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Chang

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(54) **CASCADED AUDIOVISUAL AUTOMATIC SPEECH RECOGNITION MODELS**

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G10L 15/25	(2013.01)
G10L 25/57	(2013.01)
G10L 15/30	(2013.01)

(52) **U.S. Cl.**

CPC ***G10L 15/24*** (2013.01); ***G10L 15/02*** (2013.01); ***G10L 15/063*** (2013.01); ***G10L 15/083*** (2013.01); ***G10L 15/16*** (2013.01); ***G10L 15/197*** (2013.01); ***G10L 15/22*** (2013.01); ***G10L 15/25*** (2013.01); ***G10L 25/57*** (2013.01); *G10L 15/30* (2013.01)

(58) **Field of Classification Search**

CPC G10L 15/24; G10L 15/25

See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

2017/0061966 A1* 3/2017 Marcheret G06V 20/41

OTHER PUBLICATIONS

Shi, Bowen, et al. "Learning audio-visual speech representation by masked multimodal cluster prediction." arXiv preprint arXiv: 2201.02184 (2022). (Year: 2022).*

(Continued)

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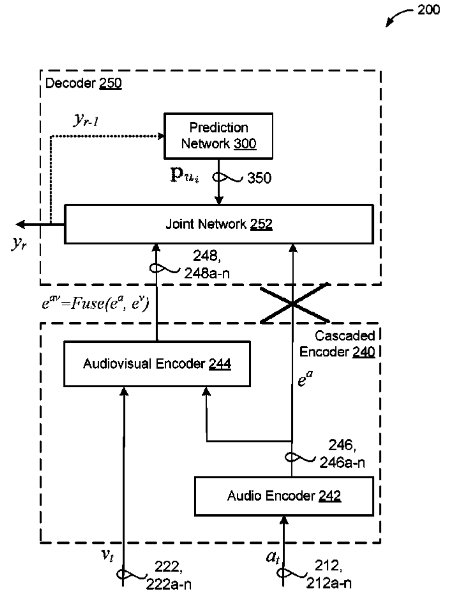
(57) **ABSTRACT**

A method includes receiving a sequence of acoustic frames and generating, by an audio encoder, at each of a plurality of output steps, an acoustic higher-order feature representation for a corresponding acoustic frame in the sequence of acoustic frames. For each acoustic frame in the sequence of acoustic frames paired with a corresponding video frame, the method includes generating, by an audiovisual encoder, an audiovisual higher-order feature representation for the corresponding acoustic higher-order feature frame and the corresponding video frame; and generating, by a joint network, at an output step, a probability distribution over possible speech recognition hypotheses based on the audiovisual higher-order feature representation. The method, for each corresponding acoustic frame in the sequence of acoustic frames not paired with a corresponding video frame, includes generating, by the joint network, at an output step, a probability distribution over possible speech recognition hypotheses based on the acoustic higher-order feature representation.

21 Claims, 8 Drawing Sheets



(56) **References Cited**

OTHER PUBLICATIONS

Goh, Yeh-Huann, Kai-Xian Lau, and Yoon-Ket Lee. "Audio-visual speech recognition system using recurrent neural network." 2019 4th International Conference on Information Technology (InCIT). IEEE, 2019. (Year: 2019).*

Petridis, Stavros, et al. "Audio-visual speech recognition with a hybrid ctc/attention architecture." 2018 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2018. (Year: 2018).*

Ma, Pingchuan, Stavros Petridis, and Maja Pantic. "End-to-end audio-visual speech recognition with conformers." ICASSP 2021—2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021. (Year: 2021).*

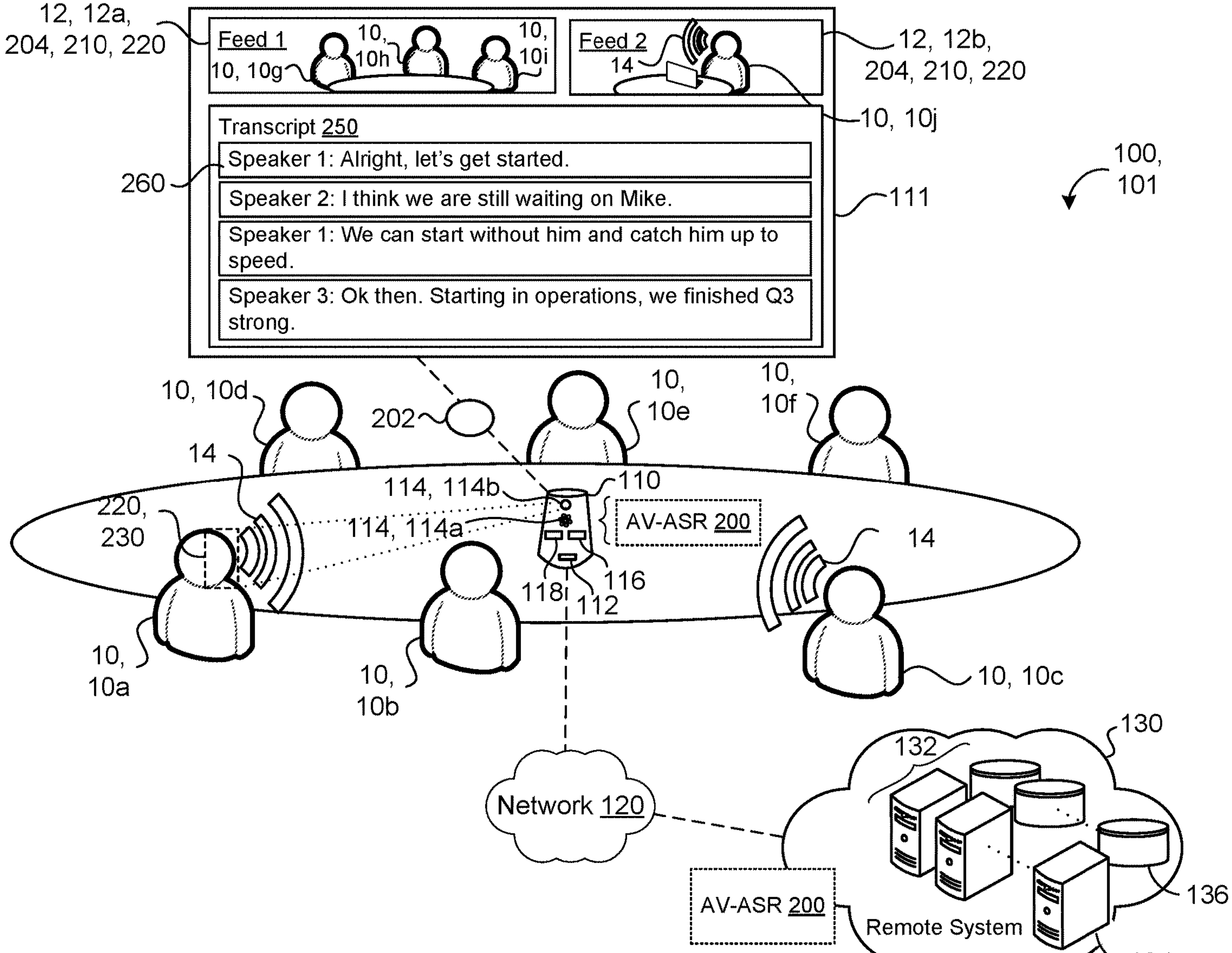
International Search Report and Written Opinion issued in related PCT Application No. PCt/US2024/013946, dated Apr. 29, 2024.

Chang, Oscar et al. "On Robustness to Missing Video for Audio-visual Speech Recognition." Trans. Mach. Learn. Res. Aug. 11, 2022 (Aug. 11, 2022), p. 1-32.

Jiadong Wang et al, "Predict-and-Update Network: Audio-Visual Speech Recognition Inspired by Human Speech Perception", arxiv. org, Cornell University Library, 201 Olin Library Cornell University Ithaca, NY 14853, Sep. 5, 2022 (Sep. 5, 2022).

Gong Yuan et al, "UAVM: Towards Unifying Audio and Visual Models", Nov. 24, 2022 (Nov. 24, 2022), vol. {0} 29, p. 2437-2441.

* cited by examiner



Transcript 250

Speaker 1: Alright, let's get started.

Speaker 2: I think we are still waiting on Mike.

Speaker 1: We can start without him and catch him up to speed.

Speaker 3: Ok then. Starting in operations, we finished Q3 strong.

FIG. 1

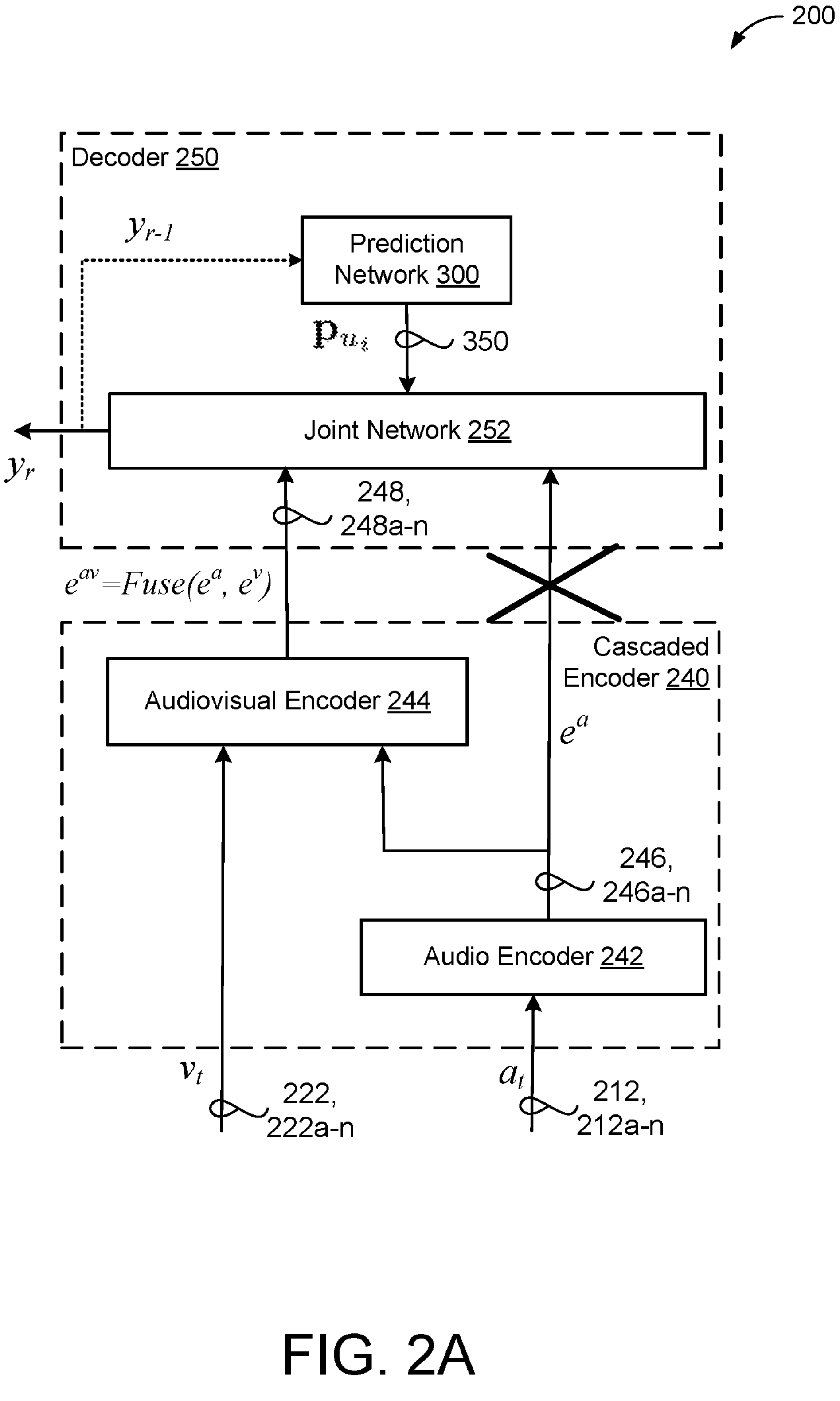

200
Decoder 250
y_{r-1}
Prediction Network 300
$\mathbf{p}_{u_i}$
350
Joint Network 252
y_r
248, 248a-n
$e^{av}=Fuse(e^a, e^v)$
Cascaded Encoder 240
Audiovisual Encoder 244
e^a
246, 246a-n
Audio Encoder 242
v_t
222, 222a-n
a_t
212, 212a-n

