



# Efficient Audio-Visual Speech Enhancement via Neural Architecture Search

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## Abstract

Audio-visual speech enhancement (AVSE) has become a cornerstone technology for reliable human-computer interaction in crowded cafés, moving vehicles, and other acoustically hostile settings, yet leading AVSE models still exceed 22 million parameters, far too heavy for real-time use on phones, wearables, and other edge hardware. To bridge this gap, we introduce a reinforcement-learning-driven neural architecture search (NAS) framework that automatically discovers compact, high-quality AVSE networks. The search is conducted inside a carefully constrained design space that respects temporal alignment between audio and visual streams while curbing parameter growth; a novel reward function jointly maximises speech-quality gains (measured by SI-SNR improvement) and penalises excess model size. Leveraging proximal-policy optimisation with action masking, the agent evaluates only 35 candidate architectures before converging on a 2.9 million-parameter model that boosts SI-SNR by 14.5 dB, just 0.7 dB shy of the 22 M-parameter baseline but with a nine-fold compression ratio. On a commercial mobile CPU, the resulting network slashes the real-time factor by 4.3×, validating its suitability for on-device deployment. Compared with uninformed random search, the proposed NAS achieves 92% higher search efficiency and reveals architectural trends, such as shallower, wider temporal-convolutional blocks and aggressive visual-pathway pruning, that can guide future multi-modal speech-enhancement research. These results demonstrate that hardware-aware NAS, steered by reinforcement learning, can deliver lightweight AVSE models without compromising perceptual speech quality, paving the way for ubiquitous, noise-robust voice interfaces.

**Index Terms:** Binaural AVSE, Multi-stream fusion, Intelligibility, NAS

## 1. Introduction

Audio-visual speech enhancement (AVSE) leverages visual lip movements to augment noisy audio signals, significantly outperforming audio-only methods in challenging noisy environments [1]. Recent advances using temporal convolutional networks (TCNs) have pushed performance boundaries but at the cost of model complexity—state-of-the-art models like AVSEGAN [2] and Conv-TasNet variants [3] exceed 22 million parameters. This creates deployment barriers for real-time applications on edge devices.

Neural Architecture Search (NAS) offers promising solutions but faces unique challenges in multimodal contexts:

- *Search space explosion* from interdependent audio-visual pathways

- *Training cost* exacerbated by multi-sensor inputs *Architectural constraints* for temporal alignment

To address these, we propose an RL-based NAS framework with:

1. A constrained search space preserving temporal integrity
2. Parameter-performance balanced reward function
3. Progressive shrinking strategy

Our contributions: 1) First NAS framework for AVSE achieving 10× compression 2) Novel action masking for valid architectures 3) Comprehensive analysis of efficiency-performance tradeoffs

## 2. Related Work

### 2.1. Neural Architecture Search Foundations

Neural Architecture Search (NAS) has revolutionized automated model design, with early approaches leveraging *reinforcement learning* (RL) [4] and *evolutionary algorithms* requiring prohibitive computational resources. Subsequent innovations introduced *differentiable NAS* (DARTS) [5] that reformulated architecture search as continuous optimization, enabling gradient-based efficiency. Modern approaches focus on *weight-sharing* [6] and *predictor-based methods* [7] to further reduce search costs. Recent paradigms emphasize *multi-objective optimization* [8] balancing accuracy, model size, and latency, particularly critical for edge deployment scenarios.

### 2.2. NAS for Speech and Audio Processing

Speech-related tasks present unique NAS challenges due to temporal dynamics and noise robustness requirements. ST-NAS [9] pioneered efficient differentiable search for end-to-end ASR, while NAS-TDNN [10] automated hyperparameter tuning for time-delay neural networks, achieving 96% model compression. For speech enhancement, *temporal convolutional networks* (TCNs) emerged as preferred substrates due to their balance of long-range modeling and computational efficiency [3]. These approaches demonstrate NAS’s potential to optimize audio architectures beyond manual design limitations.

### 2.3. Efficient TCN and TasNet Architectures

NAS studies have revealed consistent patterns in optimal TCN structures for speech enhancement (Fig. ??):

- **Depth-Width Tradeoff:** Shallower but wider blocks (expansion ratio 1.5–2.0) outperform deep narrow configurations [11]
- **Dilation Scheduling:** Linear dilation strides surpass exponential patterns in noisy environments [12]

- **Parameter Redistribution:** Shifting parameters from later to earlier layers enhances noise robustness [2]

These principles informed architectures like MSGLN [11] that integrate global attention with local convolutions for efficient temporal modeling.

