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(54) # JOINT AUTOMATIC SPEECH RECOGNITION AND TEXT TO SPEECH CONVERSION USING ADVERSARIAL NEURAL NETWORKS

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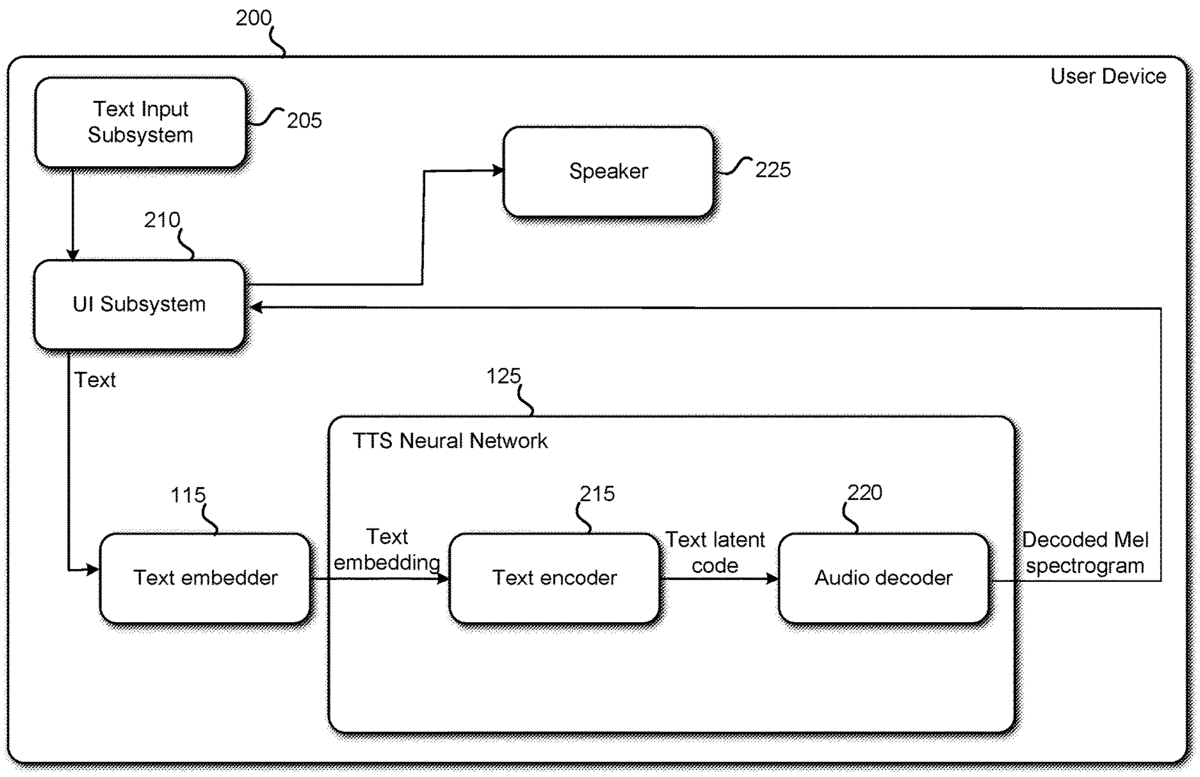
(57) **ABSTRACT**

An end-to-end deep-learning-based system that can solve both ASR and TTS problems jointly using unpaired text and audio samples is disclosed herein. An adversarially-trained approach is used to generate a more robust independent TTS neural network and an ASR neural network that can be deployed individually or simultaneously. The process for training the neural networks includes generating an audio sample from a text sample using the TTS neural network, then feeding the generated audio sample into the ASR neural network to regenerate the text. The difference between the regenerated text and the original text is used as a first loss for training the neural networks. A similar process is used for an audio sample. The difference between the regenerated audio and the original audio is used as a second loss. Text and audio discriminators are similarly used on the output of the neural network to generate additional losses for training.



