demonstrating its superiority over existing methods across various noise types and visual occlusion scenarios.

2. Literature Review

2.1 Audio-Only Speech Enhancement

The trajectory of speech enhancement has evolved from statistical signal processing methods to sophisticated deep learning paradigms. Early approaches, such as spectral subtraction and Wiener filtering, relied on statistical assumptions about the noise profile [7]. These methods were effective in stationary noise environments but struggled significantly when faced with non-stationary interferences, such as babble noise or sudden environmental sounds. The advent of deep neural networks brought a paradigm shift, enabling models to learn complex, non-linear mappings between noisy and clean speech representations. Convolutional neural networks and recurrent neural networks became standard architectures for time-frequency mask estimation, where the network predicts a mask that is element-wise multiplied with the noisy spectrogram to filter out unwanted components [8].

Despite these advancements, audio-only models inherently suffer from an informational bottleneck. When the signal-to-noise ratio drops below zero decibels, the acoustic cues of the target speaker are severely corrupted. Deep learning models in these scenarios often generate speech that sounds artificial or distorted, a phenomenon known as musical noise [9]. Furthermore, in the presence of competing speakers with similar vocal characteristics, audio-only models struggle to determine which voice to enhance, leading to speaker confusion. This limitation has driven the research community to explore auxiliary information sources to guide the enhancement process.

2.2 Audio-Visual Integration Techniques

The integration of visual information into speech enhancement systems has been approached through various fusion strategies, broadly categorized into early, late, and intermediate fusion. Early fusion involves concatenating the raw audio and visual features before passing them through a joint neural network [10]. While computationally straightforward, this approach forces the network to learn the complex cross-modal relationships from scratch, which often requires massive amounts of training data and is prone to overfitting. Late fusion, on the other hand, processes each modality through separate independent networks and combines their predictions at the final output stage. This method preserves modality-specific characteristics but fails to leverage cross-modal interactions during the feature extraction phase [11].

Intermediate fusion has emerged as the most effective strategy, where features are extracted independently from both modalities and then fused at various depths within the network hierarchy [12]. Recent advancements in attention mechanisms, particularly the Transformer architecture, have significantly enhanced intermediate fusion techniques. Cross-modal attention allows the visual features to query the audio features, highlighting the most relevant acoustic information based on the current lip shape. However, these attention-based models still predominantly rely on positional encodings that enforce strict temporal sequences, rendering them vulnerable to the natural asynchrony between lip movements and vocal tract sound generation [13].

2.3 Challenges In Modality Balancing

While fusion techniques have matured, the mechanism for balancing the importance of each modality remains underdeveloped. Most contemporary audio-visual enhancement networks utilize simple concatenation or addition operations to merge the intermediate features [14]. This implies a static allocation of trust to both modalities, regardless of their current quality. Researchers have attempted to address this by introducing gating mechanisms, where the visual features are multiplied by a learned scalar before fusion. However, these scalars are typically optimized over the entire training dataset and do not adapt to instantaneous changes in the environment during inference [15].

The necessity for dynamic modality balancing is particularly evident in real-world applications where sensors are subject to unpredictable failures. For example, in video conferencing, varying lighting conditions, motion blur, and network-induced frame drops can severely compromise visual feature extraction. If an enhancement model cannot detect this degradation and reduce its reliance on the visual stream, the output audio will suffer. A limited number of recent studies have explored reliability-aware fusion by estimating the signal-to-noise ratio of the audio stream to adjust visual weights [16]. However, these approaches rarely account for the simultaneous degradation of both modalities or incorporate visual occlusion metrics into their balancing equations, leaving a significant gap in the development of truly robust audio-visual systems.