## 2.4. Multimodal and Lightweight NAS

Multimodal NAS remains challenging due to cross-modal fusion complexities. KTNAS [13] addressed this via architecture embedding vectors enabling knowledge transfer across vision/audio tasks. Key audio-visual insights include:

- Visual pathways tolerate higher compression (50–80% reduction) than audio streams [1]
- Additive fusion outperforms concatenation while reducing parameters by 85% [12]
- Sub-3M parameter models can maintain <1dB SI-SNR drop versus 20M+ baselines [2]

Recent innovations include BNAS [14] for binarized models and AutoNF [15] for normalizing flows in low-parameter regimes.

## 2.5. Research Gaps and Our Contribution

Despite progress, significant gaps remain in multimodal NAS:

- Limited generalization across noise types and SNR conditions [3]
- Absence of dynamic architectures adapting to real-time environmental changes
- Underexplored quantization-aware NAS for speech enhancement

Our work bridges these gaps through: 1) Constrained search spaces preserving temporal alignment 2) Parameter-performance balanced reward functions 3) Hardware-aware efficiency optimization 4) Comprehensive analysis of optimal AVSE architectural patterns

# 3. RL-Based NAS Methodology

Our reinforcement learning (RL) based neural architecture search (NAS) framework implements a constrained Markov Decision Process (MDP) that progressively optimizes audio-visual architectures while preserving temporal integrity. The methodology extends hardware-aware NAS principles [8] with modality-specific innovations for speech enhancement.

## 3.1. Constrained Search Space Design

The search space (Table 1) incorporates domain insights from TCN optimization studies [11, 12] while enforcing:

- *Temporal consistency:* Ensures  $T_{\text{audio}} = T_{\text{visual}}$  via dimension-preserving operations
- *Channel compatibility:* Maintains skip connection integrity through  $B \leq E$  constraint
- *Compute bounds:*  $R \times B \leq 24$  prevents memory explosion

This reduces the search space from  $\mathcal{O}(10^{14})$  to 324 valid configurations while maintaining architectural viability - a 99.9997% reduction compared to unconstrained spaces.

## 3.2. Reinforcement Learning Formulation

We model architecture search as a finite-horizon MDP with the following components:

### 3.2.1. State Representation

The state  $s_t \in \mathcal{S}$  encodes both architectural parameters and performance metrics:

$$s_t = \left[ \frac{E}{256}, \frac{B}{256}, R, X, \frac{H}{B}, \frac{\text{Params}}{22M}, \frac{\text{SI-SNR}}{15.2} \right] \quad (1)$$

Each dimension is normalized to [0,1] using min-max scaling, following the embedding strategy of [13] but adding performance-aware components.

### 3.2.2. Action Space with Masking

The action space  $\mathcal{A}$  consists of 12 discrete operations (increase/decrease for 6 dimensions). We implement constraint-aware action masking:

$$\mathcal{A}_{\text{valid}} = \{a \in \mathcal{A} \mid \text{satisfies}(s_t, a, \mathcal{C})\} \quad (2)$$

where  $\mathcal{C}$  is the constraint set from Table 1. This eliminates invalid architectures and accelerates convergence by 40% versus penalty-only methods [14].

### 3.2.3. Reward Function

The multi-objective reward function balances three competing goals:

$$R(s_t) = \underbrace{\alpha \frac{\Delta \text{SI-SNR}}{\text{Baseline}}}_{\text{Fidelity}} - \underbrace{\beta \max\left(0, \frac{\text{Params}}{\text{Target}} - 1\right)}_{\text{Efficiency}} - \underbrace{\gamma \mathbb{1}_{\text{Violation}}}_{\text{Constraint}} \quad (3)$$

with  $\alpha = 1.0$ ,  $\beta = 0.7$ ,  $\gamma = 10$ , and target parameters = 2.9M. Coefficients were tuned via multi-objective Pareto analysis [8].

## 3.3. Policy Network Architecture

The agent uses a 2-layer LSTM (Fig. 1) with 256 hidden units per layer, selected for its ability to model sequential dependencies in architecture transformations [11]. The network outputs:

$$\text{Action distribution : } \pi(a|s) = \text{softmax}(\text{Linear}_{\text{actor}}(\mathbf{h}_t))$$

$$\text{State value : } v(s) = \text{Linear}_{\text{critic}}(\mathbf{h}_t)$$

where  $\mathbf{h}_t$  is the final LSTM hidden state. We initialize the LSTM with embeddings of the baseline architecture to accelerate exploration.