FIG. 2A

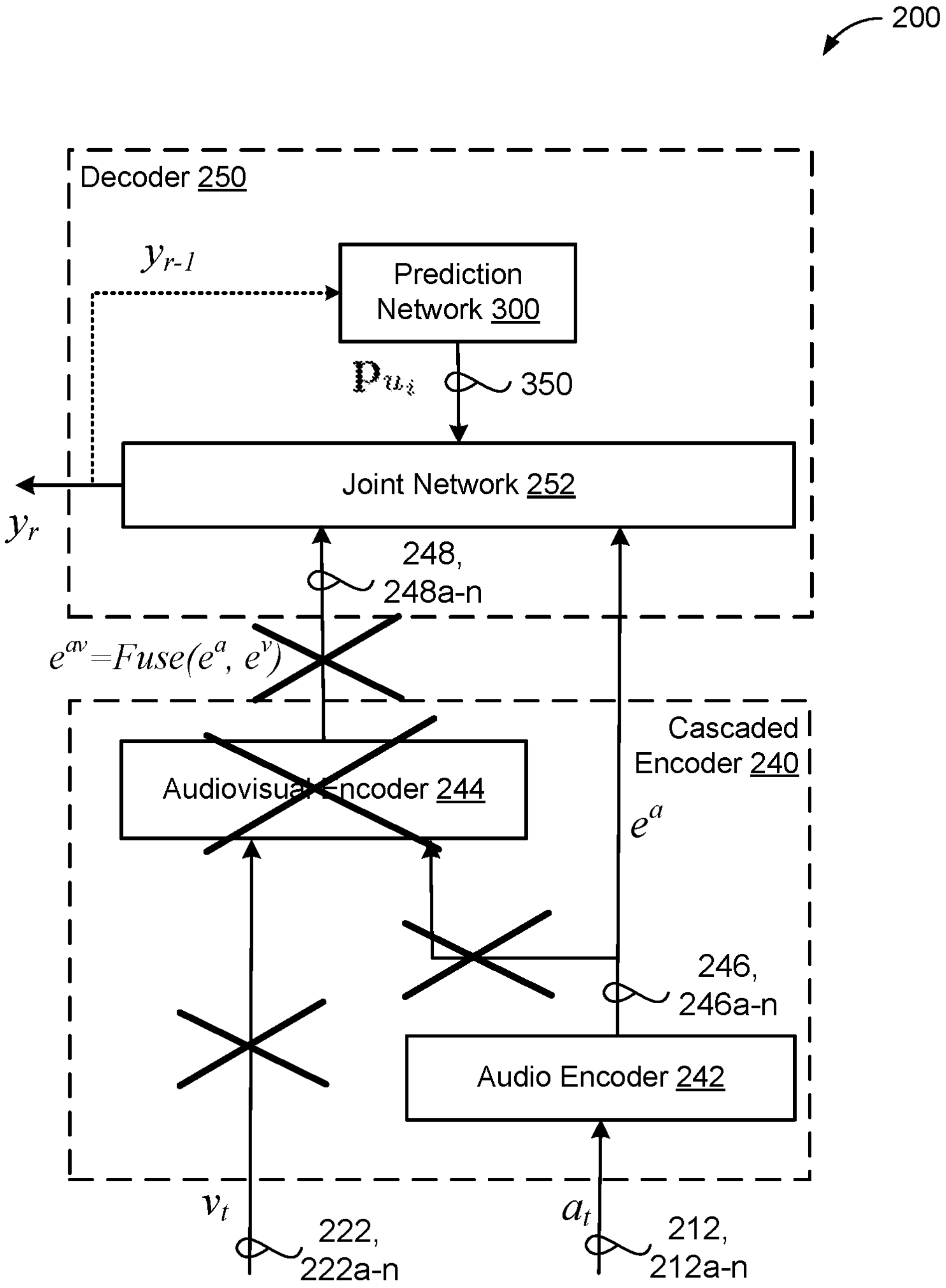

200
Decoder 250
y_{r-1}
Prediction Network 300
$\mathbf{p}_{u_i}$
350
Joint Network 252
y_r
248, 248a-n
$e^{av}=Fuse(e^a, e^v)$
Cascaded Encoder 240
Audiovisual Encoder 244
e^a
246, 246a-n
Audio Encoder 242
v_t
222, 222a-n
a_t
212, 212a-n

FIG. 2B

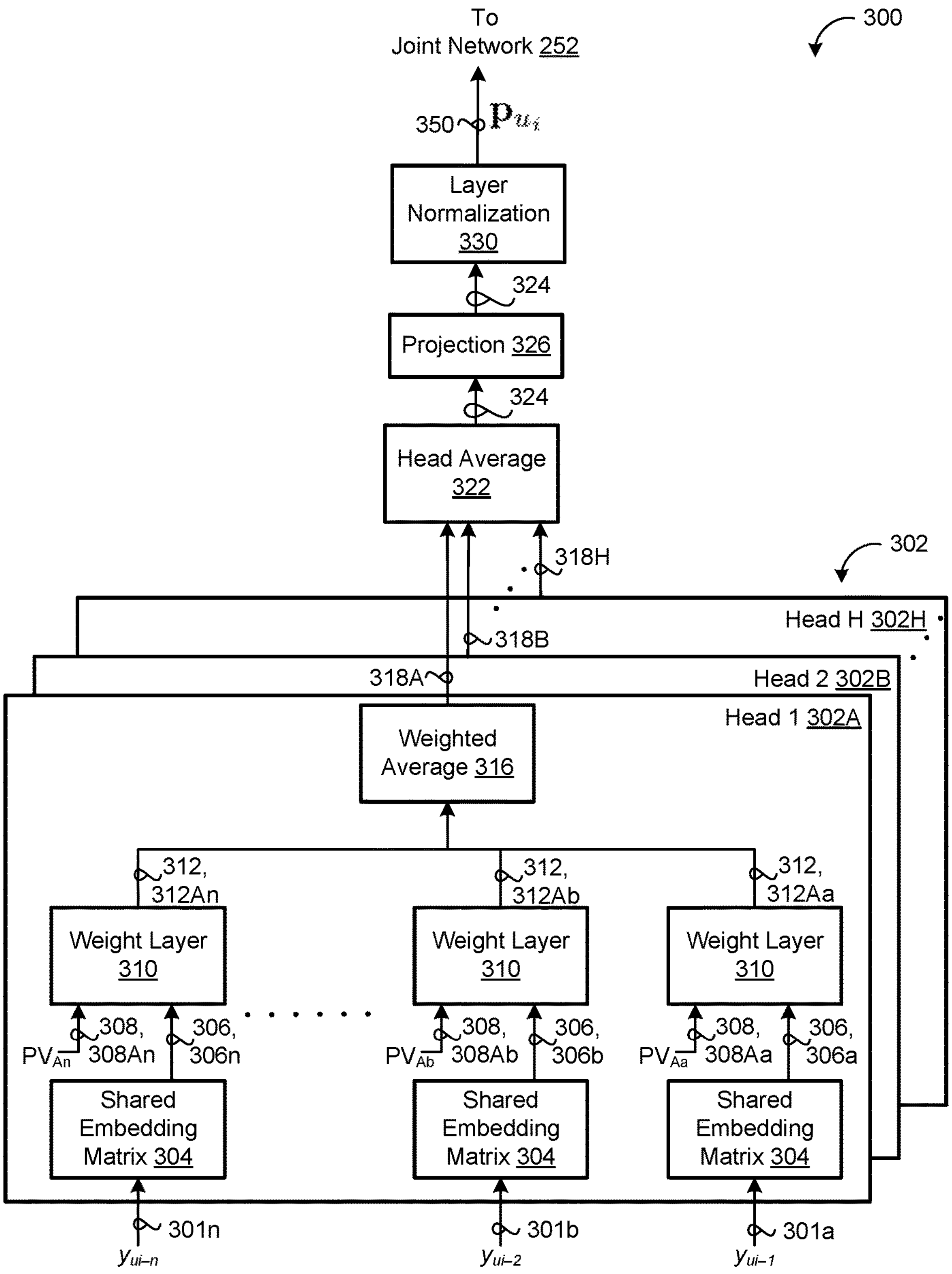

To
Joint Network 252
300
350
$\mathbf{p}_{u_i}$
Layer Normalization 330
324
Projection 326
324
Head Average 322
318H
302
Head H 302H
318B
318A
Head 2 302B
Head 1 302A
Weighted Average 316
312, 312An
312, 312Ab
312, 312Aa
Weight Layer 310
Weight Layer 310
Weight Layer 310
308, 308An
306, 306n
308, 308Ab
306, 306b
308, 308Aa
306, 306a
PV_{An}
PV_{Ab}
PV_{Aa}
Shared Embedding Matrix 304
Shared Embedding Matrix 304
Shared Embedding Matrix 304
301n
301b
301a
y_{ui-n}
y_{ui-2}
y_{ui-1}

FIG. 3

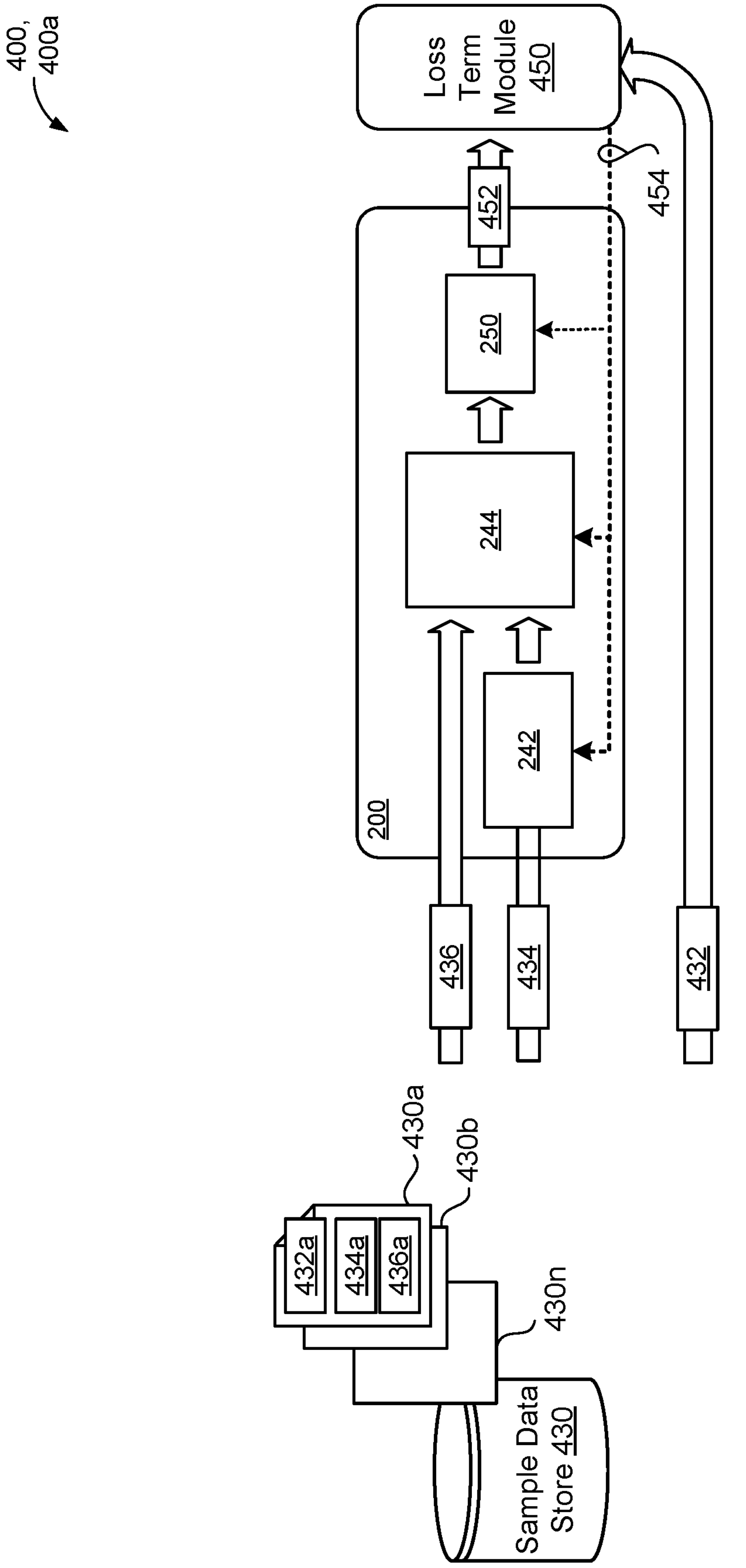

400,
400a
Loss
Term
Module
450
452
454
250
244
242
200
436
434
432
430a
430b
432a
434a
436a
430n
Sample Data
Store 430