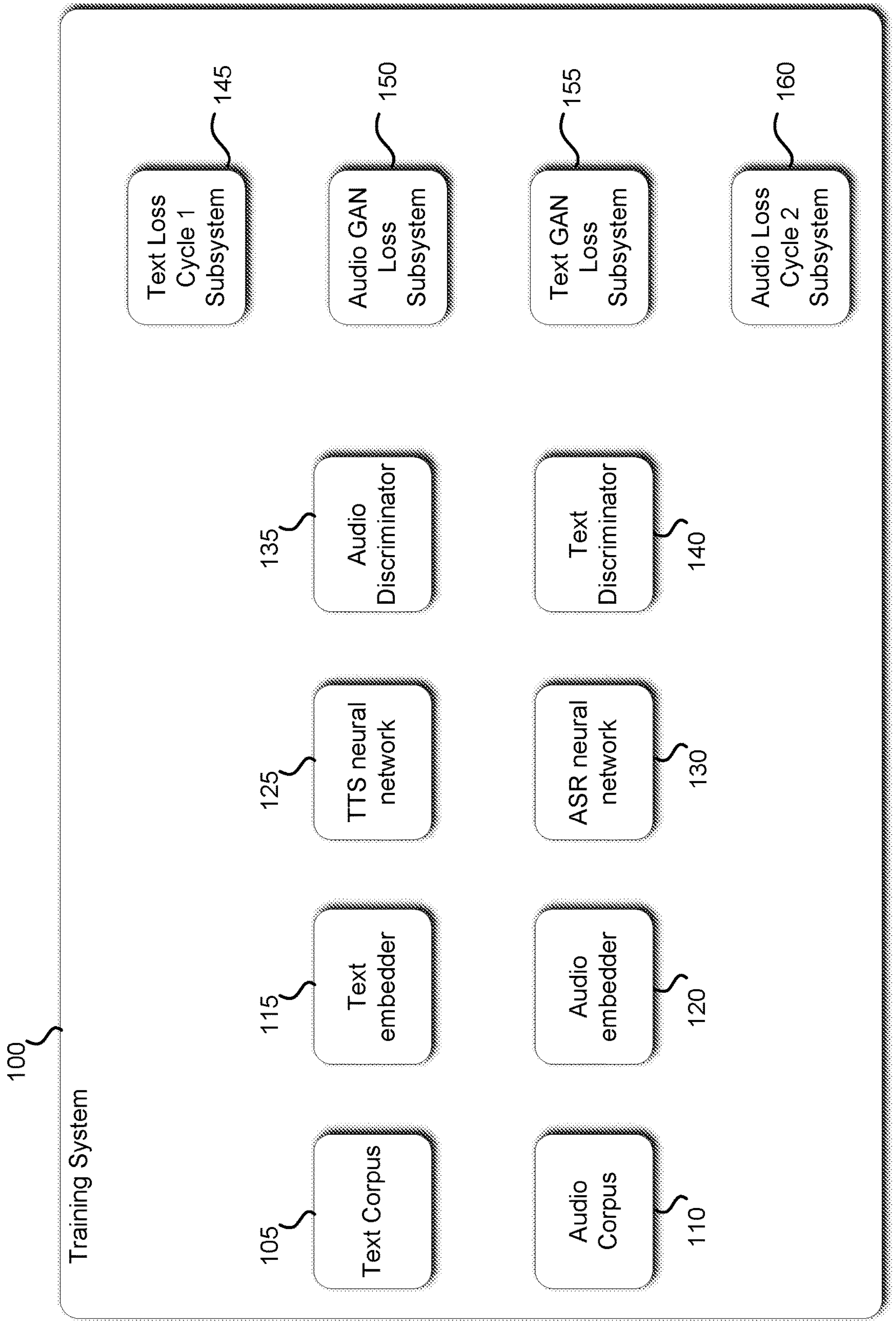

100
Training System
105
Text Corpus
110
Audio Corpus
115
Text embedder
120
Audio embedder
125
TTS neural network
130
ASR neural network
135
Audio Discriminator
140
Text Discriminator
145
Text Loss Cycle 1 Subsystem
150
Audio GAN Loss Subsystem
155
Text GAN Loss Subsystem
160
Audio Loss Cycle 2 Subsystem