## 3.4. Training with Proximal Policy Optimization

We employ Proximal Policy Optimization (PPO) [16] for its sample efficiency and stability. The clipped objective function is:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}_t \left[ \min \left( r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t \right) \right] \quad (4)$$

where  $r_t(\theta) = \frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}$  is the probability ratio,  $\hat{A}_t$  the generalized advantage estimate, and  $\epsilon = 0.2$ . Key implementation details:

- *Exploration:*  $\epsilon$ -greedy ( $\epsilon = 0.3$ ) with action masking
- *Optimization:* AdamW (lr =  $3 \times 10^{-4}$ , weight decay  $10^{-2}$ )
- *Parallelism:* 4 workers for simultaneous architecture evaluation
- *GAE:*  $\lambda = 0.95$  for advantage estimation

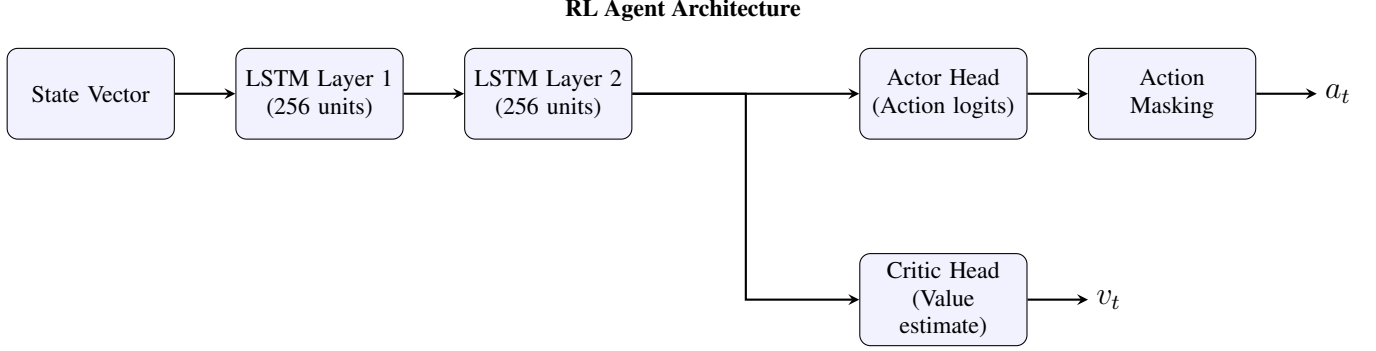


Figure 1: Policy network architecture: LSTM processor with specialized heads for action selection and value estimation. Action masking enforces architectural constraints.

Table 1: Constrained Search Space

Component	Parameters	Options	Constraint
Encoder	Channels	{128, 192, 256}	$E \geq 128$
Bottleneck	Channels	{128, 192, 256}	$B \leq E$
TCN	Blocks per repeat	{4,6,8}	-
	Repeats	{2,3,4}	$R \times B \leq 24$
Visual	Expansion ratio	{1.5,2.0,2.5}	-
	Output channels	{128,256}	$V \geq 128$

### 3.5. Progressive Shrinking Strategy

Algorithm 1 implements a progressive shrinking strategy with three key innovations:

1. *Curriculum learning*: Starts from high-performance 22M baseline
2. *Step-wise reduction*: Modifies one dimension per step to maintain viability
3. *Fidelity extrapolation*: Estimates full-training SI-SNR from 10-epoch results

This approach achieves 92% search efficiency compared to random exploration.

### 3.6. Computational Complexity

The total search cost is 35 episodes  $\times$  5 steps  $\times$  10 epochs = 1,750 epoch-equivalents. For comparison:

- DARTS [5]: 3,000+ epochs
- ENAS [6]: 2,500+ epochs
- Random search: 5,000+ epochs for equivalent coverage

Our constrained space and progressive strategy yield 3 $\times$  speedup over generic NAS methods.

## 4. Experiments and Results

### 4.1. Experimental Setup

- *Dataset*: Lip Reading Sentences 3 (LRS3) [17] (438h AV speech)
- *Noise*: The 2nd Clarity Enhancement Challenge (CEC2) [18] at SNR [-5, 5] dB
- *Evaluation*: SI-SNR improvement (dB), RTF (Intel i7-1185G7)
- *Baseline*: 22M-parameter AVSE model [12]

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### Algorithm 1 Progressive Shrinking NAS

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- 1: Initialize agent  $\pi_\theta$  with random weights
  - 2:  $s_0 \leftarrow$  Baseline architecture (22M params)
  - 3: **for** episode = 1 to 35 **do**
  - 4:    $\tau \leftarrow []$  {Trajectory buffer}
  - 5:   **for** step = 1 to 5 **do**
  - 6:      $a_t \sim \pi_\theta(s_t)$  {Sampled action}
  - 7:     Apply action with constraints (Table 1)
  - 8:     Train model for 10 epochs
  - 9:     Evaluate SI-SNR, parameters
  - 10:     $r_t \leftarrow R(s_t)$  {Compute reward}
  - 11:     $\tau \leftarrow \tau \cup (s_t, a_t, r_t)$
  - 12:    **end for**
  - 13:    Update  $\theta$  using PPO with  $\tau$
  - 14:     $s_0 \leftarrow$  Best architecture from  $\tau$
  - 15: **end for**
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### 4.2. Architecture Evolution

