Unified Speech Recognition: A Single Model for Auditory, Visual, and Audiovisual Inputs

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Abstract

Research in auditory, visual, and audiovisual speech recognition (ASR, VSR, and AVSR, respectively) has traditionally been conducted independently. Even recent self-supervised studies addressing two or all three tasks simultaneously tend to yield separate models, leading to disjoint inference pipelines with increased memory requirements and redundancies. This paper proposes unified training strategies for these systems. We demonstrate that training a single model for all three tasks enhances VSR and AVSR performance, overcoming typical optimisation challenges when training from scratch. Moreover, we introduce a greedy pseudo-labelling approach to more effectively leverage unlabelled samples, addressing shortcomings in related self-supervised methods. Finally, we develop a self-supervised pre-training method within our framework, proving its effectiveness alongside our semi-supervised approach. Despite using a single model for all tasks, our unified approach achieves state-of-the-art performance compared to recent methods on LRS3 and LRS2 for ASR, VSR, and AVSR, as well as on the newly released WildVSR dataset. Code and models are available at https://github.com/ahaliassos/usr.

1 Introduction

Speech recognition can be achieved using auditory signals (known as auditory/automatic speech recognition; ASR) [1, 2], visual cues from lip movements (visual speech recognition; VSR) [3, 4], or both (audiovisual speech recognition; AVSR) [5, 6]. Audio typically offers the most relevant information in videos of talking faces, but lipreading can greatly enhance recognition, especially when the audio is noisy or wholly unavailable [6]. Despite the similarities between ASR, VSR, and AVSR, research in these fields has largely developed independently [7, 8, 3, 9].

The Transformer architecture's versatility [10, 11, 12] has spurred efforts to unify speech recognition by pre-training a single model on various unlabelled inputs (visual, auditory, and audiovisual) through self-supervision [13, 14, 15]. However, these methods often require separate fine-tuning stages for ASR, VSR, and AVSR, leading to separate models for each task, which increases computational load and complexity. u-HuBERT [16] shows that a single pre-trained model *can* be fine-tuned for all three tasks, yet does not reach the performance of separately fine-tuned models [17, 18].

In this paper, we delve deeper into strategies for unified speech recognition (USR) by training a single model to perform ASR, VSR, and AVSR. We find that training such a model *from scratch* on the LRS3 dataset [19] achieves competitive performance on all tasks. This is notable given the known

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optimisation difficulties in VSR training, which previously required self-supervised pre-training [13], supervised feature extractor pre-training [6], or curriculum learning strategies [9]. Our findings suggest that including audio improves the optimisation landscape for VSR and AVSR supervised training, as observed in a different context by [20].

Furthermore, we propose a semi-supervised pseudo-labelling approach to leverage unlabelled audiovisual data, addressing shortcomings of standard fine-tuning in self-supervised methods [13, 14, 17, 18]. Fine-tuning often leads to overfitting due to using fewer samples than pre-training, requiring various "tricks" to reach optimal performance [13, 17]. This issue is particularly pronounced in encoder-decoder architectures where usually only the encoder is pre-trained, and attempts to pre-train the decoder have yielded inconsistent results [21, 22]. Our semi-supervised approach generates pseudo-labels via an encoder-decoder momentum-based teacher [23] to leverage unlabelled samples throughout training, effectively mitigating overfitting. Training on all three modalities simultaneously helps alleviate the computational cost of pseudo-labelling as the cost is amortised across the inputs.

Lastly, inspired by recent self-supervised works, we design a pre-training method within our unified framework. We combine pre-training with pseudo-labelling and show that our semi-supervised approach is complementary to self-supervision. Our final unified models achieve state-of-the-art results across multiple settings, surpassing existing methods that use separate models for each task.

2 Related Work

Audiovisual self-supervised speech representation learning. Recent interest in audiovisual self-supervised learning for speech recognition has focused on leveraging the correspondence between audio waveforms and silent lip movements to capture shared semantic content across the modalities [13, 17, 14, 15, 18]. These methods employ cross-modal learning and masked prediction [24] to develop contextualised representations from large unlabelled datasets, which are more readily available than transcribed datasets. After pre-training, a randomly initialised decoder is appended to the encoder, often with an optional CTC layer [25]. The system is then fine-tuned on a smaller set of labelled samples for tasks such as ASR, VSR, and AVSR, usually resulting in different models for each task [13, 15]. However, these methods may fail to leverage unlabelled samples fully since the pretext tasks are not directly aligned with speech recognition. Furthermore, the decoder, trained on limited data during fine-tuning, is highly susceptible to overfitting, necessitating strategies such as freezing encoder layers [13] or employing variable learning rates across layers to optimise performance [17, 26].

Pseudo-labelling for speech recognition. Pseudo-labelling has been explored in audiovisual speech recognition literature, with methods such as offline pseudo-labelling [9, 27] and frame-wise distillation using frozen teacher models [28]. While these approaches rely on frozen external ASR models trained on large-scale datasets [7, 29], our USR method eliminates this dependency using a randomly initialised teacher model that improves throughout training.

Iterative pseudo-labelling has shown promise for ASR. Some employ multiple rounds of pseudo-labelling using costly beam search and filtering strategies [30, 31, 32, 33], while others continuously and efficiently update pseudo-labels using a CTC-only loss [34, 35]. However, eliminating filtering and attention losses can impact training due to low-quality pseudo-labels, as observed in a recent method [36] that aims to apply these approaches for ASR, VSR, and AVSR but lags behind the state-of-the-art (see Appendix J). In contrast, USR uses an encoder-decoder architecture to generate CTC and attention pseudo-labels at each iteration through a greedy approach, while pseudo-label quality is maintained via a token-wise filtering mechanism inspired by the semi-supervised FixMatch technique [37] in image recognition. We note that sharing the same pseudo-labels across auditory, visual, and audiovisual inputs amortises generation costs, leading to efficient CTC-attention training.

Single model for multiple modalities. An earlier study [38] trained a single recurrent neural network [39] for ASR, VSR, and AVSR, but noted significant performance differences compared to modality-specific models. Recent works have shown that the Transformer architecture [10] can handle multiple modalities using the same weights, with minimal performance degradation [11, 12]. In speech recognition, some [13, 14, 15] use the same Transformer encoder for auditory, visual, and audiovisual inputs during pre-training, but then separately fine-tune the parameters for ASR, VSR, and AVSR, resulting in separate models during deployment. u-HuBERT [16] uses the same weights for all