FIG. 1

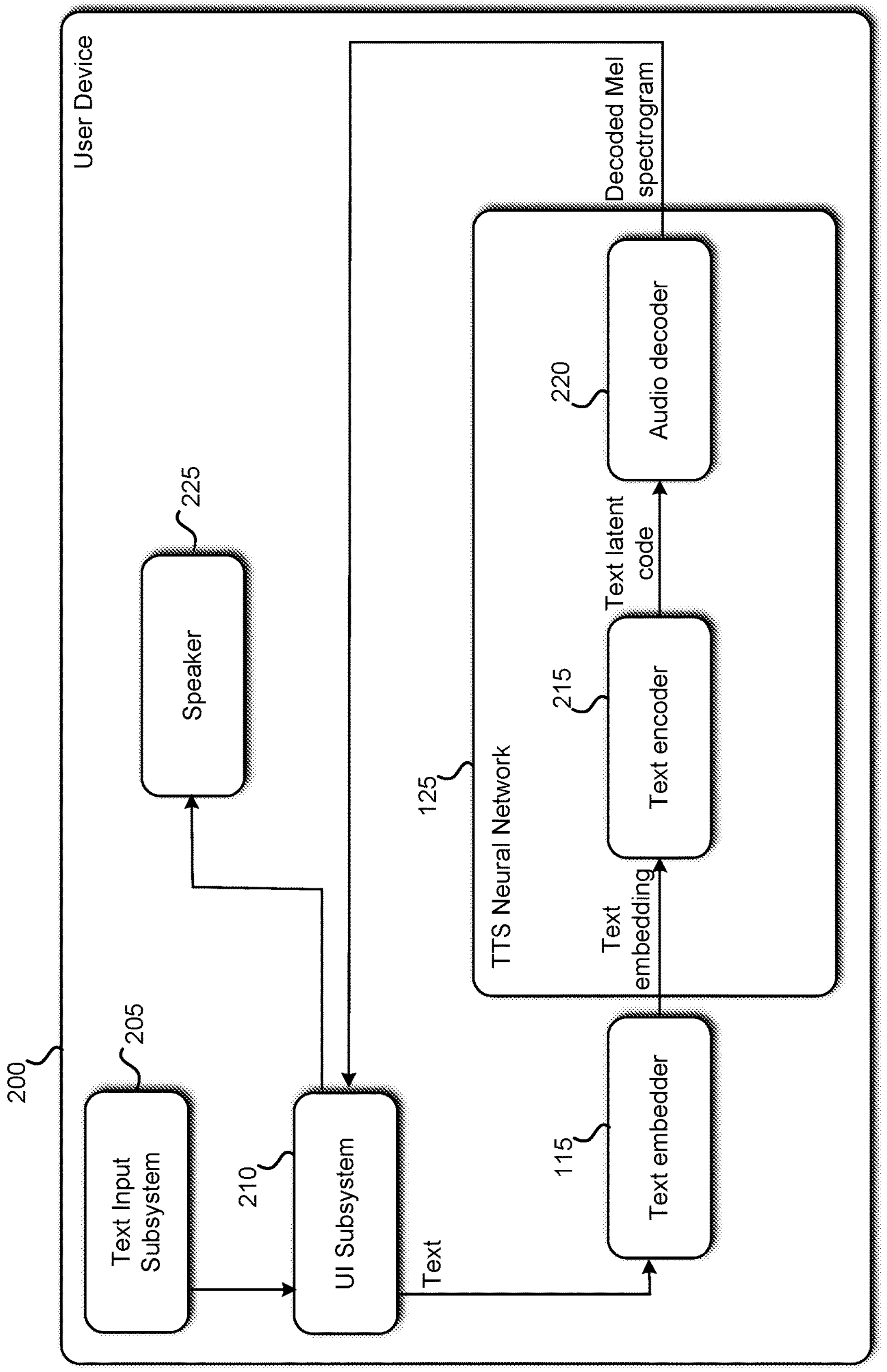

200
User Device
205
Text Input Subsystem
210
UI Subsystem
225
Speaker
Text
125
TTS Neural Network
115
Text embedder
Text embedding
215
Text encoder
Text latent code
220
Audio decoder
Decoded Mel spectrogram

FIG. 2

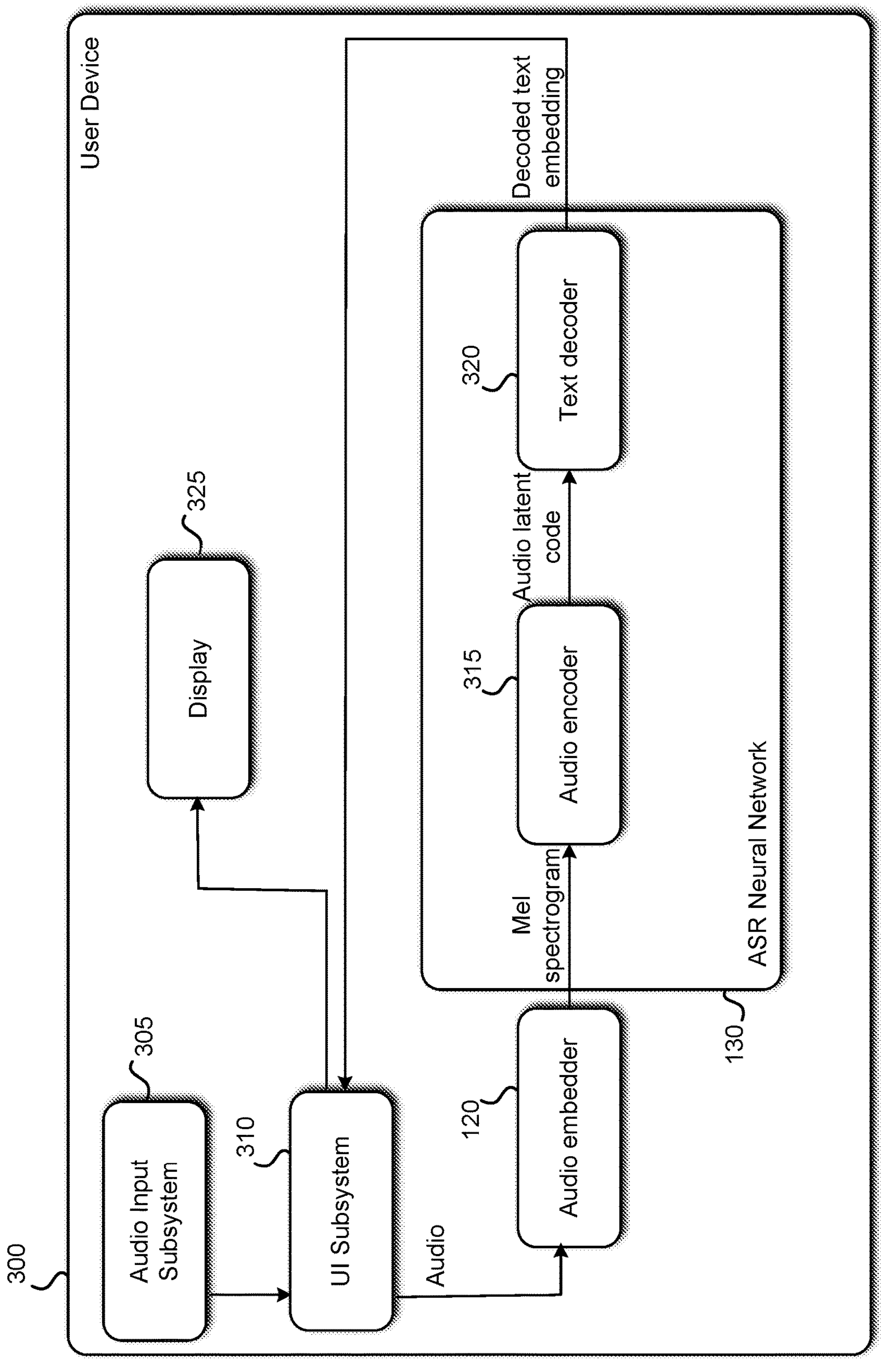

300
User Device
Audio Input Subsystem
305
UI Subsystem
310
Display
325
Audio
Audio embedder
120
130
ASR Neural Network
Mel spectrogram
Audio encoder
315
Audio latent code
Text decoder
320
Decoded text embedding