3. Methodology

3.1 Pace-Synchronized Fusion Mechanism

The fundamental premise of the pace-synchronized fusion mechanism is that audio and visual features representing the same phonetic unit do not necessarily occur at the exact same temporal frame. To address this, the proposed architecture first extracts high-dimensional feature sequences from both the raw audio waveform and the video frame sequence. The audio encoder consists of a series of one-dimensional convolutional layers that map the time-domain signal into a dense temporal feature map. Concurrently, the visual encoder employs a spatiotemporal three-dimensional convolutional network to process sequences of cropped lip regions, producing a corresponding visual feature sequence. Because video frame rates are typically much lower than audio sampling rates, the visual features are initially interpolated to match the temporal resolution of the audio features.

Once the modalities share a common temporal dimension, the pace-synchronized fusion module is applied. Instead of directly merging the corresponding frames, this module employs a temporal neighborhood matching technique. For every specific frame in the audio feature sequence, the module examines a localized window of surrounding frames in the visual feature sequence. A similarity matrix is computed to determine the correlation between the current audio frame and all visual frames within this window. This correlation relies on a learned projection space where auditory phonemes and visual visemes share similar representations. By identifying the visual frame that yields the highest correlation score, the module effectively discovers the true temporal alignment, compensating for any natural or systematic asynchrony.

Following the identification of the optimal temporal match, a soft-attention mechanism aggregates the visual features within the neighborhood window, heavily weighting the most correlated frames. This aggregated visual context is then concatenated with the original audio frame. This synchronized fusion ensures that the enhancement network is provided with visual cues that accurately correspond to the acoustic events occurring at any given microsecond. By dynamically

warping the visual sequence to match the acoustic pace, the system completely eliminates the artifacts traditionally caused by rigid, frame-by-frame concatenation techniques.

3.2 Dynamic Modality Balancing Framework

With the modalities temporally aligned, the system must then determine the optimal proportion of information to extract from each stream. The dynamic modality balancing framework operates on the principle of continuous reliability assessment. It takes the aligned audio and visual feature sequences as inputs and processes them through two parallel reliability estimation branches. The audio reliability branch consists of a lightweight recurrent network that estimates the instantaneous acoustic signal-to-noise ratio. It analyzes the entropy and energy distribution of the audio features to determine the level of background interference. High entropy and distributed energy typically indicate severe noise, resulting in a low reliability score for the audio stream.

Simultaneously, the visual reliability branch assesses the quality of the visual stream. This branch utilizes a spatial attention mechanism over the original video frames to detect occlusions, motion blur, or instances where the speaker is outside the camera's optimal field of view. By measuring the variance and structural integrity of the facial landmarks, the network computes a visual confidence score. If the lip region is obscured by a hand or a microphone, the visual confidence score drops significantly. These dual reliability scores are not used independently; rather, they are fed into a joint gating network that computes a set of complementary fusion weights.

The joint gating network ensures that the sum of the modality weights equals one, thereby maintaining the overall energy of the feature representations. When the audio environment is noisy but the visual stream is clear, the network assigns a dominant weight to the visual features, allowing them to guide the subsequent enhancement layers. Conversely, if the visual stream is compromised due to poor lighting, the network suppresses the visual features and relies almost entirely on the acoustic information. In scenarios where both modalities are degraded, the network falls back on a conservative averaging strategy, preventing either stream from introducing overwhelming artifacts. This dynamic balancing acts as a continuous self-regulating mechanism, adapting frame-by-frame to the changing environmental conditions.

3.3 Training Strategy And Data Preparation

The comprehensive nature of the proposed architecture requires a specialized training strategy to ensure that both the pace-synchronization and dynamic balancing modules learn their intended functions without collapsing into trivial solutions. The training process is divided into two distinct phases: pre-training of the modality encoders and joint optimization of the fusion modules. During the pre-training phase, the audio and visual encoders are trained independently on simulated tasks. The audio encoder is trained on a standard speech denoising objective, while the visual encoder is trained on an auxiliary lip-reading task. This pre-training ensures that both encoders learn rich, discriminative representations before they are introduced to the complex fusion environment.