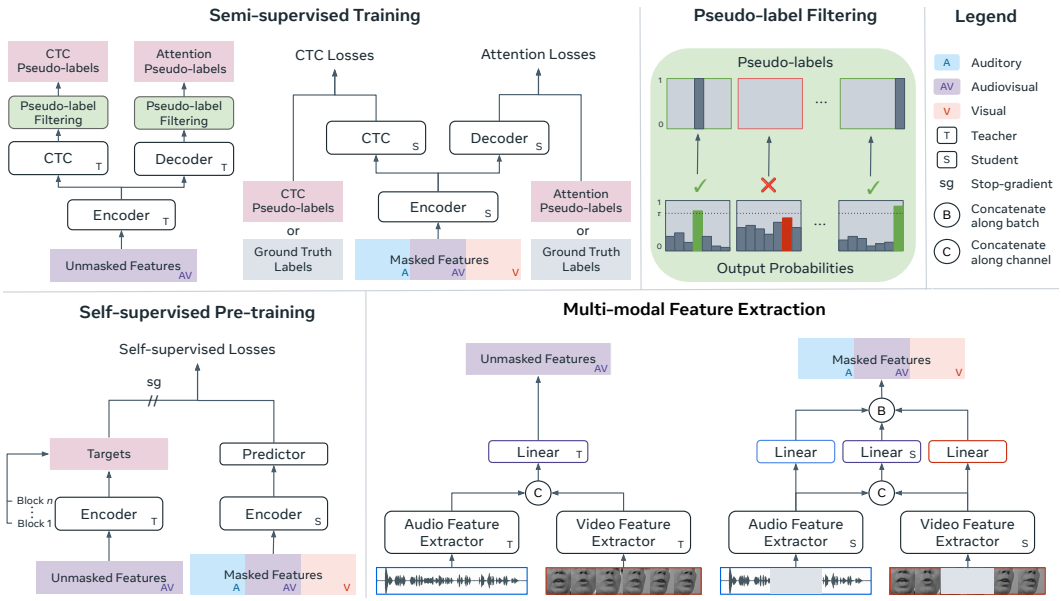


Figure 1: **Unified Speech Recognition.** Our USR method combines self-supervised pre-training with semi-supervised fine-tuning. For **semi-supervised training**, pseudo-labels are generated from unmasked audiovisual features using an EMA (exponential moving average)-based teacher. The student, intaking masked inputs, predicts pseudo-labels for unlabelled data and ground-truth labels for labelled data. **To obtain the pseudo-labels**, an argmax operation is applied to the CTC and attention teacher output probabilities; the tokens with predicted probability below a fixed threshold are discarded. For **self-supervised pre-training**, a student encoder processes masked visual, auditory, and audiovisual samples and predicts targets, generated by an EMA-based teacher intaking unmasked audiovisual samples, via a shallow predictor. The targets are the average outputs of the teacher blocks. The resulting student weights are used to initialise the student and teacher in semi-supervised fine-tuning. **Feature extraction** is achieved through modality-specific feature extractors, whose features are concatenated along the channel dimension to produce the audiovisual inputs. The auditory, visual, and audiovisual student inputs are batched together for training efficiency.

modalities when fine-tuning a pre-trained AV-HuBERT backbone [13], demonstrating the viability of a unified model. However, it encounters limitations common to other self-supervised approaches, such as proneness to overfitting during supervised fine-tuning. Our proposed semi-supervised approach leverages unlabelled samples during the fine-tuning stage, significantly alleviating these concerns.

3 Unified Speech Recognition

Our unified method trains a pre-LN [40] Transformer [10] encoder-decoder model for ASR, VSR, and AVSR. Section 3.1 describes the task of unified speech recognition using supervised training, where we have ground-truth annotation for each audio-visual pair. Sections 3.2 and 3.3 then introduce our proposed idea, which employs semi-supervised training and self-supervised pre-training to effectively utilise unlabelled samples. An overview of USR's components is depicted in Figure 1.

3.1 Unified Supervised Training

Inputs. Let $\{(\mathbf{v}_b, \mathbf{a}_b, \mathbf{y}_b) : b \in [1, B]\}$ be a batch of B labelled samples, where $\mathbf{v}_b$ denotes a T_v-frame video of lip movements, $\mathbf{a}_b$ denotes the corresponding (raw) audio waveform of $T_\text{a} = 640T_\text{v}$ frames[1], and $\mathbf{y}_b$ denotes the label sequence of length T_l. Following [9, 17], $\mathbf{v}_b$ and $\mathbf{a}_b$ are zero-masked with a maximum duration of 0.4 and 0.6 seconds for each second of video and audio, respectively.

[1]We assume the video is sampled at 25 frames per second and the audio at 16,000kHz.

Multi-modal feature extraction. The raw video and audio are fed into ResNet-18 [41] architectures: a 2D version with a 3D stem [42] for video and a 1D version for audio, sub-sampling the audio to match the video's sampling rate [17]. Linear layers follow the feature extractors to produce the visual and auditory features. The audiovisual features are formed by concatenating the feature extractor outputs along the channel dimension and applying a linear transformation. Finally, the features from the three modalities are concatenated along the batch dimension for efficient processing. We provide the model with all three input types, enabling it to perform well on ASR, VSR, and AVSR.

Losses. The encoder outputs pass through a linear + softmax layer to yield output probabilities $\mathbf{c}_{b,m}$ for each modality $m \in \{\mathrm{v}, \mathrm{a}, \mathrm{av}\}$. The CTC loss for each modality is given by

$$\mathcal{C}_m = \frac{1}{B}\sum_{b=1}^{B} l_{\text{ctc}}(\mathbf{c}_{b,m}, \mathbf{y}_b), \tag{1}$$

where l_{ctc} is the standard CTC loss [25]. Further, let $\mathbf{a}_{b,m}$ denote the attention probabilities from the outputs of the decoder in *teacher forcing* mode [43]. The batch attention loss can be expressed as

$$\mathcal{A}_m = \frac{1}{B}\sum_{b=1}^{B} l_{\text{ce}}(\mathbf{a}_{b,m}, \mathbf{y}_b), \tag{2}$$

where l_{ce} is the summed cross-entropy loss for each token. The CTC and attention losses are combined to obtain

$$\mathcal{L}_m = \lambda_{\text{ctc}}\mathcal{C}_m + (1-\lambda_{\text{ctc}})\mathcal{A}_m, \tag{3}$$

where λ_{ctc} is the relative weight placed on the CTC loss versus the attention loss. We set λ_{ctc} to 0.1, following [27, 17, 18]. The overall labelled loss is given by

$$\mathcal{L}^{\text{lab}} = \lambda_{\text{v}}\mathcal{L}_{\text{v}} + (1-\lambda_{\text{v}})(\mathcal{L}_{\text{a}} + \mathcal{L}_{\text{av}}), \tag{4}$$

where λ_{v} controls the weight of the video loss relative to the audio/audiovisual losses. We do not use separate weights for the audio/audiovisual losses due to similar training dynamics observed in preliminary experiments.

3.2 Unified Semi-supervised Training

We introduce a student-teacher pseudo-labelling framework to utilise *unlabelled* samples alongside labelled examples. The student, equipped with labelled losses, mirrors the model in Section 3.1.

Inputs. In addition to the labelled batch from Section 3.1, we now also have B^{u} *unlabelled* video and audio samples $\{(\mathbf{v}^{\text{u}}_b, \mathbf{a}^{\text{u}}_b) : b \in [1, B^{\text{u}}]\}$. The student inputs are masked as before.

Pseudo-labels. The teacher, sharing the same architecture as the student, generates pseudo-labels for unlabelled samples. The student is optimised as usual, but no gradients are passed to the teacher. Instead, the teacher's weights θ_t are updated at each iteration via an exponential moving average (EMA) of the student's weights θ_s [44]: $\theta_t \leftarrow \mu\theta_t + (1-\mu)\theta_s$, where μ increases throughout training from 0.999 to 1 using a cosine scheduler.

For an unmasked audiovisual sample, let $\tilde{\mathbf{c}}_b$ and $\tilde{\mathbf{a}}_b$ denote the CTC probabilities from the teacher encoder and the attention probabilities from the teacher decoder, respectively. The CTC and attention pseudo-labels are given by $\arg\max(\tilde{\mathbf{c}}_b)$ and $\arg\max(\tilde{\mathbf{a}}_b)$, respectively, where $\arg\max$ is applied token-wise. Hence, the pseudo-labels correspond to units with the maximum probability across the vocabulary for each input/output time-step. The attention targets are generated auto-regressively by selecting, at each time-step, the most likely unit as the input for the next time-step, without using a costly beam search strategy. Our greedy approach allows for efficient label generation.