FIG. 4A

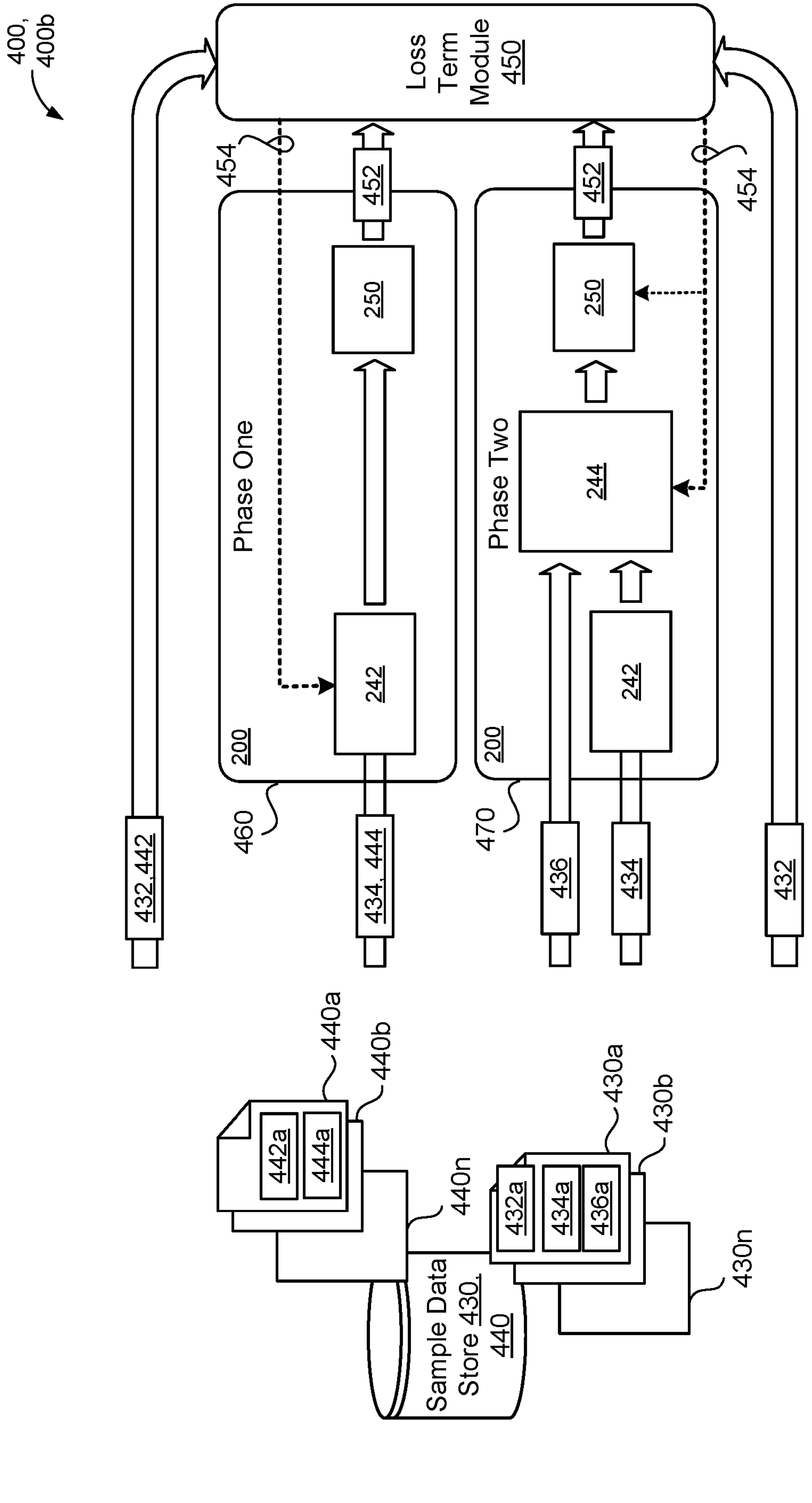

400, 400b
Loss Term Module 450
454
452
452
454
Phase One
Phase Two
200
200
242
250
242
244
250
460
470
432, 442
434, 444
436
434
432
440a
440b
442a
444a
440n
430a
430b
432a
434a
436a
430n
Sample Data Store 430, 440

FIG. 4B

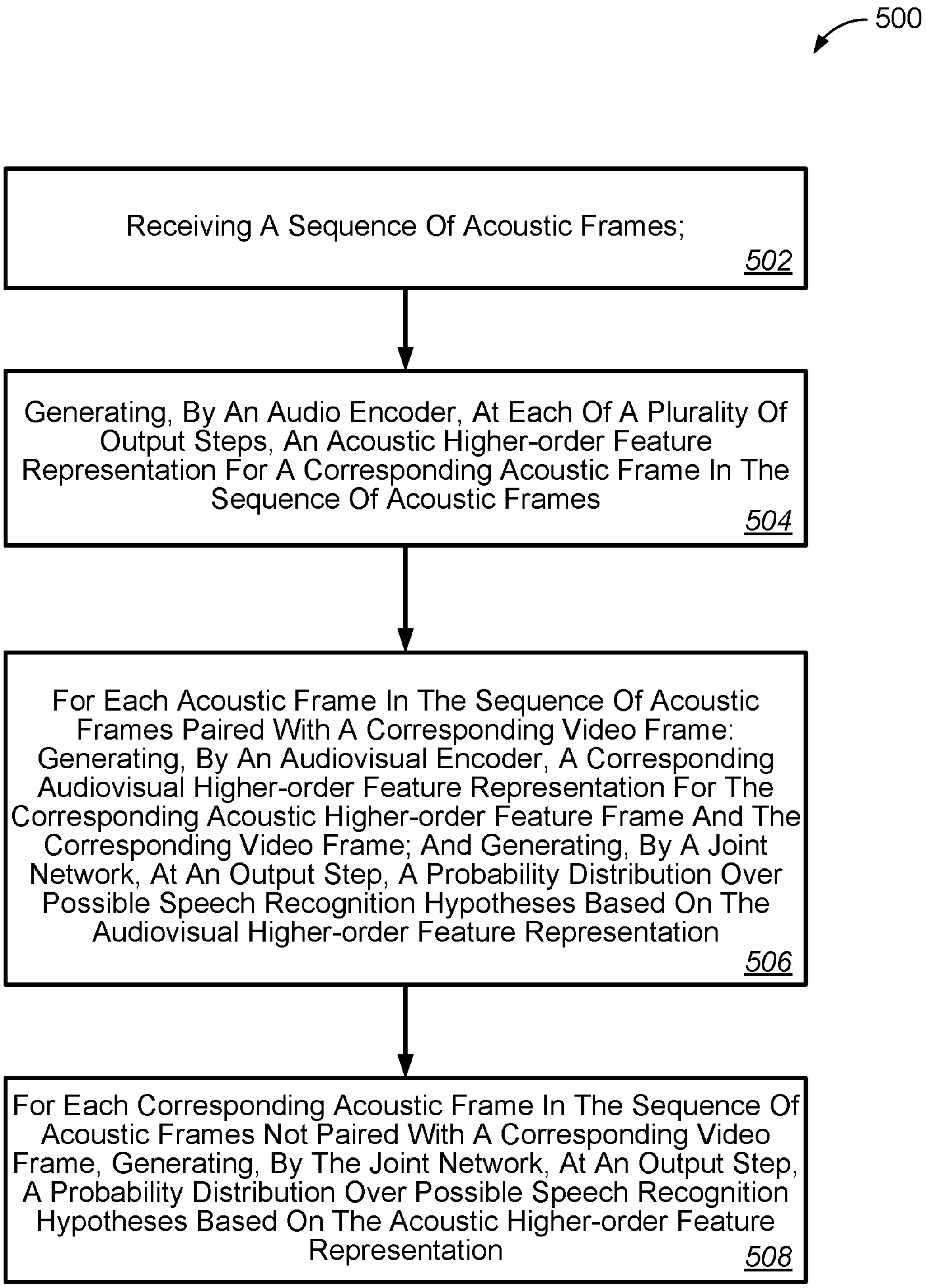

500
Receiving A Sequence Of Acoustic Frames;
502
Generating, By An Audio Encoder, At Each Of A Plurality Of Output Steps, An Acoustic Higher-order Feature Representation For A Corresponding Acoustic Frame In The Sequence Of Acoustic Frames
504
For Each Acoustic Frame In The Sequence Of Acoustic Frames Paired With A Corresponding Video Frame: Generating, By An Audiovisual Encoder, A Corresponding Audiovisual Higher-order Feature Representation For The Corresponding Acoustic Higher-order Feature Frame And The Corresponding Video Frame; And Generating, By A Joint Network, At An Output Step, A Probability Distribution Over Possible Speech Recognition Hypotheses Based On The Audiovisual Higher-order Feature Representation
506
For Each Corresponding Acoustic Frame In The Sequence Of Acoustic Frames Not Paired With A Corresponding Video Frame, Generating, By The Joint Network, At An Output Step, A Probability Distribution Over Possible Speech Recognition Hypotheses Based On The Acoustic Higher-order Feature Representation
508

FIG. 5

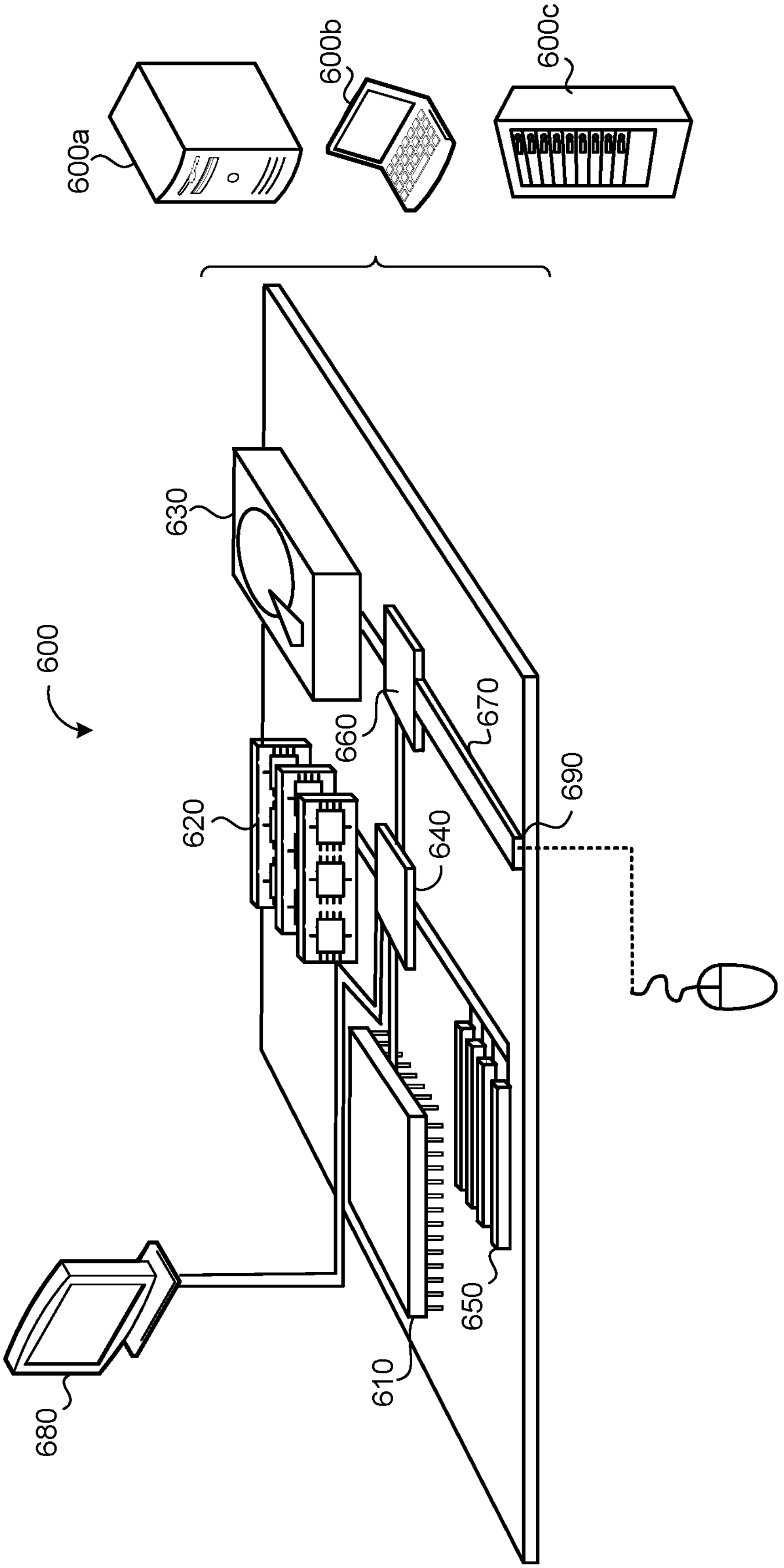


FIG. 6

CASCADED AUDIOVISUAL AUTOMATIC SPEECH RECOGNITION MODELS

TECHNICAL FIELD

This disclosure relates to audiovisual automatic speech recognition.