FIG. 3

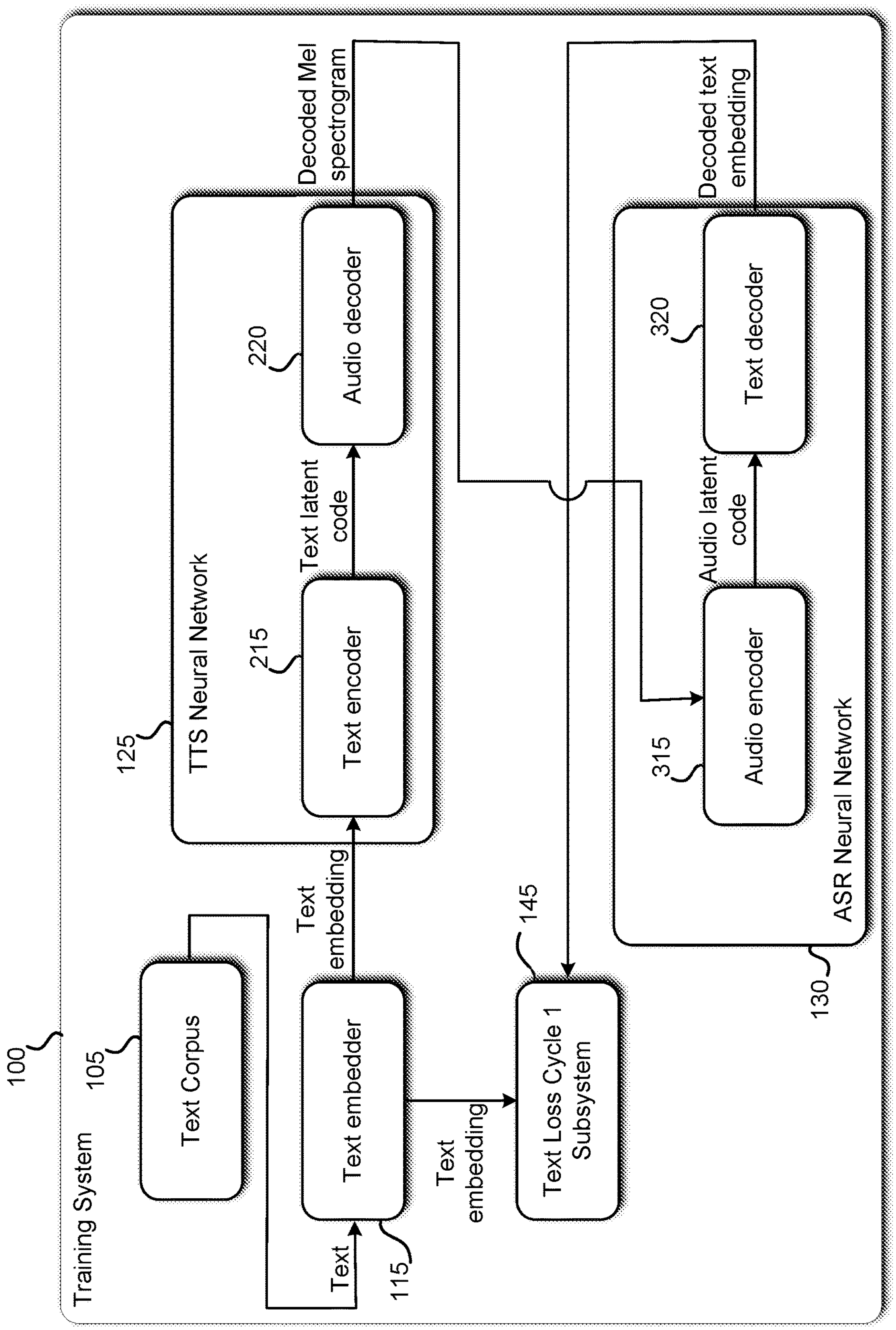

100
Training System
105
Text Corpus
Text
115
Text embedder
Text embedding
Text embedding
145
Text Loss Cycle 1 Subsystem
125
TTS Neural Network
215
Text encoder
Text latent code
220
Audio decoder
Decoded Mel spectrogram
130
ASR Neural Network
315
Audio encoder
Audio latent code
320
Text decoder
Decoded text embedding