Filtering. The teacher may not consistently generate high-quality predictions, especially early in training. We propose a straightforward token-wise filtering mechanism, creating masks $\mathbb{1}(\max(\tilde{\mathbf{c}}_b) \geq \tau)$ and $\mathbb{1}(\max(\tilde{\mathbf{a}}_b) \geq \tau)$, where the operations are applied token-wise. We thus discard a pseudo-label for a given time-step if its confidence falls below a certain threshold τ. This mechanism draws inspiration from image recognition literature [37] and is adapted to sequences.

Unlabelled losses. The unlabelled losses are computed via the cross-entropy between the student predictions and the teacher pseudo-labels. That is, the per-modality CTC losses are given by

$$\mathcal{C}_m^{\mathrm{u}} = \frac{1}{B^{\mathrm{u}}} \sum_{b=1}^{B^{\mathrm{u}}} \mathbb{1}(\max(\tilde{\mathbf{c}}_b) \geq \tau) \odot l_{\mathrm{ce}}(\mathbf{c}_{b,m}^{\mathrm{u}}, \arg\max(\tilde{\mathbf{c}}_b)), \tag{5}$$

where $\odot$ denotes the Hadamard product and $\mathbf{c}_{b,m}^{\mathrm{u}}$ the student outputs. The attention losses $\mathcal{A}_m^{\mathrm{u}}$ are computed similarly. The unlabelled losses $\mathcal{L}_m^{\mathrm{u}}$ are obtained as in Eq. 3:

$$\mathcal{L}_m^{\mathrm{u}} = \lambda_{\mathrm{ctc}} \mathcal{C}_m^{\mathrm{u}} + (1 - \lambda_{\mathrm{ctc}}) \mathcal{A}_m^{\mathrm{u}}, \tag{6}$$

Final loss. The total semi-supervised loss $\mathcal{L}^{\mathrm{semi}}$ combines the per-modality labelled (see Eq. 3) and unlabelled losses (see Eq. 6):

$$\mathcal{L}^{\mathrm{semi}} = \gamma_{\mathrm{v}} \lambda_{\mathrm{v}} \mathcal{L}_{\mathrm{v}} + \gamma_{\mathrm{a}} (1 - \lambda_{\mathrm{v}})(\mathcal{L}_{\mathrm{a}} + \mathcal{L}_{\mathrm{av}}) + (1 - \gamma_{\mathrm{v}}) \lambda_{\mathrm{v}} \mathcal{L}_{\mathrm{v}}^{\mathrm{u}} + (1 - \gamma_{\mathrm{a}})(1 - \lambda_{\mathrm{v}})(\mathcal{L}_{\mathrm{a}}^{\mathrm{u}} + \mathcal{L}_{\mathrm{av}}^{\mathrm{u}}), \tag{7}$$

where γ_{a} and γ_{v} weigh the contribution of the labelled loss versus the unlabelled loss for audio/audiovisual and visual inputs, respectively. In Section 4.2, we show the benefits of using separate weights for each modality rather than a single weight for both.

3.3 Unified Self-supervised Pre-training

Transformers typically benefit from self-supervised pre-training [45, 13, 17, 15], even with the same data used during fine-tuning [46, 45]. Inspired by recent work [17, 18, 15], we propose a self-supervised method within our framework that can precede semi-supervised fine-tuning.

Inputs. For pre-training, we use only the unlabelled B^u samples from Section 3.2. Following [17], we mask the student inputs by selecting each video frame index as the start of a three-frame mask with a 0.4 probability, applying a corresponding enlarged mask to the audio in temporal alignment. The elements of the mask $\mathbf{h}_b$ are set to 0 and 1 for unmasked and masked tokens, respectively.

Targets. The targets are generated by an EMA-based teacher encoder model from unmasked *audiovisual* inputs, similarly to Section 3.2. Following [15, 18], the targets $\mathbf{e}_b$ are generated by averaging the outputs from all encoder blocks and applying instance normalisation [47]. Using only audio targets, as in [15], can make the student's final layers more relevant to speech, which has proven beneficial for fine-tuning with few samples, where there is high chance of overfitting [17]. Our fine-tuning process instead uses abundant unlabelled data with pseudo-labels which help reduce overfitting and allow the network to learn from rich audiovisual targets.

Predictor. Following [17], we employ a 512-dimensional two-block Transformer predictor that processes student encoder outputs and mask tokens to produce predictions $\mathbf{p}_{b,m}$. Unlike the separate predictors for video and audio used in [17], we use a single predictor for all inputs.

Loss. The loss for modality m can be expressed as

$$\mathcal{L}_m^{\mathrm{self}} = -\frac{1}{B^{\mathrm{u}}} \sum_{b=1}^{B^{\mathrm{u}}} \mathbf{h}_b \odot \cos(\mathbf{p}_{b,m}, \mathbf{e}_b), \tag{8}$$

where cos denotes cosine similarity, applied token-wise. Thus, the student aims to predict the teacher targets corresponding to the masked inputs. The self-supervised loss $\mathcal{L}^{\mathrm{self}}$ is then

$$\mathcal{L}^{\mathrm{self}} = \lambda_{\mathrm{v}} \mathcal{L}_{\mathrm{v}}^{\mathrm{self}} + (1 - \lambda_{\mathrm{v}})(\mathcal{L}_{\mathrm{a}}^{\mathrm{self}} + \mathcal{L}_{\mathrm{av}}^{\mathrm{self}}). \tag{9}$$

4 Main Properties

In this section, we investigate the behaviour of our unified model. For all experiments, we use a 12-block Base model with hidden size of 512 (see Appendix C.4 for model details). We report test set word error rates (WER) for direct comparison with the main results. Note that we used the validation set from [13] in the exploration stage to avoid overfitting to the test set.

Table 1: **Supervised ablations** on the full LRS3 dataset using our Base model. Default settings are in gray in all tables of the paper.

(a) **Sharing model parameters vs. using modality-specific models.**

Params	WER (%)		
	V	A	AV
Shared	**36.4**	2.3	**2.1**
Unshared	85.5	**2.1**	63.4

(b) **Modality sampling.** Random sampling is trained for 3× more epochs as it sees one-third of the data at each iteration.

Mod	WER (%)		
	V	A	AV
Rand	**36.2**	**2.3**	2.2
All	36.4	**2.3**	**2.1**

(c) **Relative weight for video loss.**

λ_v	WER (%)		
	V	A	AV
0.1	42.9	**2.2**	**1.9**
0.3	36.4	2.3	2.1
0.5	**35.2**	2.4	2.2

4.1 Unified Supervised Training

In Table 1, we investigate properties of training our unified model from scratch on the full LRS3 dataset [19] (see Section 3.1). Training details are provided in Section C.5.

Sharing weights. Table 1a studies the impact of weight sharing versus separate models per task (ASR, VSR, AVSR). While using only auditory inputs yields strong performance, training VSR and AVSR models from scratch encounters optimisation challenges, in line with prior research [13, 17]. Interestingly, these hurdles are overcome with weight sharing, resulting in robust VSR and AVSR performance without self-supervised pre-training [17] or training techniques like curriculum learning [9]. This is likely due to audio containing denser verbal information than video, enhancing the optimisation landscape for visual modalities [20].