BACKGROUND

Automatic speech recognition (ASR) is an important technology that is increasingly used in mobile devices and other devices. In general, ASR systems provide accurate transcriptions of what a person has said. However, in noisy environments, or when audio quality of a recorded utterance is poor, obtaining accurate ASR results can be difficult. When video of a speaker is available, the video can be leveraged to help improve ASR results. For instance, the video of the speaker may provide information regarding motion of the lips while the speaker is speaking an utterance, and can be combined with audio of the utterance to assist in transcribing the utterance.

SUMMARY

One aspect of the disclosure provides a cascaded audiovisual automatic speech recognition (AV-ASR) model for transcribing speech from audiovisual data. The cascaded AV-ASR model includes an audio encoder, an audiovisual encoder, and a decoder. The audio encoder is configured to receive, as input, a sequence of acoustic frames, and generate, at each of a plurality of output steps, a corresponding acoustic higher-order feature representation for a corresponding acoustic frame in the sequence of acoustic frames. The audiovisual encoder is configured to receive, as input, a sequence of video frames. For each corresponding acoustic frame in the sequence of acoustic frames paired with a corresponding one of the video frames in the sequence of video frames, the audiovisual encoder is configured to receive, as input, the corresponding acoustic higher-order feature representation for the corresponding acoustic frame generated by the audio encoder; and generate a corresponding audiovisual higher-order feature representation for the corresponding acoustic higher-order feature frame and the corresponding one of the video frames in the sequence of video frames. The decoder is configured to, for each corresponding acoustic frame in the sequence of acoustic frames paired with the corresponding one of the video frames in the sequence of video frames, receive, as input, the corresponding audiovisual higher-order feature representation, and, for each corresponding acoustic frame in the sequence of acoustic frames that is not paired with any video frame in the sequence of video frames, receive, as input, the corresponding acoustic higher-order feature representation. The decoder is further configured to generate, at each of the plurality of output steps a probability distribution over possible speech recognition hypotheses.

Implementations of the disclosure may include one or more of the following optional features. In some implementations, the audio encoder includes at least one of a first plurality of multi-head attention layers, a first conformer, or a first plurality of long short term memory (LSTM) layers. The audiovisual encoder may include at least one of a second plurality of multi-head attention layers, a second conformer, or a second plurality of LSTM layers.

In some examples, the audiovisual encoder is configured to generate the corresponding audiovisual higher-order feature representation by: generating, at each of the plurality of output steps, a corresponding visual higher-order feature representation for the corresponding one of the video frames in the sequence of video frames; and fusing the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation. In some implementations, the audiovisual encoder includes concatenation to fuse the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation. In alternative implementations, the audiovisual encoder includes cross-model attention to fuse the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation. In some examples, the cascaded AV-ASR model includes a cascaded audiovisual recurrent neural network-transducer (RNN-T) model architecture.

In some implementations, the decoder includes a prediction network and a joint network. The prediction network is configured to: receive, as input, a sequence of non-blank symbols output by a final softmax layer; and generate, at each of the plurality of output steps, a dense representation. The joint network is configured to: receive, as input, the dense representation generated by the prediction network at each of the plurality of output steps and one of: for each corresponding acoustic frame in the sequence of acoustic frames paired with the corresponding one of the video frames in the sequence of video frames, the corresponding audiovisual higher-order feature representation; or for each corresponding acoustic frame in the sequence of acoustic frames that is not paired with any video frame in the sequence of video frames, the acoustic higher-order feature representation; and generate, at each of the plurality of output steps, a probability distribution over possible speech recognition hypotheses. In some examples, the prediction network includes a two-layer bidirectional long short term memory (LSTM) model; and the joint network includes a multi-layer perceptron model.

In some examples, the audio encoder and the audiovisual encoder are trained jointly. In alternative examples, the cascaded AV-ASR model is trained by: during a first training phase: receiving a first set of training utterances including acoustic frames without corresponding video frames; and training the audio encoder using the first set of training utterances; and, during a second training phase: receiving a second set of training utterances including acoustic frames and corresponding video frames; and training, while holding coefficients of the audio encoder fixed after the first training phase is complete, the audiovisual encoder using the second set of training utterances while the coefficients of the audio encoder are held fixed.

Another aspect of the disclosure provides a computer-implemented method for transcribing speech from audiovisual data that, when executed by data processing hardware, causes the data processing hardware to perform operations. The operations include: receiving a sequence of acoustic frames; and generating, by an audio encoder, at each of a plurality of output steps, a corresponding acoustic higher-order feature representation for a corresponding acoustic frame in the sequence of acoustic frames. The operations further include, for each acoustic frame in the sequence of acoustic frames paired with a corresponding video frame in a sequence of video frames: generating, by an audiovisual encoder, a corresponding audiovisual higher-order feature representation for the corresponding acoustic higher-order feature frame and the corresponding video frame; and generating, by a joint network, at an output step, a probability distribution over possible speech recognition hypotheses based on the corresponding audiovisual higher-order feature representation. The operations also include, for each corresponding acoustic frame in the sequence of acoustic frames not paired with a corresponding video frame, generating, by the joint network, at an output step, a probability distribution over possible speech recognition hypotheses based on the corresponding acoustic higher-order feature representation.

Implementations of the disclosure may include one or more of the following optional features. In some implementations, the audio encoder includes at least one of a first plurality of multi-head attention layers, a first conformer, or a first plurality of long short term memory (LSTM) layers. In some implementations, the audiovisual encoder includes at least one of a second plurality of multi-head attention layers, a second conformer, or a second plurality of LSTM layers.

In some examples, generating the corresponding audiovisual higher-order feature representation includes: generating, at each of the plurality of output steps, a corresponding visual higher-order feature representation for the corresponding one of the video frames in the sequence of video frames; and fusing the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation. In some implementations, fusing the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation includes concatenating the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation. In alternative implementations, fusing the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation includes applying cross-model attention to the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation.

In some implementations, the operations further include: receiving a sequence of non-blank symbols output by a final softmax layer; generating, by a prediction network, based on the sequence of non-blank symbols, at each of the plurality of output steps, a dense representation. The operations also include selecting one of: for each corresponding acoustic frame in the sequence of acoustic frames paired with the corresponding one of the video frames in the sequence of video frames, the corresponding audiovisual higher-order feature representation; or for each corresponding acoustic frame in the sequence of acoustic frames that is not paired with any video frame in the sequence of video frames, the acoustic higher-order feature representation. The operations further include generating, by the joint network, based on the dense representation and the selected one of the corresponding audiovisual higher-order feature representation or the corresponding acoustic higher-order feature representation, at each of the plurality of output steps, a probability distribution over possible speech recognition hypotheses. In some examples, the prediction network includes a two-layer bidirectional long short term memory (LSTM) model; and the joint network includes a multi-layer perceptron model.

In some examples, the audio encoder and the audiovisual encoder are trained jointly. In alternative examples, the operations further include: during a first training phase: receiving a first set of training utterances including acoustic frames without corresponding video frames; and training the audio encoder using the first set of training utterances; and, during a second training phase: receiving a second set of training utterances including acoustic frames and corresponding video frames; and training, while holding coefficients of the audio encoder fixed after the first training phase is complete, the audiovisual encoder using the second set of training utterances while the coefficients of the audio encoder are held fixed.

The details of one or more implementations of the disclosure are set forth in the accompanying drawings and the description below. Other aspects, features, and advantages will be apparent from the description and drawings, and from the claims.

DESCRIPTION OF DRAWINGS

FIG. **1** is a schematic view of an example multi-speaker environment including a cascaded audiovisual automated speech recognition (AV-ASR) model for transcribing speech from audiovisual data.

FIG. **2**A is a schematic view of the cascaded AV-ASR model operating in an audiovisual mode.

FIG. **2**B is a schematic view of the cascaded AV-ASR model operating in an acoustic-only mode.

FIG. **3** is a schematic view of an example prediction network.

FIGS. **4**A and **4**B are schematic views of example training processes for training the cascaded AV-ASR model.

FIG. **5** is an example arrangement of operations for a method of transcribing speech from audiovisual data using the cascaded AV-ASR model.

FIG. **6** is a schematic view of an example computing device that may be used to implement the systems, models, processes, and methods described herein.

Like reference symbols in the various drawings indicate like elements.

DETAILED DESCRIPTION

Automatic speech recognition (ASR) is an important technology that is increasingly used in mobile devices and other devices. In general, ASR systems provide accurate transcriptions of what a person has said. However, in noisy environments, or when audio quality of a recorded utterance is poor, obtaining accurate ASR results can be difficult. When video of a speaker is available, the video can be leveraged to help improve ASR results. For instance, the video of the speaker may provide information regarding motion of the lips while the speaker is speaking an utterance, and can be combined with audio of the utterance to assist in transcribing the utterance.

Learning from multiple modalities (e.g., using audio and video) using large-scale datasets has increasingly been shown to produce more accurate predictions over those learned from a single modality (e.g., only audio). Such approaches have led to state-of-the-art performance on numerous tasks in computer vision, natural language processing, and speech recognition. For example, audiovisual ASR (AV-ASR) models (i.e., ASR models that use both audio data representing an utterance spoken by a speaker and video data representing the face of the speaker while they speak the utterance) have consistently achieved transcription performance superior to audio-only ASR (AO-ASR) models, especially for noisy or overlapping speech. However, it is common for the video of a speaker to be partially or entirely missing in some typical ASR applications like providing closed captions for online meetings. For example, a speaker might move off screen, a camera may be turned off, a speaker may occasionally be occluded by other on-screen objects or changes in lighting conditions, etc. Unfortunately, conventional AV-ASR models perform poorly when video is missing. For example, when video is missing, conventional AV-ASR models may perform worse than a corresponding AO-ASR model.

Implementations herein are directed toward a cascaded AV-ASR model architecture that is robust to missing video. Here, the goal is robustness to missing video, and not missing audio, because current lip-reading models (e.g., video-only ASR models) do not perform well enough for many practical applications of ASR. Notably, while the performance of the cascaded AV-ASR model is improved by the presence of video during training or inference, a lack of video during inference does not degrade the performance of the cascaded AV-ASR model below that of an AO-ASR model. In particular, when video is absent, the cascaded AV-ASR model operates in an acoustic-only mode, and performs the same as an AO-ASR model. But, when video is present, the cascaded AV-ASR model improves ASR performance by fusing acoustic and video information. In disclosed implementations, the cascaded AV-ASR model includes a cascaded encoder and a decoder. The cascaded encoder includes an audiovisual encoder stacked on top of an acoustic encoder. When video is absent, outputs of the acoustic encoder are routed to the decoder model for decoding to generate a transcription of an utterance. However, when video is present, outputs of the acoustic encoder and the video are routed to the audiovisual encoder, and outputs of the audiovisual encoder are router to the decoder model for decoding to generate a transcription of an utterance.

Referring to FIG. **1**, in some implementations, an environment **100** includes a plurality of participants **10**, **10***a-j* that are attending a meeting (e.g., a video conference). Here, the environment **100** includes a host meeting room with six participants **10***a-f* that are attending the meeting (e.g., the video conference) in the host meeting room. The environment **100** includes a system **101** that includes a user device **110**, a network **120**, and a remote system **130**. The user device **110** receives one or more content feeds **12**, **12***a-n* (also referred to as a multi-media feed, a content stream, or a feed) via a network **120** from a remote system **130**. In the example shown, the user device **110** receives two feeds **12***a*, **12***b* that each correspond to a different remote meeting room. Here, the first feed **12***a* includes three participants **10**, **10***g-i* participating in the meeting from a remote office, and the second feed **12***b* includes a single participant **10**, **10***j* participating from a remotely-located residence of the participant **10***j*. User devices associated with the remote meeting participants **10***g*-**10***j* may likewise receive feeds **12** of the other meeting locations. Each content feed **12** may correspond to audiovisual data **204** including an audio portion **210** corresponding to an audio track, and a video portion **220** including a video track. As used herein, the terms "audio track" and "audio portion" may be used interchangeably. The video portion **220** may be associated with image data such as video content, video signal, or video stream. Here, the video portion **220** may include video face tracks **230** each associated with faces of one or more of the participants **10***a-f*. The user device **110** includes, or is in communication with, a display **111** configured to display the video portions **220** of the audiovisual data **204** for the feeds **12**. The user device **110** also includes, or is in communication with, an audio speaker **112** configured to audibly output the audio portions **210** of the audiovisual data **204** for the feeds **12**.