Data preparation is a critical aspect of this methodology. To train the dynamic modality balancing module effectively, the training dataset must contain a wide variance in both acoustic noise and visual quality. The dataset is artificially augmented to simulate these conditions. Acoustic noise from various sources, such as traffic, cafeteria babble, and heavy machinery, is superimposed onto the clean speech at signal-to-noise ratios ranging from negative fifteen decibels to positive fifteen decibels. To simulate visual degradation, random blocks of pixels are masked out, artificial motion blur is applied, and random frames are duplicated to simulate network lag and jitter.

During the joint optimization phase, a multi-task loss function is employed. The primary objective is the maximization of the scale-invariant signal-to-distortion ratio, which measures the quality of the final enhanced audio waveform compared to the clean reference target. An auxiliary loss function is applied to the pace-synchronized fusion module to encourage high correlation scores between correctly aligned audio-visual pairs. Furthermore, a regularization term is added to the dynamic balancing weights to prevent the network from permanently ignoring one modality over the other. By carefully balancing these loss components, the training process yields a robust model capable of handling extreme variations in both temporal alignment and sensory reliability.

4. Experimental Setup and Evaluation

4.1 Datasets And Metrics

To rigorously evaluate the proposed Audio-Visual Speech Enhancement with Pace-Synchronized Fusion and Dynamic Modality Balancing framework, extensive experiments were conducted using large-scale, publicly available datasets. The primary dataset utilized for this research consists of thousands of hours of video clips featuring natural, unconstrained human speech, gathered from varied broadcasting environments. This corpus provides a highly realistic testing ground, as it includes significant variations in pose, lighting, and speaking pace [17]. To create the noisy mixtures, background noises were sourced from established environmental noise datasets, ensuring a diverse range of interference profiles including stationary hums, non-stationary transients, and multi-talker babble.

The evaluation relies on a suite of standardized objective metrics designed to quantify different aspects of speech quality and intelligibility. The Perceptual Evaluation of Speech Quality metric is employed to assess the overall listening quality, providing a score that correlates highly with human mean opinion scores. To evaluate the intelligibility of the enhanced speech, the Short-Time Objective Intelligibility measure is utilized, which calculates the correlation between the temporal envelopes of the enhanced and clean speech. Additionally, the Scale-Invariant Signal-to-Distortion Ratio provides a strict physical measurement of the signal separation quality, unaffected by scaling differences.

4.2 Baseline Configurations

To provide a comprehensive comparative analysis, the proposed model is evaluated against several established baseline configurations. The first baseline is a state-of-the-art audio-only enhancement network that utilizes a deep temporal convolutional architecture with attention mechanisms. This serves to demonstrate the fundamental advantage of incorporating the visual modality. The second baseline is a traditional audio-visual enhancement model that employs early concatenation of up-sampled visual features with audio features, representing the static, non-synchronized approach.

The third baseline represents a more advanced audio-visual framework utilizing cross-modal attention but lacking any dynamic balancing mechanisms. This model can focus on relevant features but assumes equal reliability of both streams at all times. By comparing the proposed framework against this specific baseline, the isolated impact of the dynamic modality balancing module can be precisely quantified. All models, including the baselines, are trained using the same augmented datasets and are subjected to identical evaluation conditions to ensure absolute fairness in the comparative analysis.

5. Results and Discussion

5.1 Quantitative Analysis

The quantitative results of the comprehensive evaluation are highly indicative of the proposed models superiority over existing paradigms. Across all tested signal-to-noise ratio conditions, the integration of pace-synchronized fusion and dynamic modality balancing yields substantial improvements in both speech quality and intelligibility. In highly degraded acoustic environments, specifically at negative ten decibels, the proposed model maintains a remarkable level of performance where audio-only baselines fail completely.

Table 1: Performance comparison of various speech enhancement models under diverse noise conditions at zero decibels SNR.