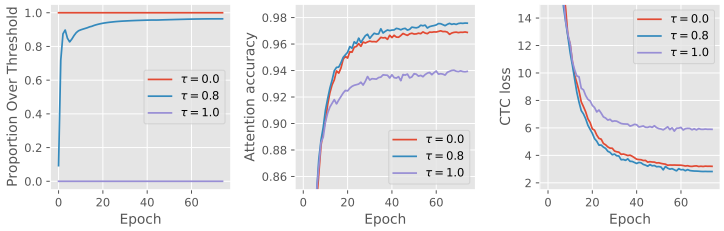
Modality sampling. We employ a weighted average to combine the per-modality losses (see Eq. 4). In contrast, other methods [13, 15] randomly sample, at each iteration, input types with different probabilities, which may vary during training. Table 1b shows that our approach performs similarly with random sampling when training the latter for 3× more epochs. Our approach offers benefits such as sharing computational costs among feature extractor forward passes and amortising the cost of pseudo-label generation across input types (see Section 3.2), as all modalities use the same targets.

Input type weight. Table 1c studies the effect of using different weights for the visual modality. We observe that using a higher λ_v for the VSR loss improves VSR but worsens ASR/AVSR. We choose $\lambda_v = 0.3$ as our default setting, striking a balance in performance among the different tasks.

4.2 Unified Semi-supervised Training

In Table 2, we ablate various components to better understand our unified semi-supervised framework (see Section 3.3). We adopt the common low-resource setting [13]: the 30-hour "trainval" partition of LRS3 serves as our labelled dataset, while the remaining portion of LRS3 (without labels) provides our unlabelled samples. See Appendix C.5 for training details.

Filtering predicted tokens. Figure 2 investigates the impact of the threshold parameter $\tau \in \{0, 0.8, 1\}$. We plot (from left to right) (1) the proportion of tokens exceeding τ, (2) the validation attention accuracy of the decoder using teacher forcing, and (3) the CTC loss, as a function of the epoch number. We also show the final WER. We observe that $\tau = 1$, where only labelled samples contribute to training, results in poor attention accuracy, high CTC loss, and high WER across input types. Conversely, $\tau = 0$, implying no filtering (*i.e.*, all tokens are considered regardless of confidence level), yields competitive performance, suggesting some robustness to low-quality pseudo-labels. Finally, for $\tau = 0.8$, the proportion of tokens with confidence over τ begins at a low level and steadily increases throughout training as the teacher network improves. This yields improved performance in terms of attention accuracy, CTC loss, and final WER, demonstrating the efficacy of filtering via a simple confidence threshold. A more fine-grained analysis of τ values are given in Section D.1.



τ	WER (%)		
	V	A	AV
0.0	40.7	4.9	4.7
0.8	**37.8**	**4.0**	**3.9**
1.0	61.8	8.9	8.4

Figure 2: **Pseudo-label filtering threshold. Left**: Validation plots for different values of threshold τ. **Right**: Final WER for different values of τ.

Table 2: **Semi-supervised ablations** under the LRS3 low-resource setting using our Base model.

(a) **Relative labelled weight for audio and video.**

γ_a	γ_v	WER (%)		
		V	A	AV
0.5	0.5	42.3	4.1	4.0
0.2	0.2	38.0	4.2	4.1
0.5	0.2	**37.8**	**4.0**	**3.9**

(b) **Teacher's EMA momentum parameter.**

μ	WER (%)		
	V	A	AV
0	38.9	4.1	4.0
0.999	**37.8**	**4.0**	**3.9**

(c) **CTC vs. CTC-attention losses.**

Loss type	WER (%)		
	V	A	AV
CTC	45.6	5.2	5.0
CTC-att	**37.8**	**4.0**	**3.9**

Quantity/quality trade-off. Pseudo-labels tend to be abundant but noisy, while ground-truth transcriptions are scarce yet high-quality. The balance between quantity and quality is adjustable via the hyperparameters γ_v and γ_a in Eq. 7. Table 2a explores different values for γ_v and γ_a, revealing better performance when $\gamma_a > \gamma_v$. Noisy pseudo-labels generated from audiovisual samples may suffice for VSR, which often performs worse than ASR/AVSR and benefits from data abundance. Conversely, ASR/AVSR is less prone to overfitting and may suffer with excessive reliance on low-quality pseudo-labels, requiring a higher relative weight on labelled losses.

Momentum. Table 2b shows the effect of updating the teacher's weight via EMA ($\mu = 0.999$) compared to simply copying the student's weights at every iteration ($\mu = 0$). Using EMA results in better performance, yet good results are achieved even without it.

Loss types. CTC and attention-based encoder-decoder frameworks are dominant approaches in speech recognition. While attention typically outperforms CTC, it may struggle with proper alignment prediction, requiring tuning of various decoding hyperparameters [48]. To address these challenges, we adopt a CTC-attention hybrid framework [48], as in [17, 9, 27]. The costly auto-regressive attention pseudo-label generation is made computationally feasible via our greedy strategy and multi-modal feature extraction (which amortises pseudo-label generation costs). Table 2c demonstrates a significant improvement in results by using both CTC and attention compared to CTC alone.

4.3 Unified Self-supervised Pre-training

Table 3 examines the main properties of our self-supervised method (see Section 3.3). We fine-tune pre-trained models with different hyperparameters using our semi-supervised approach (Section 3.2). We use the LRS3 low-resource setting, as in Section 4.2. See Appendix C.6 for training details.

Target modality. In Table 3a, we evaluate our method with targets derived from the different input modalities. Across all cases, pre-training outperforms training from scratch, highlighting the complementarity of semi- and self-supervised training. Visual targets enhance VSR but diminish ASR/AVSR performance compared to auditory targets; overall, audiovisual targets consistently perform best. These results suggest that cross-modal-only pre-training may lose crucial modality-specific information, reducing generalisation when fine-tuning *on all data* (including unlabelled samples), *i.e.*, via pseudo-labelling. Our observations are in contrast to previous findings with

Table 3: **Self-supervised ablations** under the LRS3 low-resource setting using our Base model.

(a) **Target type.** "Scratch" refers to semi-supervised training only.

Target	WER (%)		
	V	A	AV
Scratch	37.8	4.0	3.9
V	36.2	3.7	3.4
A	37.3	**3.2**	3.1
AV	**36.0**	**3.2**	**3.0**

(b) **Averaging blocks vs. using only last encoder block.**

Target	WER (%)		
	V	A	AV
Last block	37.2	3.4	3.1
Avg blocks	**36.0**	**3.2**	**3.0**

(c) **Predictor depth.**

Depth	WER (%)		
	V	A	AV
1	37.0	3.2	3.0
2	**36.0**	3.2	3.0
4	36.9	**3.1**	**2.9**

supervised fine-tuning, where visual or audiovisual pre-training targets tend to underperform [13, 17, 15]. See Appendix F for an in-depth analysis comparing supervised and semi-supervised fine-tuning.

Averaging targets. [15, 18] demonstrate that using the average of encoder blocks as targets outperforms using the last block alone. Table 3b confirms this finding in our setting.

Predictor depth. In Table 3c, we study the influence of predictor depth. A deeper predictor yields more abstract encoder representations, while a shallower one retains more task-specific features [17]. We observe strong performance at our default depth of 2. Notably, our semi-supervised fine-tuning approach is less sensitive to predictor depth than standard methods [17, 18].