In addition to receiving audiovisual data **204** from the remote meeting rooms via respective content feeds **12**, the user device **110** includes, or is in communication with, one or more peripherals **114**, **114***a-n* for capturing audiovisual data **204** from the host meeting room. For instance, an audio capture device **114**, **114***a* (e.g., an array of one or more microphones) is configured to capture utterances **14** spoken by the participants **10***a-f* and convert the captured utterances **14** into audio data that corresponds to an audio portion **210** of the audiovisual data **204** for the host meeting room. On the other hand, an image capture device **114**, **114***b* (e.g., one or more cameras) is configured to capture image data that corresponds to a video portion **220** of the audiovisual data **204** for the host meeting room. Here, the video portion **220** may include video face tracks **230** each associated with faces of one or more of the participants **10***a-f*. In some configurations, the image capture device **114***b* is configured to capture a 360-degree view about the user device **110** to capture a full view of the host meeting room. For instance, the image capture device **114***b* may include an array of cameras configured to capture the 360-degree view. While not shown for clarity of illustration, in some instances, the display **111** also displays video portions **220** of the audiovisual data **204** for the host meeting room.

In the example shown, the user device **110** includes data processing hardware **116**, and memory hardware **118** in communication with the data processing hardware **116** and storing instructions that, when executed on the data processing hardware **116**, cause the data processing hardware **116** to perform operations. The operations may correspond to any of the disclosed methods, models, and processes. In some examples, a face tracker module (not shown for clarity of illustration) executes on the data processing hardware **116** to detect video face tracks **230** in the video portions **220** of the audiovisual data **204**. Some examples of the user device **110** include, but are not limited to, a video conference computing device, a computer, a laptop, a tablet, a mobile computing device, a television, a monitor, a smart device (e.g., smart speaker, smart display, and smart appliance), and a wearable device.

The remote system **130** may be a distributed system (e.g., cloud computing environment or storage abstraction) having scalable/elastic resources **132**. The resources **132** include computing resources **134** (e.g., data processing hardware) and/or storage resources **136** (e.g. memory hardware). In some implementations, the remote system **130** hosts software that coordinates the environment **100** (e.g., on the computing resources **132**). For instance, the computing resources **132** of the remote system **130** may execute software, such as a real-time communication application or a specialty meeting platform. In some examples, a face tracker module executes on the remote system **130** to detect video face tracks **230** in video portions **220** of the audiovisual data **204**.

A cascaded audiovisual automated speech recognition (AV-ASR) model **200** processes the audiovisual data **204** to generate a transcription **260** for the audiovisual data **204**. Notably, and as described in greater detail below with reference to FIGS. **2**A and **2**B, the cascaded AV-ASR model **200** includes a cascaded encoder **240** and a decoder **250**. The cascaded encoder **240** includes an audiovisual encoder **244** stacked on top of an audio encoder **242**. When a portion of audiovisual data **204** that is being transcribed includes a paired video portion **220** having one or more video frames **222** corresponding to one or more acoustic frames **212** of an audio portion **210** of the portion of audiovisual data **204**, the audio encoder **242** encodes the acoustic frames **212**, the audiovisual encoder **244** encodes the encoded acoustic frames and the video frames **222**, and the decoder **250** decodes the encoded audiovisual representation of the acoustic frames **212** and the video frames **222** to generate a transcription **260**. However, when the portion of audiovisual data **204** being transcribed does not include a paired video frame corresponding to an acoustic frame **212** of an audio portion **210** of the portion of audiovisual data **204** (i.e., includes the audio portion **210** only), the audio encoder **242** encodes the acoustic frames **212**, and the decoder **250** decodes the encoded acoustic representation of the acoustic frames **212** to generate the transcription **260**. In this way, when corresponding video frames **222** are not available, the cascaded AV-ASR model **200** operates in a mode similar to an AO-ASR model using the un-paired audio portion **210**.

As shown, the display **111** associated with the user device **110** may display the transcription **260** generated by the cascaded AV-ASR model **200**. The cascaded AV-ASR model **200** may stream the transcription **260** in real time for output on the display **111** and/or on displays associated with remotely located participants **10***g-j*. Additionally or alternatively, the transcription **260** may be saved on memory hardware **118**, **136** and retrieved at a later time for viewing. The cascaded AV-ASR model **200** may execute on the data processing hardware **116** of the user device **110**, thereby enabling the user device **110** to perform on-device speech recognition without the need to perform speech recognition on a server (e.g., remote system **130**). On-device speech recognition alleviates the requirement of establishing a network connection with a server, incurring latency due to bandwidth constraints, and also preserve data that a user may not want to share with the server. Moreover, executing the cascaded AV-ASR model **200** on the user device **110** may permit the use of higher fidelity audiovisual data **204** since neither one of the audio portions **210** or the video portions **220** would need to be compressed to satisfy network bandwidth constraints, as may be required if the audiovisual data **204** were sent to a server via a network for processing.

The cascaded AV-ASR model **200** may also execute on the data processing hardware **134** of the remote system **130**. For instance, the data processing hardware **134** of the remote system **130** may execute instructions stored on the memory hardware **136** of the remote system **130** for executing disclosed methods, processes and models (e.g., the cascaded AV-ASR model **200**). Here, the cascaded AV-ASR model **200** may process the multi-speaker audiovisual data **204** to generate the transcription **260**, as discussed above. The remote system **130** may transmit the transcription **260** over the network **120** to the user device **110** for display on the display **111**. The remote system **130** may similarly transmit the transcription **260** to computing devices/display devices associated with the participants **10***g-i* corresponding to the first feed **12***a*, and/or the participant **10***j* corresponding to the second feed **12***b*.

The data processing hardware **134** of the remote system **130** may provide increased processing capabilities that are not achievable on client devices and may have more available memory resources, thereby enabling the use of larger models with more parameters for increased transcription accuracy. In some examples, one or more portions of the cascaded AV-ASR model **200** execute on the user device **110** while one or more other portions of the cascaded AV-ASR model **200** execute on the remote system (e.g., server) **130**.

FIG. **2**A is schematic view of the cascaded AV-ASR model **200** while operating in an audiovisual mode. That is, when a portion of audiovisual data **204** that is being transcribed by the cascaded AV-ASR model **200** includes a video portion **220** having one or more video frames **222**, **222***a-n* paired with and corresponding to one or more acoustic frames **212**, **212***a-n* of an audio portion **210** of the portion of audiovisual data **204**. Here, paired and corresponding does not require that there is a one-to-one correspondence between video and acoustic frames. For example, some video frames may be dropped (for any reason) such that a video frame corresponds to more than one acoustic frame. FIG. **2**B is schematic view of the cascaded AV-ASR model **200** while operating in an acoustic-only (AO) mode. That is, when a portion of audiovisual data **204** that is being transcribed by the cascaded AV-ASR model **200** does not include a paired video frame **222** corresponding to an acoustic frame **212** of the portion of audiovisual data **204**. Stated differently, when the portion of the audiovisual data **204** includes unpaired acoustic frames **212** (i.e., no corresponding video frame is available), the AV-ASR model **200** operates in the AO mode.

The example cascaded AV-ASR model **200** includes the cascaded encoder **240** and the decoder **250**. The cascaded encoder **240** refers to a model structure where the encoding pathway includes two encoders that can cascade such that the output of one encoder can feed an input of the other encoder prior to decoding. Here, the cascaded encoder **240** includes an audiovisual encoder **244** stacked on top of an audio encoder **242**. When operating in audiovisual mode (see FIG. **2**A), the audiovisual encoder **244** can improve transcription accuracy of the cascaded AV-ASR model **200** by fusing acoustic higher-order feature representations **246**, **246***a-n* generated by the audio encoder **242** with visual higher-order feature representations generated from the video frames **222** to generate audiovisual higher-order feature representations **248**, **248***a-n*. The decoder **250** then decodes the audiovisual higher-order feature representations **248** to generate transcriptions **260**. However, when operating in acoustic-only mode (see FIG. **2**B), the audiovisual encoder **244** is bypassed, and the decoder **250** instead decodes the acoustic higher-order feature representations **246** to generate the transcriptions **260**. When operating in the acoustic-only mode (see FIG. **2**B), the cascaded AV-ASR model **200** operates like, and produces the same predictions as, an AO-ASR model. Thus, the lack of corresponding video frames **222** does not cause a decrease in the transcription accuracy of the cascaded AV-ASR model **200**. In some instances, the video frames **222** represent a partial set of the video frames **222** for the video portions **220**. For example, video frames **222** may be missing or video portions **220** may be downsampled. In some implementations, the video frames **222** may represent video face tracks **230** corresponding to particular speakers who are detected as speaking. The cascaded AV-ASR model **200** is applicable to streaming and non-streaming speech recognition.

In some implementations, the cascaded AV-ASR model **200** is trained during a single pass such that the audio encoder **242** and the audiovisual encoder **244** are trained jointly. Alternatively, the audio encoder **242** is trained in a first phase, and the audiovisual encoder **244** is trained in a second phase while weights of the audio encoder **242** are held fixed. Such a two phase training process may be used, for example, to teach an arbitrary or pre-existing AO-ASR model to use video frames to increase transcription accuracy. In other words, a pre-trained audio encoder **242** trained on audio-only data for use in a pre-existing AO-ASR model may be incorporated into the AV-ASR model **200**, whereby the AV-ASR model **200** is trained by training the audiovisual encoder **244** (and optionally the decoder **250**) on audio visual data **204** while parameters/weights of the pre-trained audio encoder **242** are held fixed/frozen.

The audio encoder **242** receives, as input, a sequence of d-dimensional acoustic frames **212** $a=(a_1, a_2, \ldots, a_T)$, where $a_t \in \mathbb{R}^d$ and produces, at each time step, an acoustic higher-order feature representation **246**. Here, the acoustic higher-order feature representation **246** is denoted as e^a. In the audiovisual mode shown in FIG. **2**A, the audiovisual encoder **244** is connected in cascade with the audio encoder **242** and is trained to: receive the acoustic higher-order feature representation e^a **246** as an input; receive, as another input, a sequence of k-dimensional video frames **222** $v=(v_1, v_2, \ldots, v_T)$, where $v_t \in \mathbb{R}^k$; produce, at each time step, a visual higher-order feature representation e^v; and fuse the acoustic higher-order feature representation e^a **246** and the visual higher-order feature representation e^v to generate an audiovisual higher-order feature representation **248**. Here, the audiovisual higher-order feature representation **248** is denoted as e^{av}, where e^{av}=Fuse(e^a e^v), and Fuse( ) represents, for example, concatenation or cross-modal attention. The audiovisual encoder **244** is connected to the decoder **250**, and the decoder **250** receives the audiovisual higher-order feature representation e^{av} **248** as input. In the acoustic-only mode shown in FIG. **2**B, the audiovisual encoder **244** is bypassed, the audio encoder **242** is connected to the decoder **250**, and the decoder **250** instead receives the acoustic higher-order feature representation e^a **246** as input.

The decoder **250** includes a joint network **252** and a prediction network **300**. The prediction network **300** may be a long short term memory (LSTM) network, which, like a language model (LM), processes a sequence of non-blank symbols y_r output by a final softmax layer (not shown for clarity of illustration) so far, $y_0, \ldots, y_{ui-1}$, into a representation p_{u_i}, **350**. As described in greater detail below, the representation p_{u_i}, **350** includes a single embedding vector. Notably, a sequence of non-blank symbols y_r received at the prediction network **300** captures linguistic dependencies between non-blank symbols predicted during the previous time steps so far to assist the joint network **252** in predicting the probability of a next output symbol or blank symbol during the current time step. As described in greater detail below, to contribute to techniques for reducing the size of the prediction network **300** without sacrificing accuracy/performance of the cascaded AV-ASR model **200**, the prediction network **300** may receive a limited-history sequence of non-blank symbols $y_{ui-n}, \ldots, y_{ui-1}$ that is limited to the N previous non-blank symbols output by the final softmax layer.