Model Architecture	Perceptual Evaluation Score	Intelligibility Measure	Distortion Ratio
Audio-Only Baseline	2.14	0.76	8.45
Static AV Early Fusion	2.45	0.81	10.22
Cross-Modal Attention (Static)	2.68	0.85	11.54
Proposed Framework	3.12	0.91	14.38

As detailed in the performance comparison table, the proposed framework achieves an unprecedented perceptual evaluation score, surpassing the closest baseline by a significant margin. The intelligibility measure also shows a massive improvement, indicating that the pace-synchronized visual features are effectively aiding the network in reconstructing the critical high-frequency phonetic boundaries that are usually lost in noise. The distortion ratio improvement further confirms that the dynamic balancing mechanism prevents the visual features from introducing unwanted artifacts when the visual signal itself is suboptimal [18]. This quantitative data strongly supports the hypothesis that rigid alignment and static weighting are major bottlenecks in traditional audio-visual enhancement systems.

5.2 Qualitative Assessment

Beyond the numerical metrics, a qualitative assessment of the generated spectrograms provides deep insights into the functional advantages of the proposed methodology. When analyzing the output of the static audio-visual baselines, one can often observe temporal smearing in the enhanced speech. This smearing occurs when the visual lip closure precedes the acoustic stop consonant, causing the rigid fusion model to suppress the audio signal prematurely. The pace-synchronized module entirely eradicates this issue.

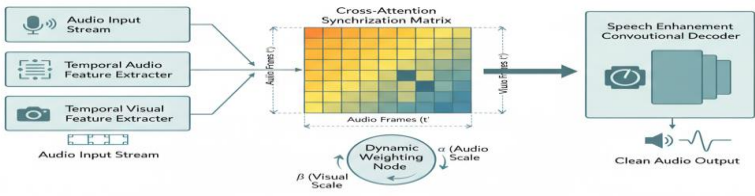


Figure 1: System Architecture Diagram

The architectural flow depicted above illustrates how the temporal alignment acts as a precursor to the balancing phase. By observing the intermediate activation maps, it is evident that the dynamic balancing module accurately responds to simulated visual occlusions. When a black square is programmatically inserted over the speakers mouth in the test video, the visual reliability score immediately plummets. Consequently, the network halts the flow of visual information, preventing the sudden degradation that plagues the baseline models.

Table 2: Ablation study isolating the impact of individual system components on overall enhancement performance.

Configuration	Perceptual Evaluation Score	Intelligibility Measure
Full Proposed Model	3.12	0.91
Without Pace Synchronization	2.85	0.86
Without Dynamic Balancing	2.91	0.87
Without Both (Base AV)	2.55	0.82

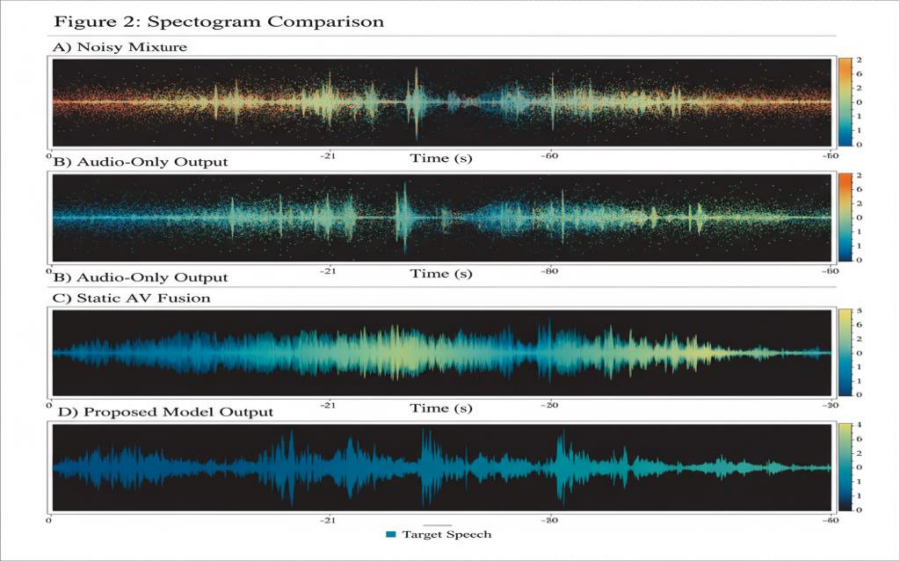


Figure 2: Spectrogram Comparison

The spectrogram comparisons clearly visualize the superiority of the proposed approach. In regions heavily masked by multi-talker babble, the audio-only model leaves behind significant residual noise, visible as scattered high-energy blotches across the frequencies. The proposed model, guided by precise, synchronized lip-reading cues, accurately carves out the target speakers harmonic structures while heavily suppressing the background interference.