5 Comparisons with Previous Results

5.1 Comparisons with Self-supervised Methods

Table 4 compares our approach on LRS3 [19] with self-supervised methods under similar model sizes and data settings. We combine pre-training (Section 3.3) with standard fine-tuning (Section 3.1) when using identical pre-training and fine-tuning data, and with semi-supervised fine-tuning (Section 3.2) when using extra unlabelled data. In addition to the low-resource labelled data setting outlined in Section 4.2, we test in a high-resource setting using the full 433-hour LRS3 dataset for fine-tuning. Our pre-training employs either LRS3 alone or combined with a 1,326-hour English-only version of VoxCeleb2 [49, 13]. We experiment with Base, Base+, and Large Transformers (see Appendix C.4).

Low-resource. Using the Base model and LRS3 for pre-training, our approach significantly exceeds the previous state-of-the-art across VSR, ASR, and AVSR, when fine-tuning on 30 hours. Increasing the pre-training data and model size enhances performance, demonstrating our method's scalability. With the Large model and LRS3+Vox2 as pre-training data, we achieve 26.9% WER for VSR and 2.4% WER for both ASR and AVSR, matching BRAVEn on ASR and surpassing it on VSR. Unlike other methods, which use separate models for each task, *USR employs a single model for all tasks*.

High-resource. In the high-resource setting, our results are comparable to modality-specific models for ASR/AVSR and superior for VSR across all settings. Our top model obtains 22.3% WER for VSR, 1.2% WER for ASR, and 1.1% WER for VSR, significantly outperforming u-HuBERT, which also uses a single model for all modalities. Furthermore, USR's low-resource VSR performance is superior to u-HuBERT's high-resource VSR result.

5.2 Comparisons with the State-of-the-Art

LRS3. In Table 5, we compare our best model against the state-of-the-art on LRS3. We present our USR results with a language model incorporated via shallow fusion [17, 27], improving VSR performance from 22.3% to 21.5%. Despite using a shared model for all tasks, our performance exceeds multiple supervised methods and approaches top results [27, 52, 53], which use significantly more labelled data. USR surpasses Auto-AVSR on VSR (21.5% vs. 23.5%) despite the latter using more total data and external ASR models for transcription. Finally, we outperform self-supervised

Table 4: **Comparisons with self-supervised methods.** LRS3 results for the low-resource (LR) and high-resource (HR) labelled data settings, with 30 and 433 hours of labelled data, respectively. Best results in **bold**, second-best underlined.

Method	Pre-train data	Shared params	WER (%) LR			WER (%) HR		
			V	A	AV	V	A	AV
Base(+) models								
AV-HuBERT [13]	LRS3	✗	51.8	4.9	4.7	44.0	3.0	2.8
VATLM [14]	LRS3	✗	48.0	-	3.6	-	-	-
RAVEn [17]	LRS3	✗	47.0	4.7	-	39.1	2.2	-
AV-data2vec [15]	LRS3	✗	45.2	4.4	4.2	39.0	2.0	1.8
Lip2Vec [20]	LRS3	✗	49.5	-	-	42.0	-	-
BRAVEn [18]	LRS3	✗	43.4	4.0	4.0	36.0	**1.9**	-
USR	LRS3	✓	**36.0**	**3.2**	**3.0**	**34.3**	**1.9**	**1.6**
Base(+) models								
AV-HuBERT [13]	LRS3+Vox2	✗	46.1	4.6	4.0	34.8	2.0	1.8
VATLM [14]	LRS3+Vox2	✗	42.6	-	3.4	34.2	-	1.7
RAVEn [17]	LRS3+Vox2	✗	40.2	3.8	-	33.1	1.9	-
AV-data2vec [15]	LRS3+Vox2	✗	37.8	3.7	3.3	32.9	1.7	1.4
Lip2Vec [20]	LRS3+Vox2	✗	40.6	-	-	34.1	-	-
BRAVEn [18]	LRS3+Vox2	✗	35.1	3.0	-	28.8	**1.4**	-
USR	LRS3+Vox2	✓	**28.4**	**2.6**	**2.5**	**26.5**	1.6	**1.3**
Large models								
AV-HuBERT [13]	LRS3+Vox2	✗	32.5	2.9	3.3	28.6	1.3	1.4
VATLM [14]	LRS3+Vox2	✗	31.6	-	2.7	28.4	-	1.2
RAVEn [17]	LRS3+Vox2	✗	32.5	2.7	-	28.2	1.4	-
AV-data2vec [15]	LRS3+Vox2	✗	30.8	2.7	2.7	28.5	1.3	1.3
Lip2Vec [20]	LRS3+Vox2	✗	31.2	-	-	26.0	-	-
BRAVEn [18]	LRS3+Vox2	✗	30.8	**2.3**	-	26.6	**1.2**	-
u-HuBERT [16]	LRS3+Vox2	✓	-	-	-	29.1	1.5	1.3
USR	LRS3+Vox2	✓	**26.9**	2.4	**2.4**	**22.3**	**1.2**	**1.1**

Table 5: **Comparisons with the state-of-the-art on LRS3.** *Labels include automatic transcriptions from ASR models trained on large-scale, often non-public datasets. "ST" desnote offline self-training.

Method	Labelled hours	Unlabelled hours	Language model	Shared params	WER (%)		
					V	A	AV
Supervised*							
V2P [50]	3,886	-	✗	✗	55.1	-	-
RNN-T [38]	31,000	-	✗	✓	33.6	4.8	4.5
VTP [51]	2,676	-	✓	✗	30.7	-	-
Auto-AVSR [27]	1,902	-	✓	✗	23.5	**1.0**	1.0
Auto-AVSR [27]	3,448	-	✓	✗	19.1	**1.0**	**0.9**
ViT3D-CM [52]	90,000	-	✗	✗	17.0	-	1.6
SynthVSR [53]	6,720	-	✓	✗	16.9	-	-
LP Conf [54]	100,000	-	✗	✗	**12.8**	-	**0.9**
Self/semi-supervised							
AV-HuBERT w/ ST [13]	433	1,326	✗	✗	28.6	-	-
RAVEn w/ ST [17]	433	1,326	✓	✗	23.1	1.4	-
USR	433	1,326	✓	✓	**21.5**	**1.2**	**1.1**

Table 6: **Comparisons with the state-of-the-art on LRS2.** *Includes methods that use automatic transcriptions from ASR models trained on large-scale datasets. "ST" stands for self-training.

Method	Labelled hours	Unlabelled hours	Language model	Shared params	WER (%)		
					V	A	AV
Supervised*							
CM-seq2seq [6]	380	-	✓	✗	37.9	3.9	3.7
CM-aux [9]	1,459	-	✓	✗	25.5	-	-
VTP [51]	698	-	✓	✗	28.9	-	-
VTP [51]	2,676	-	✓	✗	22.6	-	-
Auto-AVSR [27]	818	-	✓	✗	27.9	2.6	-
Auto-AVSR [27]	3,448	-	✓	✗	**14.6**	**1.5**	**1.5**
Self/semi-supervised							
Uni-AVSR [55]	223	60,000	✗	✗	43.2	2.7	2.6
LiRA [56]	223	433	✓	✗	38.8	-	-
RAVEn [17]	223	1,759	✗	✗	23.2	2.5	-
RAVEn w/ ST [17]	223	1,759	✓	✗	17.9	2.3	-
USR	223	1,759	✗	✓	16.0	2.0	**1.9**
USR	223	1,759	✓	✓	**15.4**	**1.9**	**1.9**

methods [13, 17] using self-training that require a costly beam search strategy combining CTC, attention, and language model scores. Our simpler, greedy approach is effective, and we aim to explore additional offline pseudo-labelling for USR in future work.