FIG. **3** shows the prediction network **300** of the cascaded AV-ASR model **200** receiving, as input, a sequence of non-blank symbols $y_{ui-n}, \ldots, y_{ui-1}$ that is limited to the N previous non-blank symbols **301***a-n* output by the a softmax layer. In some examples, N is equal to two. In other examples, N is equal to five, however, the disclosure is non-limiting and N may equal any integer. The sequence of non-blank symbols **301***a-n* indicates a speech recognition result (i.e., the transcription **260** of FIG. **1**). In some implementations, the prediction network **300** includes a multi-headed attention mechanism **302** that shares a shared embedding matrix **304** across each head **302**A-**302**H of the multi-headed attention mechanism. In one example, the multi-headed attention mechanism **302** includes four heads. However, any number of heads may be employed by the multi-headed attention mechanism **302**. Notably, the multi-headed attention mechanism improves performance significantly with minimal increase to model size. As described in greater detail below, each head **302**A-H includes its own row of position vectors **308**, and rather than incurring an increase in model size by concatenating outputs **318**A-H from all the heads, the outputs **318**A-H are instead averaged by a head average module **322**.

Referring to the first head **302**A of the multi-headed attention mechanism **302**, the head **302**A generates, using the shared embedding matrix **304**, a corresponding embedding **306**, **306***a-n* (e.g., $X \in \mathbb{R}^{N \times d_e}$) for each non-blank symbol **301** among the sequence of non-blank symbols $y_{ui-n}, \ldots, y_{ui-1}$ received as input at the corresponding time step from the plurality of time steps. Notably, since the shared embedding matrix **304** is shared across all heads of the multi-headed attention mechanism **302**, the other heads **302**B-H all generate the same corresponding embeddings **306** for each non-blank symbol. The head **302**A also assigns a respective position vector PV_{Aa-An} **308**, **308**Aa-An (e.g., $P \in \mathbb{R}^{H \times N \times d_e}$) to each corresponding non-blank symbol in the sequence of non-blank symbols $y_{ui-n}, \ldots, y_{ui-1}$. The respective position vector PV **308** assigned to each non-blank symbol indicates a position in the history of the sequence of non-blank symbols (e.g., the N previous non-blank symbols output by the final softmax layer). For instance, the first position vector PV_{Aa} is assigned to a most recent position in the history, while the last position vector PV_{An} is assigned to a last position in the history of the N previous non-blank symbols output by the final softmax layer. Notably, each of the embeddings **306** may include a same dimensionality (i.e., dimension size) as each of the position vectors PV **308**.

While the corresponding embedding generated by shared embedding matrix **304** for each for each non-blank symbol **301** among the sequence of non-blank symbols **301***a-n*, $y_{ui-n}, \ldots, y_{ui-1}$, is the same at all of the heads **302**A-H of the multi-headed attention mechanism **302**, each head **302**A-H defines a different set/row of position vectors **308**. For instance, the first head **302**A defines the row of position vectors PV_{Aa-An}**308**Aa-An, the second head **302**B defines a different row of position vectors PV_{Ba-Bn} **308**$_{Ba-Bn}$, . . . , and the H^{th} head **302** H defines another different row of position vectors PV_{Ha-Hn}**308**$_{Ha-Hn}$.

For each non-blank symbol in the sequence of non-blank symbols **301***a-n* received, the first head **302**A also weights, via a weight layer **310**, the corresponding embedding **306** proportional to a similarity between the corresponding embedding and the respective position vector PV **308** assigned thereto. In some examples, the similarity may include a cosine similarity (e.g., cosine distance). In the example shown, the weight layer **310** outputs a sequence of weighted embeddings **312**, **312**Aa-An each associated the corresponding embedding **306** weighted proportional to the respective position vector PV **308** assigned thereto. Stated differently, the weighted embeddings **312** output by the weight layer **310** for each embedding **306** may correspond to a dot product between the embedding **306** and the respective position vector PV **308**. The weighted embeddings **312** may be interpreted as attending over the embeddings in proportion to how similar they are to the positioned associated with their respective position vectors PV **308**. To increase computational speed, the prediction network **300** includes non-recurrent layers, and therefore, the sequence of weighted embeddings **312**Aa-An are not concatenated, but instead, averaged by a weighted average module **316** to generate, as output from the first head **302**A, a weighted average **318**A of the weighted embeddings **312**Aa-An represented by.

$$Prediction(X, P) = \frac{1}{H * N} \sum_{h,n} X_n * \sum_{e} (X_{n,e} * P_{h,n,e}) \tag{1}$$

In Equation 1, h represents the index of the heads **302**, n represents position in context, and e represents the embedding dimension. Additionally, in Equation 1, H, N, and d_e include the sizes of the corresponding dimensions. The position vector PV **308** does not have to be trainable and may include random values. Notably, even though the weighted embeddings **312** are averaged, the position vectors PV **308** can potentially save position history information, alleviating the need to provide recurrent connections at each layer of the prediction network **300**.

The operations described above with respect to the first head **302**A, are similarly performed by each other head **302**B-H of the multi-headed attention mechanism **302**. Due to the different set of positioned vectors PV **308** defined by each head **302**, the weight layer **310** outputs a sequence of weighted embeddings **312**Ba-Bn, **312**Ha-Hn at each other head **302**B-H that is different than the sequence of weighted embeddings **312**Aa-Aa at the first head **302**A. Thereafter, the weighted average module **316** generates, as output from each other corresponding head **302**B-H, a respective weighted average **318**B-H of the corresponding weighted embeddings **312** of the sequence of non-blank symbols.

In the example shown, the prediction network **300** includes a head average module **322** that averages the weighted averages **318**A-H output from the corresponding heads **302**A-H. A projection layer **326** with swish activation may receive, as input, an output **324** from the head average module **322** that corresponds to the average of the weighted averages **318**A-H, and generate, as output, a projected output **328**. A final layer normalization **330** may normalize the projected output **328** to provide the single embedding vector Pu_i **350** at the corresponding time step from the plurality of time steps. The prediction network **300** generates only a single embedding vector Pu_i **350** at each of the plurality of time steps subsequent to an initial time step.

In some configurations, the prediction network **300** does not implement the multi-headed attention mechanism **302** and only performs the operations described above with respect to the first head **302**A. In these configurations, the weighted average **318**A of the weighted embeddings **312**Aa-An is simply passed through the projection layer **326** and layer normalization **330** to provide the single embedding vector Pu_i **350**.

Referring back to FIGS. **2**A and **2**B, the joint network **252** combines the representations produced by the cascaded encoder **240** and the prediction network **300**. In the audiovisual mode shown in FIG. **2**A, the joint network **252** receives, as input x, the audiovisual higher-order feature representation e^{av} **248**, and process the input x to produce a joint network output. In the acoustic-only mode shown in FIG. **2**B, the joint network **252** instead receives, as the input x, the acoustic higher-order feature representation e^{a} **246**, and process the input x to produce the joint network output. The joint network output can be a probability distribution, $P(y_i|y_{i-1}, \ldots, y_0, x)$, over the current sub-word unit, y_i, given the sequence of the N previous non-blank symbols previous units, $\{y_{i-1}, \ldots, y_{i-N}\}$, and the input x.

The joint network **252** is configured to generate, at each output step, a probability distribution over possible speech recognition hypotheses. Stated differently, the joint network **252** generates, at each output step (e.g., time step), a probability distribution over possible speech recognition hypotheses. Here, the "possible speech recognition hypotheses" correspond to a set of output labels/symbols (also referred to as "speech units") each representing a grapheme (e.g., symbol/character) or a word piece in a specified natural language. For example, when the natural language is English, the set of output labels may include twenty-seven (27) symbols, e.g., one label for each of the 26-letters in the English alphabet and one label designating a space. Accordingly, the joint network **252** may output a set of values indicative of the likelihood of occurrence of each of a predetermined set of output labels. This set of values can be a vector (e.g., a one-hot vector) and can indicate a probability distribution over the set of output labels. In some cases, the output labels are graphemes (e.g., individual characters, and potentially punctuation and other symbols), but the set of output labels is not so limited. For example, the set of output labels can include wordpieces and/or entire words, in addition to or instead of graphemes. The output labels could also be other types of speech units, such as phonemes or sub-phonemes. The output distribution of the joint network **252** can include an aposteriori probability value for each of the different output labels. Thus, if there are 100 different output labels representing different graphemes or other symbols, the output of the joint network **252** can include 100 different probability values, one for each output label. The probability distribution can then be used to select and assign scores to candidate orthographic elements (e.g., graphemes, wordpieces, and/or words) in a beam search process (e.g., by the softmax layer) for determining the transcription **260**.

In some implementations, to further reduce the size of the decoder **250**, i.e., the prediction network **300** and the joint network **252**, parameter tying between the prediction network **300** and the joint network **252** is applied. Specifically, for a vocabulary size |V| and an embedding dimension d_e, the shared embedding matrix **304** at the prediction network **300** is $E \in \mathbb{R}^{|V| \times d_e}$. Meanwhile, a last hidden layer includes a dimension size d_h at the joint network **252**, feed-forward projection weights from the hidden layer to the output logits will be $W \in \mathbb{R}^{d_h \times |V+1|}$, with an extra blank token in the vocabulary. Accordingly, the feed-forward layer corresponding to the last layer of the joint network **252** includes a weight matrix $[d_h, |V]|$. By having the prediction network **300** to tie the size of the embedding dimension d_e to the dimensionality d_h of the last hidden layer of the joint network **252**, the feed-forward projection weights of the joint network **252** and the shared embedding matrix **304** of the prediction network **300** can share their weights for all non-blank symbols via a simple transpose transformation. Since the two matrices share all their values, the decoder **250** only needs to store the values once on memory, instead of storing two individual matrices. By setting the size of the embedding dimension d_e equal to the size of the hidden layer dimension d_h, the decoder **250** reduces a number of parameters equal to the product of the embedding dimension d_e and the vocabulary size |V|. This weight tying corresponds to a regularization technique.

The softmax layer may employ any technique to select the output label/symbol with the highest probability in the distribution as the next output symbol predicted by the cascaded AV-ASR model **200** at the corresponding output step. In this manner, the cascaded AV-ASR model **200** does not make a conditional independence assumption, rather the prediction of each symbol is conditioned not only on the acoustic and video frames but also on the sequence of labels output so far. The cascaded AV-ASR model **200** does assume an output symbol is independent of future acoustic and video frames **222**, which allows the cascaded AV-ASR model **200** to be employed in a streaming fashion. In some implementations, the softmax layer is separate from the decoder **250** and processes the output from the decoder **250**. The output of the softmax layer is then used in a beam search process to select orthographic elements. In some implementations, the softmax layer is integrated with the decoder **250**, such that the output of the decoder **250** represents the output of the softmax layer.

In some implementations, the cascaded AV-ASR model **200** includes an audiovisual recurrent neural network-transducer (RNN-T) model architecture. In some examples, the audio encoder **242** includes a plurality of multi-head attention layers, a conformer having a plurality of conformer layers (e.g., **17** conformer layers), or a long short term memory (LSTM) model having a plurality of LSTM layers (e.g., 8 LSTM layers). In some examples, the audiovisual encoder **244** includes a plurality of multi-head attention layers, a conformer, or an LSTM model. Here, the conformer may include 17 layers, full context attention, a model dimension of **512**, 8 attention heads, a convolutional kernel size of 32, no dropout, and group normalization with **32** groups in place of layer normalization. Here, the LSTM model may include 8 bi-directional layers, a model dimension of **512** for each direction, and weight normalization. The types of audio encoders **242** and audiovisual encoders **244** may be combined in various ways. For example, the encoders **242**, **244** may both be conformers, the encoders **242**, **244** may both be LSTM models, a conformer-based audio encoder **242** may be used with an LSTM-based audiovisual encoder **244**, or an LSTM-based audio encoder **242** may be used with a conformer-based audiovisual encoder **244**. In some implementations, the audiovisual encoder **244** includes concatenation to fuse acoustic higher-order feature representations e^a **246** and visual higher-order feature representations e^v. Alternatively, the audiovisual encoder **244** includes cross-modal attention to fuse acoustic higher-order feature representations e^a **246** and visual higher-order feature representations e^v. In some examples, the decoder **250** includes a two-layer bidirectional LSTM model with a hidden dimension of **2048**, an embedding dimension of **128**, and a beam width of size 8; and the joint network **252** includes a multilayer perceptron (MLP) with a hidden dimension of **640**.

Within the decoder **250**, the prediction network **300** may have two 2,048-dimensional LSTM layers, each of which is also followed by a 640-dimensional projection layer. In other configurations, the prediction network **300** may instead include conformer or transformer layers in lieu of LSTM layers. In yet other configurations, the prediction network **300** includes a V2 embedding look up table that includes an embedding prediction network. At each time step, the V2 embedding lookup table may receive, as input, the previous two predictions (e.g., 1-hot vectors) output by the joint network **252**, compute a respective embedding d_1, d_2 for each of the previous two predictions, and provide a concatenated output $[d_1, d_2]$ to the joint network **252**. Comparatively, the V2 embedding lookup table may have only about two (2) million parameters, whereas an LSTM-based prediction network may include about 23.4 million parameters. Finally, the joint network **252** may also be a one-layer neural network with **640** hidden units. The softmax layer may be composed of a unified word piece or grapheme set that is generated using all unique word pieces or graphemes in a plurality of training data sets.