FIG. 4

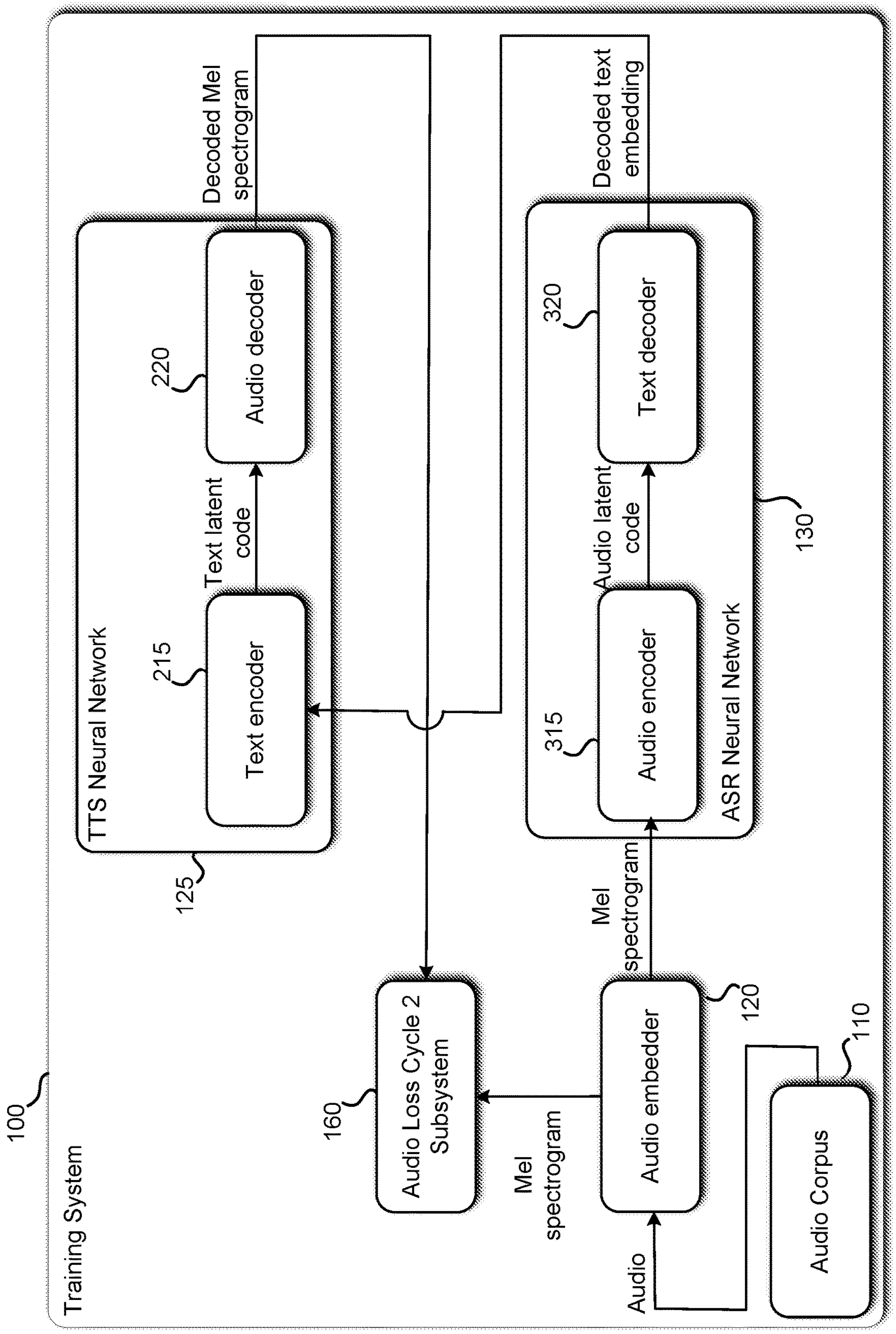

100
Training System
125
TTS Neural Network
215
Text encoder
Text latent code
220
Audio decoder
Decoded Mel spectrogram
130
ASR Neural Network
315
Audio encoder
Audio latent code
320
Text decoder
Decoded text embedding
160
Audio Loss Cycle 2 Subsystem
Mel spectrogram
120
Audio embedder
Mel spectrogram
Audio
110
Audio Corpus