LRS2. We also compare with the state-of-the-art on the LRS2 dataset [57] (see Table 6). We train our model using the same hyperparameters as for the high-resource LRS3 setting. Consistent with our LRS3 results from Table 5, USR surpasses all other self-supervised methods across ASR, VSR, and AVSR, and outperforms strong supervised methods [27] trained with $>4\times$ more labelled data (433 vs. 1,759 hours). Results on the WildVSR dataset are in Appendix E.

6 Conclusion

Despite their similarities, research in VSR, ASR, and AVSR has typically focused on developing separate models for each task. In this paper, we propose unified training strategies that use a single model to address all three tasks simultaneously. Our USR approach combines self-supervised learning with a greedy pseudo-labelling semi-supervised technique to achieve state-of-the-art results, surpassing related methods that use separate models for each task. Future work could explore alternative encoder architectures, strategies to improve pseudo-label quality, and methods to incorporate extra audio-only data. We hope to inspire further efforts towards consolidating ASR, VSR, and AVSR systems.

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A Limitations

USR uses unlabelled samples during fine-tuning via pseudo-labelling, which is more computationally intensive than standard supervised fine-tuning due to (1) the increased data volume and (2) the high cost of pseudo-labelling. However, our semi-supervised approach *without* pre-training still outperforms state-of-the-art self-supervised methods (37.8% vs. 43.4% WER [18] in the LRS3 low-resource setting). Additionally, our approach efficiently generates pseudo-labels using a simple thresholding mechanism. Despite this, higher-quality labels are known to improve speech recognition, often enhanced by techniques like beam search, language modelling, and combining CTC and attention scores. We do not explore alternative filtering mechanisms, which we defer to future work.

B Societal Impact

Speech recognition technology can greatly benefit people with disabilities who may struggle to interact with devices using traditional input methods like keyboards. Visual speech recognition can assist individuals with aphonia, who cannot produce voiced speech. It has also been shown that models trained for visual speech recognition can also aid in detecting fake videos by understanding natural mouth movements [58].

However, speech recognition technology also poses societal risks. It can be exploited for surveillance through, *e.g.*, CCTV, necessitating appropriate government regulations. As in other machine learning applications, there may be biases in the datasets used to train the models. Biases related to gender, age, or ethnic background can lead to reduced performance for underrepresented groups. Addressing this requires training models on balanced data or employing bias-reduction techniques.

C Experiment Details

C.1 Dataset Details

LRS3. The LRS3 dataset [19] is the largest publicly accessible audio-visual dataset for continuous speech recognition with transcriptions. It includes approximately 430 hours of spoken sentences from TED Talks and features a vocabulary of over 50,000 words spoken by thousands of different speakers. The dataset is collected by automatically tracking faces, synchronising the video/audio streams, and splitting the videos into individual sentences. The test set comprises roughly 1 hour of utterances from speakers not included in the training set.

LRS2. The LRS2 dataset [57], totalling 223 hours of footage from BBC programs, is the second-largest transcribed audio-visual dataset available for continuous speech recognition. The test set is around 0.5 hours long. Like LRS3, LRS2 features an unrestricted vocabulary and includes thousands of diverse speakers. However, LRS3 tends to contain videos of more variable quality, making it a more challenging dataset for VSR.

WildVSR. WildVSR [59] is a recent VSR dataset, created by closely following the LRS3 dataset curation processes. The VSR dataset contains more challenging samples compared with LRS3, leading to significant drops in the VSR performance of models evaluated on WildVSR. The test set contains around 5 hours of footage.

VoxCeleb2. VoxCeleb2 [49] is a large-scale audio-visual dataset containing talking faces of celebrities, with about 6,000 speakers and over 2,400 hours of footage. The dataset includes elements like laughter, cross-talk, music, and other interference, with an unconstrained vocabulary. Since VoxCeleb2 is multilingual, we use an English-only version curated by [13], which consists of 1,323 hours of footage.

C.2 Data Licenses

LRS3 [19], VoxCeleb2 [49], and WildVSR [59] are licensed under CC BY-NC-ND 4.0. LRS2 [57] allows for academic, non-commercial research.

Table 7: **Configuration of our models.** Unlike in [13, 17, 18], the number of parameters includes the whole model, including the decoder and feature extractors.

	Base	Base+	Large
Parameters (M)	86	171	503
Encoder blocks	12	12	24
Decoder blocks	6	6	9
Attention dimension	512	768	1024
Attention heads	8	12	16
MLP size	2048	3072	4096

Table 8: **Supervised/semi-supervised training settings.**

Hyperparameter	Value
Training epochs	75
Warmup epochs	20
Optimiser	AdamW
Learning rate	3e-3 (LRS3), 2e-3 (LRS3+Vox2)
Optimiser (β_1, β_2)	$(0.9, 0.98)$
Weight decay	0.04
Learning rate schedule	Cosine decay
Drop rate [61]	0.1 (Base), 0.2 (Large)
Gradient clipping threshold	3.0
Video augmentations	RandomCrop + HorizontalFlip
Frames per GPU (labelled)	155 (low-resource), 700 (high-resource)
Frames per GPU (unlabelled)	2,400 (LRS3), 1,400 (LRS3+Vox2)

C.3 Pre-processing

We follow the video pre-processing protocol from related works [9, 13, 17, 18]. We remove motion jitter from the videos, crop a 96×96 region centred around the mouth for each frame, and apply a grayscale transformation. We note that raw audio is used without pre-processing. As in [13, 17, 18], we tokenise the targets using SentencePiece [60] subword units with a vocabulary size of 1,000.

C.4 Model Configurations

Following [18], we use three model sizes: Base, Base+, and Large. While the Transformer encoders and decoders vary in size, the feature extractors remain unchanged, consistent with [17, 18] (which use the same feature extractors). The configuration of the models is summarised in Table 7. Base+ corresponds to the Base models used in similar works [13, 14, 15]. We train our Base, Base+, and Large models on 32, 64, and 128 A100 40GB GPUs, respectively.

C.5 Supervised/Semi-supervised Training Settings

We use consistent settings across supervised training (Section 3.1) and semi-supervised training (Section 3.2). We train our models using AdamW [62] for 75 epochs with a 20-epoch linear warmup [63] and a cosine learning rate decay [64]. We use gradient clipping and drop path [61] for regularisation. In addition to the masking discussed in the main text, we also perform random spatial cropping (size 88×88) and horizontal flipping (probability 0.5) on the videos in a temporally consistent manner, as in [17, 18]. The hyperparameter details are presented in Table 8. We fix the seed to 42. It takes approximately 12 hours to train the Base model on the labelled data (32 GPUs). It takes around one, four, and six days to train the Base (32 GPUs), Base+ (64 GPUs), and Large (128 GPUs) models, respectively. Note that Base is trained on LRS3, and Base+ and Large on LRS3+Vox2.

Table 9: **Settings for pre-training.**

Hyperparameter	Value
Training epochs	150 (LRS3), 75 (LRS3+VoxCeleb2)
Warmup epochs	40 (LRS3), 20 (LRS3+VoxCeleb2)
Optimiser	AdamW
Learning rate	5e-3 (LRS3), 2e-3 (LRS3+VoxCeleb2)
Optimiser (β_1, β_2)	$(0.9, 0.98)$
Weight decay	0.04
Learning rate schedule	Cosine decay
Drop rate [61]	0.1 (Base), 0.2 (Large)
Gradient clipping threshold	3.0
Video augmentations	RandomCrop + HorizontalFlip
Frames per GPU	2,400 (Base), 1,800 (Base+), 900 (Large)

Table 10: **More semi-supervised ablations** under the LRS3 low-resource setting using our Base model (includes self-supervised pre-training).