FIG. **4**A is a schematic view of an example training process **400**, **400***a* for training the cascaded AV-ASR model **200**. Here, the example training process **400***a* jointly trains the audio encoder **242** and the audiovisual encoder **244**. The training process **400***a* may also train the decoder **250**. The training process **400***a* may execute on the remote system **130** (i.e., on the data processing hardware **134** or on the user device **110** (i.e., on the data processing hardware **116**).

For each audiovisual training sample **430**, **430***a-n* in a set of audiovisual trainings samples **430**, the training process **400***a* processes, using the cascaded AV-ASR model **200** operating in the audiovisual mode (see FIG. **2**A), acoustic frames **434** of an audio portion of the training sample **430** and corresponding paired video frames **436** of a video portion of the training sample **430** to obtain one or more speech recognition hypotheses **452** for the training sample **430**.

Thereafter, for each training sample **430**, a loss term module **450** receives the one or more speech recognition hypotheses **452** output by the cascaded AV-ASR model **200** for the training sample **430**, and determines a log loss term $\mathcal{L}_{\ell\ell}$ **454** based on the predicted speech recognition hypotheses **452** and a corresponding ground-truth transcription y* **432** for the training sample **430**. However, other loss terms, such as minimum word error rate or an RNN-T loss, may be used. Here, the log loss term $\mathcal{L}_{\ell\ell}$ **454** is the negative of the log of the probability Pr(y*|x) determined by the joint network **252** for the ground-truth transcription y* **432**. Based on the log loss term $\mathcal{L}_{\ell\ell}$ **454** output by the loss term module **450** for each training sample **430**, the training process **400***a* trains/updates parameters/weights/coefficients of the cascaded AV-ASR model **200** to minimize log loss term $\mathcal{L}_{\ell\ell}$ **454**. Parameters/weights/coefficients of the decoder **250** may also be trained/updated using the log loss term **454**. By reducing this log loss metric $\mathcal{L}_{ll}$ **454**, the training process **400***a* trains the cascaded AV-ASR model **200** to increase the probabilities for the set of ground truth transcriptions **432** conditioned on corresponding input acoustic frames **434** and the paired corresponding input video frames **436** as the input x.

FIG. **4**B is a schematic view of another example training process **400**, **400***b* for training the cascaded AV-ASR model **200**. The example training process **400***b* is a two-stage training process that separately trains the audio encoder **242** and the audiovisual encoder **244**. The training process **400***b* may also train the decoder **250**. The training process **400***b* may execute on the remote system **130** (i.e., on the data processing hardware **134** or on the user device **110** (i.e., on the data processing hardware **116**). The training process **400***b* may train the AV-ASR model **200** on a set of audiovisual training samples **430**, **430***a-n* that each include a ground-truth transcription **432**, a sequence of acoustic frames **434**, and corresponding paired video frames **436**. The training process **400***b* may also train the AV-ASR model **200** on a set of audio-only training samples **440**, **440***a-n* that each include a ground-truth transcription **442** and a sequence of acoustic frames **444** not paired with any corresponding video frames.

In a first training phase **460**, for each audiovisual training sample **430** and each audio-only training sample **440**, the training process **400***b* processes, using the cascaded AV-ASR model **200** operating in the AO mode (see FIG. **2**B), the corresponding acoustic frames **434**, **444** of an audio portion of the training sample **430**, **440** to obtain one or more speech recognition hypotheses **452** for the acoustic training sample **430**, **440**. Here, the acoustic training samples **430** may be formed by only using the acoustic frames **434** of the audiovisual training samples **430**.

Thereafter, for each training sample **430**, **440**, the loss term module **450** receives the one or more speech recognition hypotheses **452** output by the cascaded AV-ASR model **200** for the training sample **430**, **440**, and determines the log loss term $\mathcal{L}_{\ell\ell}$ **454** based on the predicted speech recognition hypotheses **452** and a corresponding ground-truth transcription y* **432**, **442** for the training sample **430**, **440**. However, other loss terms, such as minimum word error rate or an RNN-T loss, may be used. Here, the log loss term $\mathcal{L}_{\ell\ell}$ **454** is the negative of the log of the probability Pr(y*|x) determined by the joint network **252** for the ground-truth transcription y* **432**, **442**. Based on the log loss term $\mathcal{L}_{\ell\ell}$ **454** output by the loss term module **450** for each training sample **430**, **440**, the training process **400***b* trains/updates parameters/weights/coefficients of the audio encoder **242** to minimize the log loss term $\mathcal{L}_{\ell\ell}$ **454**. Parameters/weights/coefficients of the decoder **250** may also be trained/updated using the log loss term **454**. By reducing this log loss metric $\mathcal{L}_{ll}$ **454**, the training process **400***b* trains the audio encoder **242** to increase the probabilities for the set of ground truth transcriptions **432**, **442** conditioned on corresponding input acoustic frames **444** as the input x.

In a second training phase **470**, for each audiovisual training sample **430**, **430***a-n* in the set of audiovisual trainings samples **430**, the training process **400***b* processes, using the cascaded AV-ASR model **200** operating in the audiovisual mode (see FIG. **2**A), acoustic frames **434** of an audio portion of the training sample **430** and corresponding paired video frames **436** of a video portion of the training sample **430** to obtain one or more speech recognition hypotheses **452** for the training sample **430**.

Thereafter, for each training sample **430**, a loss term module **450** receives the one or more speech recognition hypotheses **452** output by the cascaded AV-ASR model **200** for the training sample **430**, and determines a log loss term $\mathcal{L}_{\ell\ell}$ **454** based on the predicted speech recognition hypotheses **452** and a corresponding ground-truth transcription y* **432** for the training sample **430**. However, other loss terms, such as minimum word error rate or an RNN-T loss, may be used. Here, the log loss term $\mathcal{L}_{\ell\ell}$ **454** is the negative of the log of the probability Pr(y*|x) determined by the joint network **252** for the ground-truth transcription y* **432**. Based on the log loss term $\mathcal{L}_{\ell\ell}$ **454** output by the loss term module **450** for each training sample **430**, the training process **400***b* trains/updates parameters/weights/coefficients of the audiovisual encoder **244** to minimize log loss term $\mathcal{L}_{\ell\ell}$ **454**. Parameters/weights/coefficients of the decoder **250** may also be trained/updated using the log loss term **454**. However, other loss terms, such as minimum word error rate or an RNN-T loss, may be used. Notably, coefficients/parameters/weights of the audio encoder **242** are held fixed while the coefficients/parameters/weights of the audiovisual encoder **244** are updated during the second training phase **470**. By reducing this log loss metric $\mathcal{L}_{ll}$ **454**, the training process **400***b* trains the cascaded AV-ASR model **200** to increase the probabilities for the set of ground truth transcriptions **432** conditioned on corresponding input acoustic frames **434** and the paired corresponding input video frames **436** as the input x. Notably, because the parts of the cascaded AV-ASR model **200** that activate when the cascaded AV-ASR model **200** sees acoustic-only data are frozen, the cascaded AV-ASR model **200** is guaranteed to never perform worse than its acoustic-only baseline from first training phase **460**.

FIG. **5** provides a flowchart of an example arrangement of operations for a method **500** of using the cascaded AV-ASR model **200** to transcribe speech from audiovisual data **204**. The cascaded AV-ASR model **200** and the operations for the method **500** may execute on the data processing hardware **116** of the user device **110** of FIG. **1**, the data processing hardware **134** of the remote system (e.g., distributed system) **130** of FIG. **1**, or a combination thereof.

The method **500** includes at operation **502**, receiving a sequence of acoustic frames **212**. At operation **504**, the method **500** includes generating, by an audio encoder **242**, at each of a plurality of output steps, an acoustic higher-order feature representation e^a **246** for a corresponding acoustic frame **212** in the sequence of acoustic frames **212**.

At operation **506**, the method **500** includes, for each acoustic frame **212** in the sequence of acoustic frames **212** paired with a corresponding video frame **222**: generating, by an audiovisual encoder **244**, a corresponding audiovisual higher-order feature representation e^{av} **248** for the corresponding acoustic higher-order feature representation e^a **246** and the corresponding paired video frame **222**; and generating, by a joint network **252**, at an output step, a probability distribution over possible speech recognition hypotheses based on the audiovisual higher-order feature representation e^{av} **248**.

At operation **508**, the method **500** includes, for each corresponding acoustic frame **212** in the sequence of acoustic frames **212** not paired with a corresponding video frame **222**, generating, by the joint network **252**, at an output step, a probability distribution over possible speech recognition hypotheses based on the acoustic higher-order feature representation e^a **246**.

FIG. **6** is schematic view of an example computing device **600** that may be used to implement the systems, models, processes, and methods described in this document. The computing device **600** is intended to represent various forms of digital computers, such as laptops, desktops, workstations, personal digital assistants, servers, blade servers, mainframes, and other appropriate computers. The components shown here, their connections and relationships, and their functions, are meant to be exemplary only, and are not meant to limit implementations of the disclosures described and/or claimed in this document.

The computing device **600** includes a processor **610** (i.e., data processing hardware) that can be used to implement the data processing hardware **116** and **134**), memory **620** (i.e., memory hardware) that can be used to implement the memory hardware **118** and **136**), a storage device **630** (i.e., memory hardware) that can be used to implement the memory hardware **118** and **136** and the data store **420**, a high-speed interface/controller **640** connecting to the memory **620** and high-speed expansion ports **650**, and a low speed interface/controller **660** connecting to a low speed bus **670** and a storage device **630**. Each of the components **610**, **620**, **630**, **640**, **650**, and **660**, are interconnected using various busses, and may be mounted on a common motherboard or in other manners as appropriate. The processor **610** (e.g., data processing hardware **116**, **134** of FIG. **1**) can process instructions for execution within the computing device **600**, including instructions stored in the memory **620** or on the storage device **630** to display graphical information for a graphical user interface (GUI) on an external input/output device, such as display **680** coupled to high speed interface **640**. In other implementations, multiple processors and/or multiple buses may be used, as appropriate, along with multiple memories and types of memory. Also, multiple computing devices **600** may be connected, with each device providing portions of the necessary operations (e.g., as a server bank, a group of blade servers, or a multi-processor system).

The memory **620** (e.g., memory hardware **118**, **136** of FIG. **1**) stores information non-transitorily within the computing device **600**. The memory **620** may be a computer-readable medium, a volatile memory unit(s), or non-volatile memory unit(s). The non-transitory memory **620** may be physical devices used to store programs (e.g., sequences of instructions) or data (e.g., program state information) on a temporary or permanent basis for use by the computing device **600**. The programs may, when executed by data processing hardware, cause the data processing hardware to implement any of the methods, models, and processes disclosed herein. Examples of non-volatile memory include, but are not limited to, flash memory and read-only memory (ROM)/programmable read-only memory (PROM)/erasable programmable read-only memory (EPROM)/electronically erasable programmable read-only memory (EEPROM) (e.g., typically used for firmware, such as boot programs). Examples of volatile memory include, but are not limited to, random access memory (RAM), dynamic random access memory (DRAM), static random access memory (SRAM), phase change memory (PCM) as well as disks or tapes.

The storage device **630** is capable of providing mass storage for the computing device **600**. In some implementations, the storage device **630** is a computer-readable medium. In various different implementations, the storage device **630** may be a floppy disk device, a hard disk device, an optical disk device, or a tape device, a flash memory or other similar solid state memory device, or an array of devices, including devices in a storage area network or other configurations. In additional implementations, a computer program product is tangibly embodied in an information carrier. The computer program product contains instructions that, when executed, perform one or more methods, such as those described above. The information carrier is a computer- or machine-readable medium, such as the memory **620**, the storage device **630**, or memory on processor **610**.

The high speed controller **640** manages bandwidth-intensive operations for the computing device **600**, while the low speed controller **660** manages lower bandwidth-intensive operations. Such allocation of duties is exemplary only. In some implementations, the high-speed controller **640** is coupled to the memory **620**, the display **680** (e.g., through a graphics processor or accelerator), and to the high-speed expansion ports **650**, which may accept various expansion cards (not shown). In some implementations, the low-speed controller **660** is coupled to the storage device **630** and a low-speed expansion port **690**. The low-speed expansion port **690**, which may include various communication ports (e.g., USB, Bluetooth, Ethernet, wireless Ethernet), may be coupled to one or more input/output devices, such as a keyboard, a pointing device, a scanner, or a networking device such as a switch or router, e.g., through a network adapter.