FIG. 5

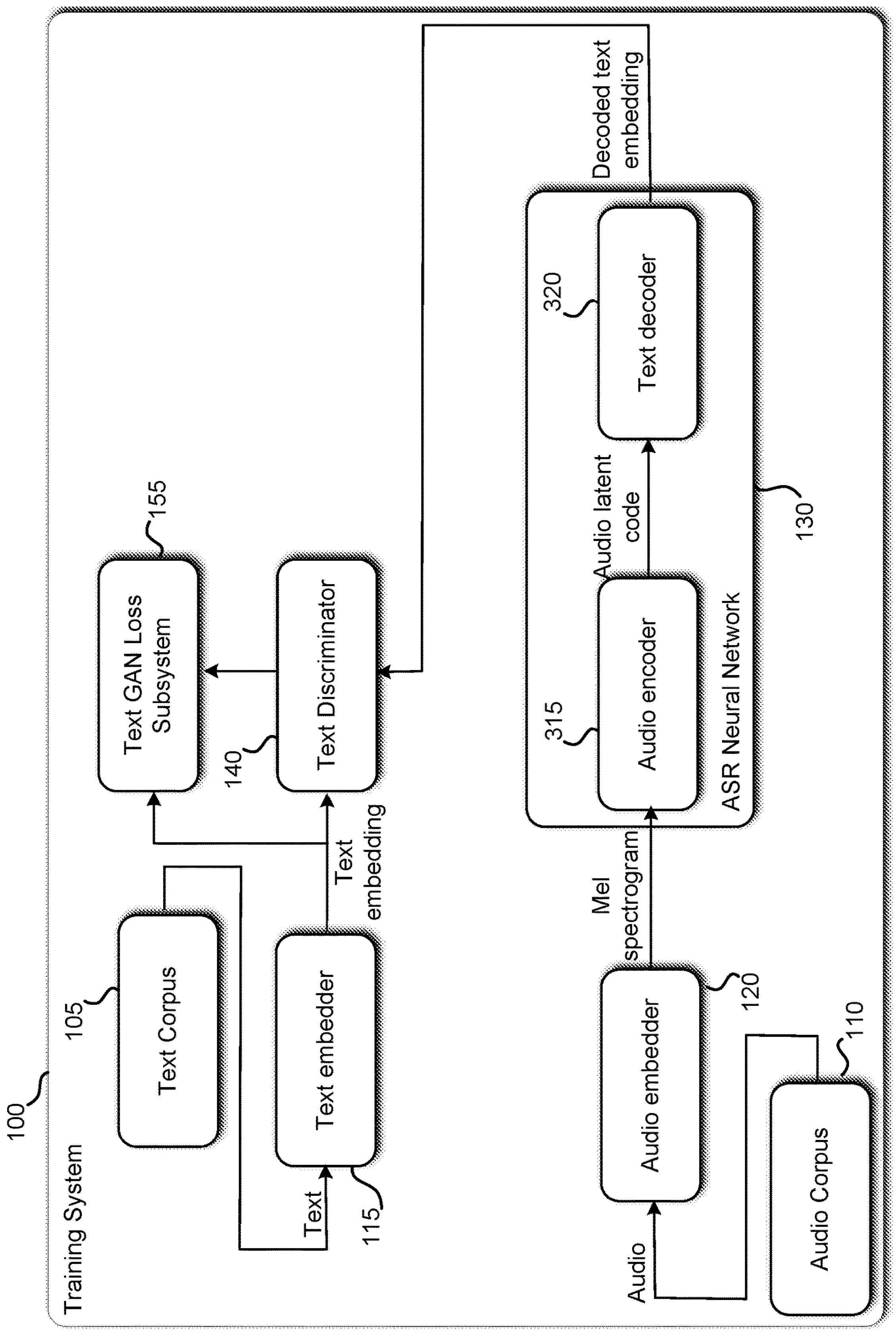

100
Training System
105
Text Corpus
Text
115
Text embedder
Text embedding
140
Text Discriminator
155
Text GAN Loss Subsystem
110
Audio Corpus
Audio
120
Audio embedder
Mel spectrogram
315
Audio encoder
Audio latent code
320
Text decoder
Decoded text embedding
ASR Neural Network
130