(a) **Filtering thresholds** τ_{ctc} and τ_{att} for CTC and attention, respectively.

τ_{ctc}	τ_{att}	WER (%)		
		V	A	AV
0.60	0.60	37.2	3.3	3.1
0.80	0.80	**36.0**	3.2	3.0
0.95	0.95	36.6	3.3	3.1
0.60	0.80	36.7	**3.1**	**2.9**
0.95	0.80	36.2	3.3	3.2
0.80	0.60	37.7	3.2	3.0
0.80	0.95	36.5	3.3	3.1

(b) **Hard versus soft sampling.**

Sampling	WER (%)		
	V	A	AV
Hard	**36.0**	**3.2**	**3.0**
Soft	37.5	3.4	3.4

C.6 Pre-training Settings

The pre-training settings are similar. We use a longer schedule (in terms of number of epochs) for LRS3 with 150 total training epochs and 40 warmup epochs. We also use a higher learning rate of 5×10^{-3}. The full settings are given in Table 9. It takes approximately two days to pre-train all models.

C.7 Decoding

We use the ESPNet framework [65] for decoding, as in [17, 18], employing beam search with a beam size of 40. The final beam search score is

$$\mathcal{S} = \alpha \mathcal{S}_{\text{ctc}} + (1 - \alpha)\mathcal{S}_{\text{att}} + \beta \mathcal{S}_{\text{lm}}, \tag{10}$$

where $\mathcal{S}_{\text{ctc}}$ and $\mathcal{S}_{\text{att}}$ are scores from the CTC and attention branches, respectively, and $\mathcal{S}_{\text{lm}}$ is the optional score from a pre-trained language model, which is incorporated through shallow fusion [66]. Following [27, 17], we set $\alpha = 0.1$ for all experiments. When using a language model, we select β from $\{0.1, 0.2, 0.3, 0.4\}$ based on the validation set.

D More Ablations

D.1 Semi-supervised ablations.

Confidence threshold. Our default setting uses a pseudo-labelling confidence threshold τ of 0.8 both for the CTC and attention losses, for simplicity. In Table 10a, we investigate different threshold values, including the use of separate thresholds for the two losses. We observe that USR's performance

Table 11: **More self-supervised ablations** under the LRS3 low-resource setting using our Base model.

(a) **Mask probability.**

Mask probability	WER (%)		
	V	A	AV
0.2	37.1	3.4	3.2
0.4	**36.0**	3.2	3.0
0.6	36.7	**3.1**	**2.9**
0.8	38.0	3.3	3.1

(b) **Pre-training target types.**

Target	WER (%)		
	V	A	AV
AV	**36.0**	**3.2**	**3.0**
A+V+AV	36.2	**3.2**	**3.0**

remains consistent across a range of different thresholds, with no clear improvement when using separate thresholds.

Hard versus soft sampling. Our greedy attention pseudo-labelling strategy involves choosing at each generation step the most likely pseudo-label according to the probability distribution given by the decoder. For comparison, we consider an alternative "soft sampling" approach as well. We use weighted sampling at each generation step, drawing a label based on the entire distribution given by the decoder. Each label has a chance of being selected proportional to its estimated probability. This approach increases the variety of pseudo-labels but may reduce their quality since low-probability pseudo-labels are more frequently used.

In Table 10b we compare the two approaches. We observe that hard sampling outperforms soft sampling for all three modalities. Future work can explore alternative methods to effectively increase pseudo-label variety.

D.2 Self-supervised ablations.

Mask probability. In Table 11a, we compare different mask probabilities for pre-training. A low mask probability can result in a trivial learning task, whereas a high probability can make the task overly challenging. We find that a probability between 0.4 and 0.6 achieves a good balance.

Combining targets. During pre-training, targets are generated from audio-visual input and predicted by students using masked auditory, visual, and audio-visual inputs. We explore predicting the combined targets from all input types by summing the corresponding outputs from the teacher, but as shown in Table 11b, this does not yield improvements over simply predicting the audio-visual targets.

E Comparisons with the State-of-the-Art on WildVSR

WildVSR [59] is a recent test set featuring more challenging "in-the-wild" samples than LRS3. In Table 12, we evaluate our Large model on WildVSR, trained using the high-resource setting (see Table 5). Our unified approach achieves similar VSR results to the modality-specific RAVEn when the latter uses an additional self-training stage.

F Supervised vs. Semi-supervised Fine-tuning

In Table 13, we closely evaluate the differences between supervised and semi-supervised fine-tuning.

Supervised fine-tuning with few labelled samples is prone to overfitting, necessitating various training "tricks" to improve performance. For example, [17, 18] use a smaller decoder for the low-resource setting, different learning rates for the encoder and decoder, and layer-wise learning rate decay [26]. We use our Base model and the low-resource setting to evaluate supervised and semi-supervised (our default) fine-tuning, with and without these strategies. As shown in Table 13a, while these "tricks" significantly benefit supervised training (consistent with [17]), they actually *hurt* semi-supervised fine-tuning. This suggests that semi-supervised training is less prone to overfitting, making these

Table 12: **WildVSR results.** We test our model from Table 5 for VSR.

Method	Labelled hours	Unlabelled hours	Shared params	WER (%)
Supervised				
CM-seq2seq [6]	1,459	-	✗	58.4
VTP [51]	698	-	✗	75.6
VTP [51]	2,676	-	✗	68.7
Auto-AVSR [27]	661	-	✗	62.3
Auto-AVSR [27]	1,759	-	✗	49.3
Auto-AVSR [27]	3,448	-	✗	38.6
Self/semi-supervised				
AV-HuBERT [13]	433	1,326	✗	51.7
AV-HuBERT w/ self-training [13]	433	1,326	✗	48.7
RAVEn [17]	433	1,326	✗	52.2
RAVEn w/ self-training [17]	433	1,326	✗	46.7
USR	433	1,326	✓	**46.4**

Table 13: **Comparisons between supervised and our semi-supervised fine-tuning.** We use the LRS3 low-resource setting and our Base model.

(a) **Fine-tuning "tricks" for supervised and semi-supervised fine-tuning.**

Fine-tuning	WER (%)		
	V	A	AV
Sup	52.5	5.8	5.4
Sup w/ tricks	**45.6**	**5.2**	**5.0**
Semi	**36.0**	**3.2**	**3.0**
Semi w/ tricks	39.3	**3.2**	**3.0**

(b) **Pre-training target types for supervised fine-tuning.**

Target	WER (%)		
	V	A	AV
V	63.2	9.0	8.9
A	**43.9**	**4.8**	**4.6**
AV	45.6	5.2	5.0

regularisation methods unnecessary. In general, we noticed that using semi-supervised fine-tuning results in less sensitivity to pre-training hyperparameters (*e.g.*, compare Tables 13b and 3a).

In Table 3a, we observed that our semi-supervised fine-tuning benefits most from audiovisual targets. Here, we fine-tune the same pre-trained model using only labeled data to assess the influence of target type on supervised fine-tuning. Table 13b shows that audio-only targets perform best for supervised fine-tuning, consistent with findings from other works [15, 17]. As discussed in the main text, semi-supervised fine-tuning allows the model to leverage the rich and diverse information in audiovisual targets, which supervised fine-tuning struggles to achieve.

Table 14: **Experiments with auditory noise.** We compare USR with the modality-specific BRAVEn method on LRS3 with different signal-to-noise-ratio (SNR) levels. We use Base models trained under the low-resource setting.