The computing device **600** may be implemented in a number of different forms, as shown in the figure. For example, it may be implemented as a standard server **600***a* or multiple times in a group of such servers **600***a*, as a laptop computer **600***b*, or as part of a rack server system **600***c*.

Various implementations of the systems and techniques described herein can be realized in digital electronic and/or optical circuitry, integrated circuitry, specially designed ASICs (application specific integrated circuits), computer hardware, firmware, software, and/or combinations thereof. These various implementations can include implementation in one or more computer programs that are executable and/or interpretable on a programmable system including at least one programmable processor, which may be special or general purpose, coupled to receive data and instructions from, and to transmit data and instructions to, a storage system, at least one input device, and at least one output device.

A software application (i.e., a software resource) may refer to computer software that causes a computing device to perform a task. In some examples, a software application may be referred to as an "application," an "app," or a "program." Example applications include, but are not limited to, system diagnostic applications, system management applications, system maintenance applications, word processing applications, spreadsheet applications, messaging applications, media streaming applications, social networking applications, and gaming applications.

The non-transitory memory may be physical devices used to store programs (e.g., sequences of instructions) or data (e.g., program state information) on a temporary or permanent basis for use by a computing device. The non-transitory memory may be volatile and/or non-volatile addressable semiconductor memory. Examples of non-volatile memory include, but are not limited to, flash memory and read-only memory (ROM)/programmable read-only memory (PROM)/erasable programmable read-only memory (EPROM)/electronically erasable programmable read-only memory (EEPROM) (e.g., typically used for firmware, such as boot programs). Examples of volatile memory include, but are not limited to, random access memory (RAM), dynamic random access memory (DRAM), static random access memory (SRAM), phase change memory (PCM) as well as disks or tapes.

These computer programs (also known as programs, software, software applications or code) include machine instructions for a programmable processor, and can be implemented in a high-level procedural and/or object-oriented programming language, and/or in assembly/machine language. As used herein, the terms "machine-readable medium" and "computer-readable medium" refer to any computer program product, non-transitory computer readable medium, apparatus and/or device (e.g., magnetic discs, optical disks, memory, Programmable Logic Devices (PLDs)) used to provide machine instructions and/or data to a programmable processor, including a machine-readable medium that receives machine instructions as a machine-readable signal. The term "machine-readable signal" refers to any signal used to provide machine instructions and/or data to a programmable processor.

The processes and logic flows described in this specification can be performed by one or more programmable processors, also referred to as data processing hardware, executing one or more computer programs to perform functions by operating on input data and generating output. The processes and logic flows can also be performed by special purpose logic circuitry, e.g., an FPGA (field programmable gate array) or an ASIC (application specific integrated circuit). Processors suitable for the execution of a computer program include, by way of example, both general and special purpose microprocessors, and any one or more processors of any kind of digital computer. Generally, a processor will receive instructions and data from a read only memory or a random access memory or both. The essential elements of a computer are a processor for performing instructions and one or more memory devices for storing instructions and data. Generally, a computer will also include, or be operatively coupled to receive data from or transfer data to, or both, one or more mass storage devices for storing data, e.g., magnetic, magneto optical disks, or optical disks. However, a computer need not have such devices. Computer readable media suitable for storing computer program instructions and data include all forms of non-volatile memory, media and memory devices, including by way of example semiconductor memory devices, e.g., EPROM, EEPROM, and flash memory devices; magnetic disks, e.g., internal hard disks or removable disks; magneto optical disks; and CD ROM and DVD-ROM disks. The processor and the memory can be supplemented by, or incorporated in, special purpose logic circuitry.

To provide for interaction with a user, one or more aspects of the disclosure can be implemented on a computer having a display device, e.g., a CRT (cathode ray tube), LCD (liquid crystal display) monitor, or touch screen for displaying information to the user and optionally a keyboard and a pointing device, e.g., a mouse or a trackball, by which the user can provide input to the computer. Other kinds of devices can be used to provide interaction with a user as well; for example, feedback provided to the user can be any form of sensory feedback, e.g., visual feedback, auditory feedback, or tactile feedback; and input from the user can be received in any form, including acoustic, speech, or tactile input. In addition, a computer can interact with a user by sending documents to and receiving documents from a device that is used by the user; for example, by sending web pages to a web browser on a user's client device in response to requests received from the web browser.

Unless expressly stated to the contrary, the phrase "at least one of A, B, or C" is intended to refer to any combination or subset of A, B, C such as: (1) at least one A alone; (2) at least one B alone; (3) at least one C alone; (4) at least one A with at least one B; (5) at least one A with at least one C; (6) at least one B with at least C; and (7) at least one A with at least one B and at least one C. Moreover, unless expressly stated to the contrary, the phrase "at least one of A, B, and C" is intended to refer to any combination or subset of A, B, C such as: (1) at least one A alone; (2) at least one B alone; (3) at least one C alone; (4) at least one A with at least one B; (5) at least one A with at least one C; (6) at least one B with at least one C; and (7) at least one A with at least one B and at least one C. Furthermore, unless expressly stated to the contrary, "A or B" is intended to refer to any combination of A and B, such as: (1) A alone; (2) B alone; and (3) A and B.

A number of implementations have been described. Nevertheless, it will be understood that various modifications may be made without departing from the spirit and scope of the disclosure. Accordingly, other implementations are within the scope of the following claims.

What is claimed is:

1. A cascaded audiovisual automated speech recognition (AV-ASR) model comprising:

an audio encoder configured to:

receive, as input, a sequence of acoustic frames; and

generate, at each of a plurality of output steps, a corresponding acoustic higher-order feature representation for a corresponding acoustic frame in the sequence of acoustic frames;

an audiovisual encoder configured to:

receive, as input, a sequence of video frames; and

for each corresponding acoustic frame in the sequence of acoustic frames paired with a corresponding one of the video frames in the sequence of video frames:

receive, as input, the corresponding acoustic higher-order feature representation for the corresponding acoustic frame generated by the audio encoder; and

generate a corresponding audiovisual higher-order feature representation for the corresponding acoustic higher-order feature frame and the corresponding one of the video frames in the sequence of video frames; and

a decoder configured to:

for each corresponding acoustic frame in the sequence of acoustic frames paired with the corresponding one of the video frames in the sequence of video frames, receive, as input, the corresponding audiovisual higher-order feature representation;

for each corresponding acoustic frame in the sequence of acoustic frames that is not paired with any video frame in the sequence of video frames, receive, as input, the corresponding acoustic higher-order feature representation; and

generate, at each of the plurality of output steps a probability distribution over possible speech recognition hypotheses.

2. The cascaded AV-ASR model of claim **1**, wherein the audio encoder comprises at least one of a first plurality of multi-head attention layers, a first conformer, or a first plurality of long short term memory (LSTM) layers.

3. The cascaded AV-ASR model of claim **2**, wherein the audiovisual encoder comprises at least one of a second plurality of multi-head attention layers, a second conformer, or a second plurality of LSTM layers.

4. The cascaded AV-ASR model of claim **1**, wherein the audiovisual encoder is configured to generate the corresponding audiovisual higher-order feature representation by:

generating, at each of the plurality of output steps, a corresponding visual higher-order feature representation for the corresponding one of the video frames in the sequence of video frames; and

fusing the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation.

5. The cascaded AV-ASR model of claim **4**, wherein the audiovisual encoder comprises concatenation to fuse the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation.

6. The cascaded AV-ASR model of claim **4**, wherein the audiovisual encoder comprises cross-model attention to fuse the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation.

7. The cascaded AV-ASR model of claim **1**, wherein the cascaded AV-ASR model comprises a cascaded audiovisual recurrent neural network-transducer (RNN-T) model architecture.

8. The cascaded AV-ASR model of claim **1**, wherein the decoder comprises:

a prediction network configured to:

receive, as input, a sequence of non-blank symbols output by a final softmax layer; and

generate, at each of the plurality of output steps, a dense representation; and

a joint network configured to:

receive, as input, the dense representation generated by the prediction network at each of the plurality of output steps and one of:

for each corresponding acoustic frame in the sequence of acoustic frames paired with the corresponding one of the video frames in the sequence of video frames, the corresponding audiovisual higher-order feature representation; or

for each corresponding acoustic frame in the sequence of acoustic frames that is not paired with any video frame in the sequence of video frames, the acoustic higher-order feature representation; and

generate, at each of the plurality of output steps, a probability distribution over possible speech recognition hypotheses.

9. The cascaded AV-ASR model of claim **8**, wherein:

the prediction network comprises a two-layer bidirectional long short term memory (LSTM) model; and

the joint network comprises a multi-layer perceptron model.

10. The cascaded AV-ASR model of claim **1**, wherein the audio encoder and the audiovisual encoder are trained jointly.

11. The cascaded AV-ASR model of claim **1**, wherein the cascaded AV-ASR model is trained by:

during a first training phase:

receiving a first set of training utterances comprising acoustic frames without corresponding video frames; and

training the audio encoder using the first set of training utterances; and

during a second training phase:

receiving a second set of training utterances comprising acoustic frames and corresponding video frames; and

training, while holding coefficients of the audio encoder fixed after the first training phase is complete, the audiovisual encoder using the second set of training utterances while the coefficients of the audio encoder are held fixed.

12. A computer-implemented method executed on data processing hardware that causes the data processing hardware to perform operations comprising:

receiving a sequence of acoustic frames;

generating, by an audio encoder, at each of a plurality of output steps, a corresponding acoustic higher-order feature representation for a corresponding acoustic frame in the sequence of acoustic frames;

for each acoustic frame in the sequence of acoustic frames paired with a corresponding video frame in a sequence of video frames:

generating, by an audiovisual encoder, a corresponding audiovisual higher-order feature representation for the corresponding acoustic higher-order feature frame and the corresponding video frame; and

generating, by a joint network, at an output step, a probability distribution over possible speech recognition hypotheses based on the corresponding audiovisual higher-order feature representation; and

for each corresponding acoustic frame in the sequence of acoustic frames not paired with a corresponding video frame, generating, by the joint network, at an output step, a probability distribution over possible speech recognition hypotheses based on the corresponding acoustic higher-order feature representation.

13. The computer-implemented method of claim **12**, wherein the audio encoder comprises at least one of a first plurality of multi-head attention layers, a first conformer, or a first plurality of long short term memory (LSTM) layers.

14. The computer-implemented method of claim **13**, wherein the audiovisual encoder comprises at least one of a second plurality of multi-head attention layers, a second conformer, or a second plurality of LSTM layers.

15. The computer-implemented method of claim **12**, wherein generating the corresponding audiovisual higher-order feature representation comprises:

generating, at each of the plurality of output steps, a corresponding visual higher-order feature representation for the corresponding one of the video frames in the sequence of video frames; and

fusing the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation.

16. The computer-implemented method of claim **15**, wherein fusing the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation comprises concatenating the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation.

17. The computer-implemented method of claim **15**, wherein fusing the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation comprises applying cross-model attention to the corresponding acoustic higher-order feature representation with the corresponding visual higher-order feature representation.

18. The computer-implemented method of claim **12**, wherein the operations further comprise:

receiving a sequence of non-blank symbols output by a final softmax layer;

generating, by a prediction network, based on the sequence of non-blank symbols, at each of the plurality of output steps, a dense representation;

selecting one of:

for each corresponding acoustic frame in the sequence of acoustic frames paired with the corresponding one of the video frames in the sequence of video frames, the corresponding audiovisual higher-order feature representation; or

for each corresponding acoustic frame in the sequence of acoustic frames that is not paired with any video frame in the sequence of video frames, the acoustic higher-order feature representation; and

generating, by the joint network, based on the dense representation and the selected one of the corresponding audiovisual higher-order feature representation or the corresponding acoustic higher-order feature representation, at each of the plurality of output steps, a probability distribution over possible speech recognition hypotheses.

19. The computer-implemented method of claim **18**, wherein:

the prediction network comprises a two-layer bidirectional long short term memory (LSTM) model; and

the joint network comprises a multi-layer perceptron model.

20. The computer-implemented method of claim **12**, wherein the audio encoder and the audiovisual encoder are trained jointly.

21. The computer-implemented method of claim **12**, wherein the operations further comprise:

during a first training phase:

receiving a first set of training utterances comprising acoustic frames without corresponding video frames; and

training the audio encoder using the first set of training utterances; and

during a second training phase:

receiving a second set of training utterances comprising acoustic frames and corresponding video frames; and

training, while holding coefficients of the audio encoder fixed after the first training phase is complete, the audiovisual encoder using the second set of training utterances while the coefficients of the audio encoder are held fixed.

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