FIG. 6

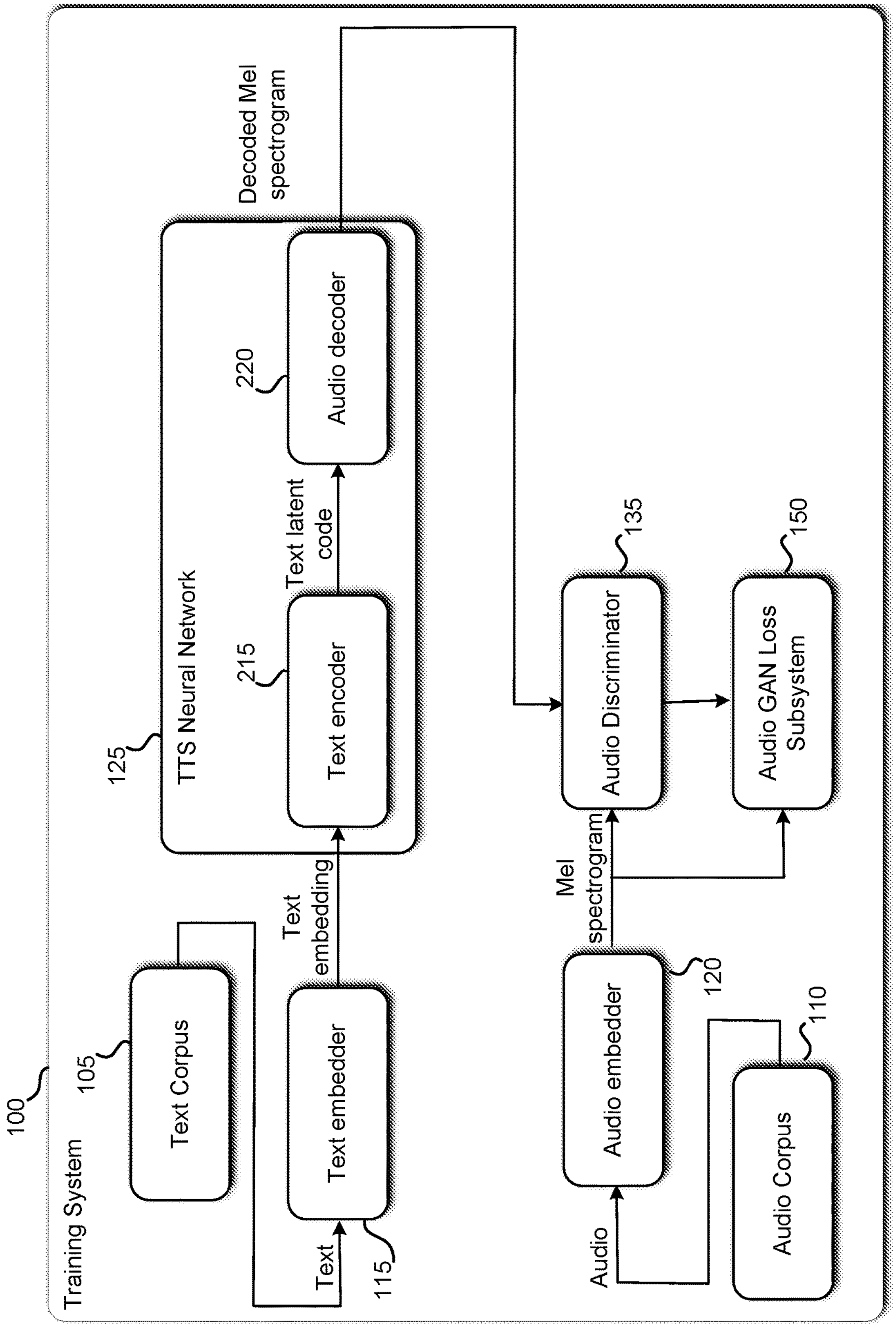

100
Training System
105
Text Corpus
Text
115
Text embedder
Text embedding
125
TTS Neural Network
215
Text encoder
Text latent code
220
Audio decoder
Decoded Mel spectrogram
Audio
Audio Corpus
110
Audio embedder
120
Mel spectrogram
Audio Discriminator
135
Audio GAN Loss Subsystem
150