		SNR (dB)		
	Clean	5	0	-5
BRAVEn (A)	**4.0**	15.6	24.6	99.0
BRAVEn (AV)	**4.0** =	**12.4** ↓3.2	**15.0** ↓9.6	**48.5** ↓50.5
USR (A)	3.2	14.3	26.9	100.4
USR (AV)	**3.0** ↓0.2	**6.1** ↓8.2	**10.1** ↓16.8	**35.7** ↓64.7

Table 15: **Error bars.** We report the mean and standard deviation over five runs with random seeds. We use our Base model with LRS3 as the pre-training dataset.

Setting	WER (%)		
	V	A	AV
Low-resource	36.2 ± 0.40	3.25 ± 0.10	3.02 ± 0.04
High-resource	34.2 ± 0.56	1.77 ± 0.18	1.68 ± 0.11

G Experiments with Auditory Noise

We have demonstrated that AVSR slightly outperforms ASR on the clean LRS3 test set. However, it is in the presence of auditory noise that AVSR truly excels, as visual cues help clarify ambiguous utterances. Table 14 presents ASR and AVSR results under varying levels of audio babble noise from the NOISEX dataset [67]. We employ our Base model under the low-resource setting with LRS3 as the pre-training dataset. Notably, the noise is added to the LRS3 test set, and the model is not trained on noisy data. We observe that as noise levels increase (and the signal-to-noise ratio decreases), the performance gap between AVSR and ASR widens. Interestingly, this gap is more pronounced for USR compared to the modality-specific BRAVEn.

H Error Bars

Due to high computational demands and in line with previous studies [13, 17, 18, 15, 16], we do not include error bars for our main results. To assess the variability of our method across multiple training runs, Table 15 presents the mean and standard deviation over five runs with different random seeds for our low- and high-resource settings, using our Base model with LRS3 as the pre-training dataset. We observe that the results are consistently stable around the mean.

I Qualitative Differences between Self-supervised Pretext Tasks

Our pre-training method shares similarities with recent audio-visual self-supervised tasks, RAVEn [17], BRAVEn [18], and AV-data2vec [15]. These methods employ an EMA-based teacher to generate targets from unmasked data, which the student predicts using masked inputs. Here, we compare and contrast our USR pretext task with these methods.

I.1 Comparisons with RAVEn/BRAVEn

RAVEn and BRAVEn pre-train separate Transformer encoders for visual and auditory inputs, which are then fine-tuned for ASR and VSR. AVSR can be performed through shallow fusion of visual and auditory features. In contrast, USR pre-trains a single student Transformer encoder for auditory, visual, and audiovisual inputs, significantly reducing training and inference costs.

We adopt the approach of using a shallow Transformer encoder as a predictor, which has been shown to improve representation learning [17]. However, while RAVEn and BRAVEn use separate predictors for visual and auditory features (with BRAVEn also using differently-sized predictors), we use a single predictor for all modalities, simplifying the architectural design.

I.2 Comparisons with AV-data2vec

AV-data2vec also unifies pre-training by using a single Transformer encoder for all modalities. However, while AV-data2vec employs random modality sampling, we compute all per-modality losses at each iteration, amortising the cost of target generation (see Section 4.1). AV-data2vec's use of a scheduler for modality probabilities increases the complexity of the pre-training process. Furthermore, AV-data2vec uses audio-only targets, whereas we use audiovisual targets, which are shown to perform best for our semi-supervised fine-tuning (see Section 3.2).

Table 16: **Comparison with AV-CPL.** LRS3 results for the low-resource (LR) and high-resource (HR) labelled data settings. We show results for the Large model using LRS3+Vox2 as the pre-training dataset.

Method	WER (%) LR			WER (%) HR		
	V	A	AV	V	A	AV
AV-CPL [36]	56.7	10.0	10.4	47.4	2.3	2.2
USR	**26.9**	**2.4**	**2.4**	**22.3**	**1.2**	**1.1**

Table 17: **Summary of the impact of semi- and self-supervised training** under the LRS3 low-resource setting using our Base model. We compare four approaches: supervised training on 30 hours of labelled data, self-supervised pre-training with supervised fine-tuning, semi-supervised training, and self-supervised pre-training with semi-supervised fine-tuning.

Setting	Self-supervised pre-training	Fine-tuning	WER (%)		
			V	A	AV
Only labelled data	✗	Supervised	61.8	8.9	8.4
Self-supervised	✓	Supervised	43.9	4.8	4.6
Semi-supervised	✗	Semi-supervised	37.8	4.0	3.9
Self- + semi-supervised	✓	Semi-supervised	**36.0**	**3.2**	**3.0**

J Comparison with AV-CPL

As mentioned in Section 2, the recent AV-CPL method [36] uses pseudo-labelling to train a single model for ASR, VSR, and AVSR, similar to our semi-supervised approach described in Section 3.2. Table 16 compares USR with AV-CPL on the low- and high-resource labelled data settings using the Large model and LRS3+Vox2 as the pre-training dataset. We observe dramatic WER differences between the two methods, which we attribute to USR's use of CTC-attention training, self-supervised pre-training, and pseudo-label filtering, among other design choices studied in Section 4.

K Summary of the Impact of Semi- and Self-supervised Training

Sections 4.2, 4.3, and Appendix F demonstrate the impact of self- and semi-supervised learning on speech recognition performance. Table 17 summarizes the contributions of each component. Self-supervised pre-training on the full LRS3 dataset, followed by supervised fine-tuning on 30 hours of LRS3 (see Appendix F), outperforms supervised training on the same 30 hours alone, as expected. Additionally, semi-supervised training (without pre-training) significantly surpasses the self-supervised baseline. Combining self-supervised pre-training with semi-supervised fine-tuning yields the best results.

L Failure Cases

Table 18 presents some failure cases from the LRS3 test set. We evaluated our Large model trained in a high-resource setting with LRS3 and VoxCeleb2. While VSR tends to produce more errors than ASR and AVSR, these errors are often related to phonetically similar sounds, such as "this" vs. "these" or "disguised" vs. "denies." Additionally, using both auditory and visual modalities (AVSR) can improve the model's ability to distinguish challenging samples, such as "Mali Wear" vs. "malware."

Table 18: **Failure cases on the LRS3 test set**. We use the Large model trained in the high-resource setting with LRS3+VoxCeleb2.

Source	Transcription
Groundtruth	And all of this matters greatly because public safety to me is the most important function
VSR	And all of these matters are crazy because public safety to me is the most important function
ASR	And all of this matters greatly because public safety to me is the most important function
AVSR	And all of this matters greatly because public safety to me is the most important function
Groundtruth	I'm here to tell you the story of crazy love, a psychological trap disguised as love
VSR	I'm here to tell you the story of crazy love, a psychological trap denies the love
ASR	I'm here to tell you the story of crazy love, a psychological trap disguised as love
AVSR	I'm here to tell you the story of crazy love, a psychological trap disguised as love
Groundtruth	It took six days to deploy a global malware campaign
VSR	It took six days to deploy our global market campaign
ASR	It took six days to deploy our global Mali Wear campaign
AVSR	It took six days to deploy a global malware campaign
Groundtruth	It worked for the Oakland A's and it worked in the state of New Jersey
VSR	It worked for the Oaklands and it worked in the state of New Jersey
ASR	It worked for the Oakland Asia and it worked in the state of New Jersey
AVSR	It worked for the Oakland A's and it worked in the state of New Jersey

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