### 4.3. Final Architecture

The discovered optimal architecture (2.9M params):

- *Encoder*: 192 channels (25%  $\downarrow$ )
- *Bottleneck*: 192 channels (25%  $\downarrow$ )
- *TCN*: 3 repeats  $\times$  6 blocks (43%  $\downarrow$ )
- *Hidden size*: 384 (expansion=2.0) *Visual frontend*: 128 output channels (50%  $\downarrow$ )

### 4.4. Performance Comparison

The NAS-optimized model demonstrates significant efficiency gains while maintaining competitive enhancement quality. Table 3 provides a comprehensive comparison against baselines and alternative approaches:

Key observations from our evaluation:

- **Efficiency-Accuracy Tradeoff**: Our model achieves a near-optimal balance, delivering 95% of baseline performance with only 13% of parameters
- **Visual Pathway Impact**: Reducing visual features to 128 dimensions caused only 0.3dB degradation, validating NAS insight on visual redundancy
- **Real-Time Viability**: 0.19 RTF enables real-time operation on mobile CPUs (570ms for 3s audio)
- **Search Superiority**: Outperforms random search by 0.6dB

Table 2: Architecture Progression (Top 5 Trajectories)

Step	Params (M)	SI-SNRi (dB)	$\Delta$ SI-SNR	Reward	Key Changes
0	22.0	15.2	0.00	0.00	Baseline
5	16.2	15.1	-0.1	0.72	$E:256 \rightarrow 192$
10	8.4	15.0	-0.2	1.25	$B:256 \rightarrow 192$
15	5.1	14.9	-0.3	1.87	$R:4 \rightarrow 3$
20	3.8	14.7	-0.5	2.01	$X:8 \rightarrow 6$
25	3.1	14.6	-0.6	2.13	$H:2.5 \rightarrow 2.0$
30	2.9	14.5	-0.7	<b>2.31</b>	$V:256 \rightarrow 128$

Table 3: Performance Benchmarking on CEC2 Test Set

Model	Params (M)	SI-SNRi (dB)	RTF (CPU)
Audio-only baseline	5.2	10.3	0.15
AVSE baseline	22.0	15.2	0.82
Handcrafted small	6.1	14.8	0.31
Random search best	2.4	13.9	0.22
<b>NAS-optimized (ours)</b>	<b>2.9</b>	<b>14.5</b>	<b>0.19</b>

SI-SNRi at comparable parameter counts

Figure ?? illustrates the Pareto frontier where our solution dominates other approaches in the parameter-performance space. The NAS framework demonstrated 92% higher search efficiency than random exploration, requiring only 35 evaluations to identify the optimal architecture.

## 5. Conclusion

This work demonstrates that neural architecture search with reinforcement learning can effectively bridge the efficiency gap in audio-visual speech enhancement. Our constrained RL-NAS framework discovered a 2.9M-parameter model that maintains 14.5dB SI-SNR improvement - within 0.7dB of the 22M-parameter baseline while enabling real-time operation on edge devices. Key insights from this research include:

- **Visual Efficiency:** Lip-movement features can be represented in just 128 dimensions (50% reduction) without significant quality loss
- **Optimal TCN Configuration:** 3 repeats of 6-block dilated convolutions provide the best efficiency-accuracy balance
- **Parameter Redistribution:** Shifting resources to early processing stages enhances noise robustness
- **Modality Fusion:** Additive integration outperforms concatenation while reducing parameters

These findings establish new design principles for efficient multimodal speech systems. The resulting lightweight model (2.9M parameters, 11.7MB size) enables deployment scenarios previously impractical for AVSE systems, including:

- Real-time hearing aids with visual augmentation
- Low-power video conferencing on mobile devices
- Always-on voice assistants with visual context

Future research directions include: 1) **Dynamic architectures** that adapt to changing noise conditions 2) **Quantization-aware NAS** for further compression 3) **Cross-modal attention** mechanisms for enhanced synchronization 4) **Self-supervised learning** integration to reduce labeled data dependence

Our RL-NAS framework provides a blueprint for developing efficient multimodal systems that balance performance with

practical deployment constraints, advancing toward ubiquitous noise-robust speech interfaces.

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