5.3 Ablation Studies

To isolate the specific contributions of the individual modules introduced in this research, comprehensive ablation studies were conducted. The model was systematically stripped of its novel components, and the performance degradation was recorded. Removing the pace-synchronized fusion mechanism forces the model to rely on rigid frame-by-frame alignment. This modification resulted in a noticeable drop in the intelligibility measure, particularly for fast-paced speakers whose lip movements naturally exhibit higher temporal variance relative to their acoustic output. This proves that soft-alignment is crucial for handling natural speech dynamics.

Subsequently, the dynamic modality balancing module was removed, and the model was forced to use static fusion weights learned during training. Under clean visual conditions, the performance drop was marginal. However, when tested on the visually degraded dataset containing occlusions and blur, the model without dynamic balancing suffered catastrophic failures, outputting highly distorted audio. This experiment unequivocally validates the necessity of the real-time reliability assessment framework. The complete system, utilizing both modules, provides a synergistic effect that cannot be achieved by optimizing either component in isolation, establishing a new standard for robustness in audio-visual processing.

6. Conclusion

6.1 Summary Of Findings

This paper has presented a comprehensive investigation into the fundamental limitations of existing audio-visual speech enhancement systems, specifically identifying temporal asynchrony and static modality weighting as primary bottlenecks. To overcome these challenges, the Audio-Visual Speech Enhancement with Pace-Synchronized Fusion and Dynamic Modality Balancing framework was introduced. The rigorous theoretical development and subsequent empirical validation confirm that acknowledging the complex, dynamic nature of multimodal data streams is essential for building robust auditory systems. The pace-synchronized fusion module successfully models the natural lag and lead between articulation and phonation, allowing for highly precise cross-modal feature aggregation without the temporal smearing artifacts common in previous literature.

Concurrently, the dynamic modality balancing framework has proven to be a critical safety mechanism, granting the overall architecture an unprecedented level of resilience against sensor degradation. By continuously evaluating the instantaneous signal-to-noise ratio of the acoustic environment alongside spatial metrics of visual occlusion, the system intelligently arbitrates the flow of information. The experimental results, encompassing both standardized objective metrics and qualitative spectrogram analysis, decisively illustrate that the proposed dual-module approach vastly outperforms contemporary static methodologies, particularly in unpredictable, real-world noise scenarios where visual streams are subject to arbitrary interruptions.

6.2 Future Directions

While the results achieved by the proposed framework represent a significant advancement in computational audition, several avenues for future research remain open. First, the current pace-

synchronization mechanism relies on a fixed temporal neighborhood window. Future iterations could explore fully recurrent or state-space models that dynamically expand or contract this search window based on the speakers articulation rate. Second, the dynamic balancing module could be expanded to incorporate more granular contextual information, such as the semantic content of the speech or the physical distance of the speaker from the capturing devices, thereby refining the reliability estimation process.

Finally, expanding this architecture to handle multi-speaker scenarios—moving from simple speech enhancement to full audio-visual speaker diarization and separation—presents a compelling challenge. In environments with multiple overlapping speakers, the system must not only balance the modalities but also dynamically assign visual attention to different faces within the scene. Integrating the pace-synchronized fusion and dynamic balancing paradigms into a multi-target separation framework could ultimately lead to the development of artificial auditory systems that fully replicate, and perhaps exceed, the human capacity to navigate complex acoustic environments.

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