FIG. 7

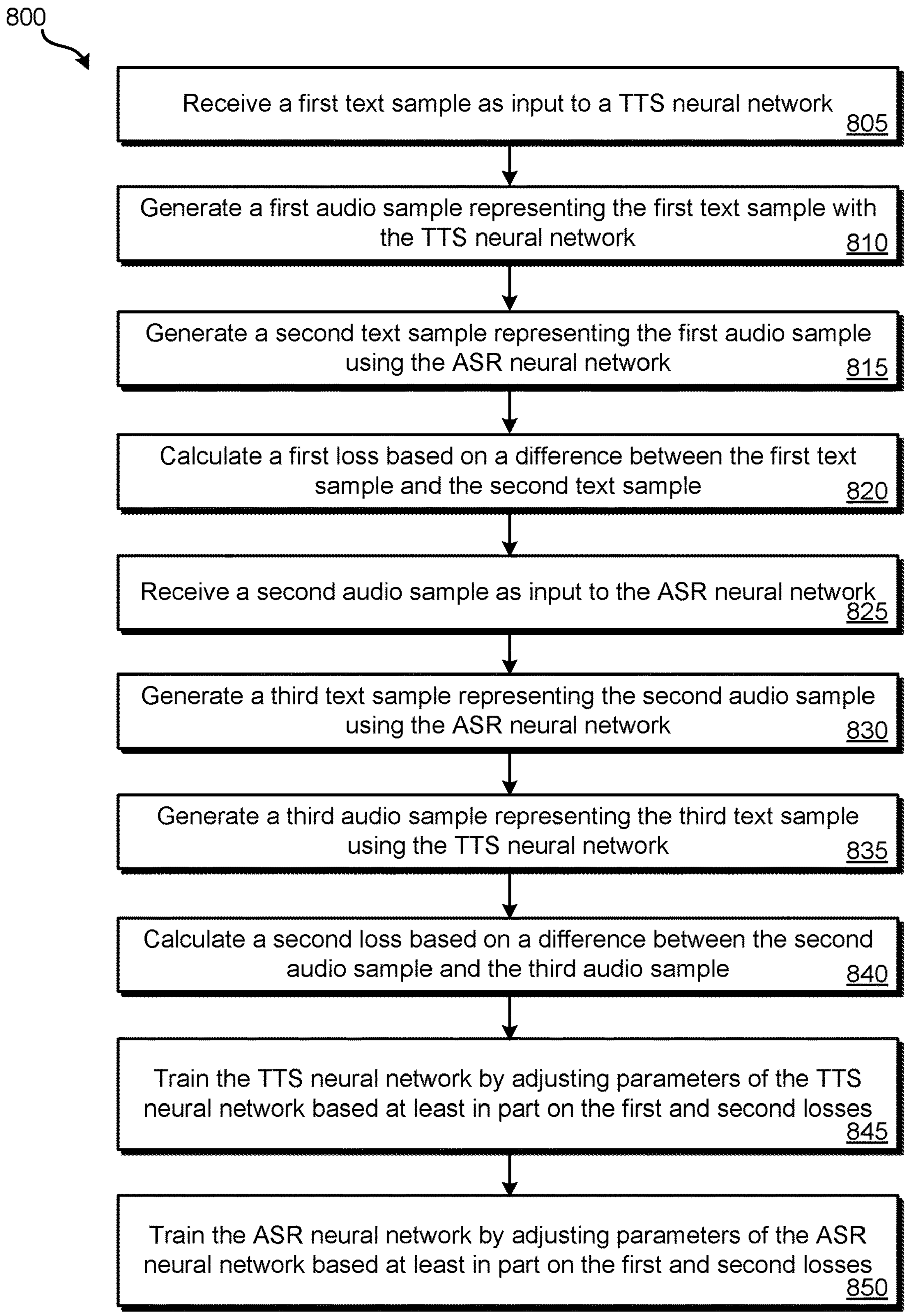

800
Receive a first text sample as input to a TTS neural network 805
Generate a first audio sample representing the first text sample with the TTS neural network 810
Generate a second text sample representing the first audio sample using the ASR neural network 815
Calculate a first loss based on a difference between the first text sample and the second text sample 820
Receive a second audio sample as input to the ASR neural network 825
Generate a third text sample representing the second audio sample using the ASR neural network 830
Generate a third audio sample representing the third text sample using the TTS neural network 835
Calculate a second loss based on a difference between the second audio sample and the third audio sample 840
Train the TTS neural network by adjusting parameters of the TTS neural network based at least in part on the first and second losses 845
Train the ASR neural network by adjusting parameters of the ASR neural network based at least in part on the first and second losses 850

FIG. 8

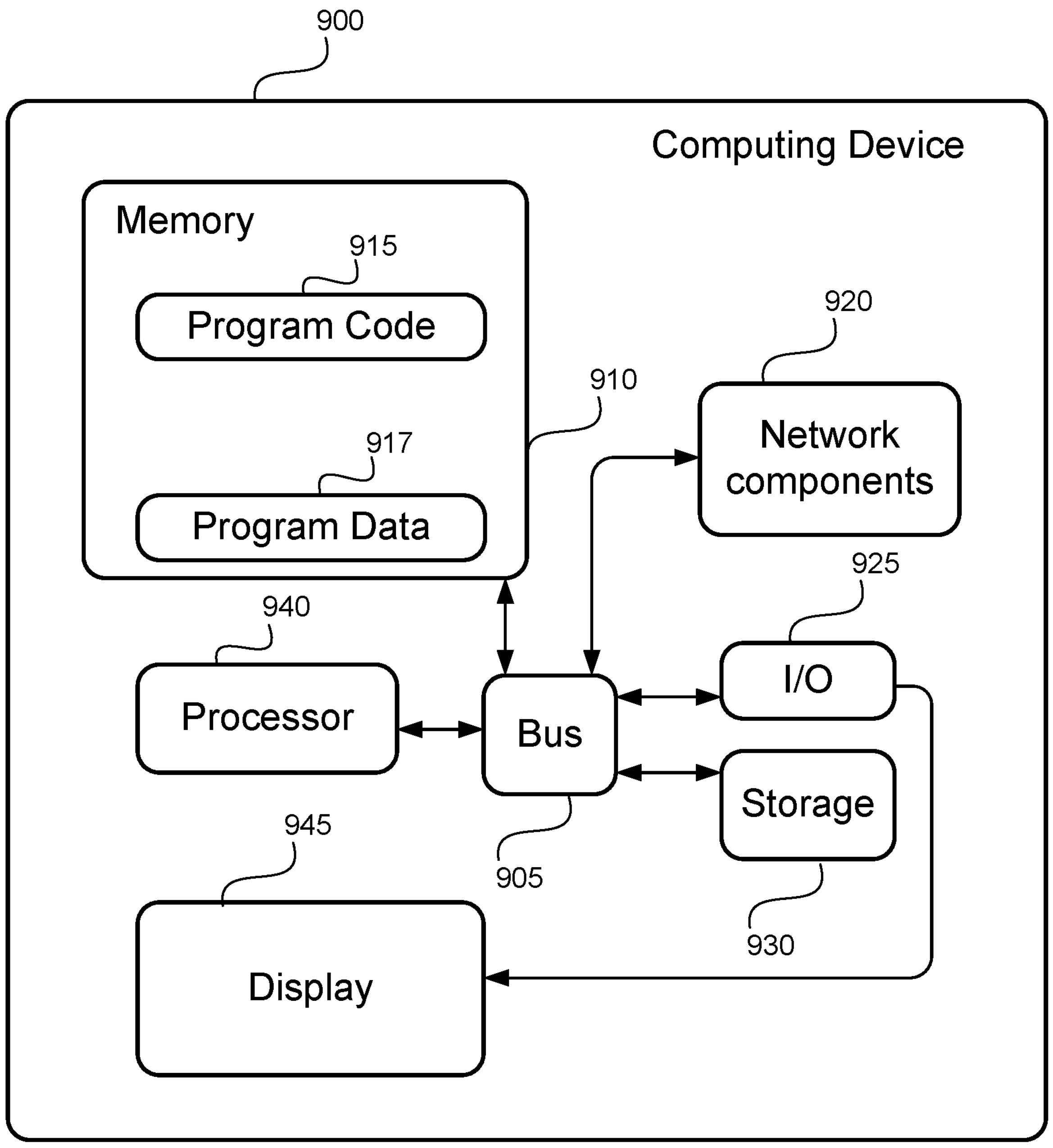

900
Computing Device
Memory
915
Program Code
917
Program Data
910
920
Network components
925
940
Processor
Bus
I/O
Storage
945
905
930
Display

FIG. 9

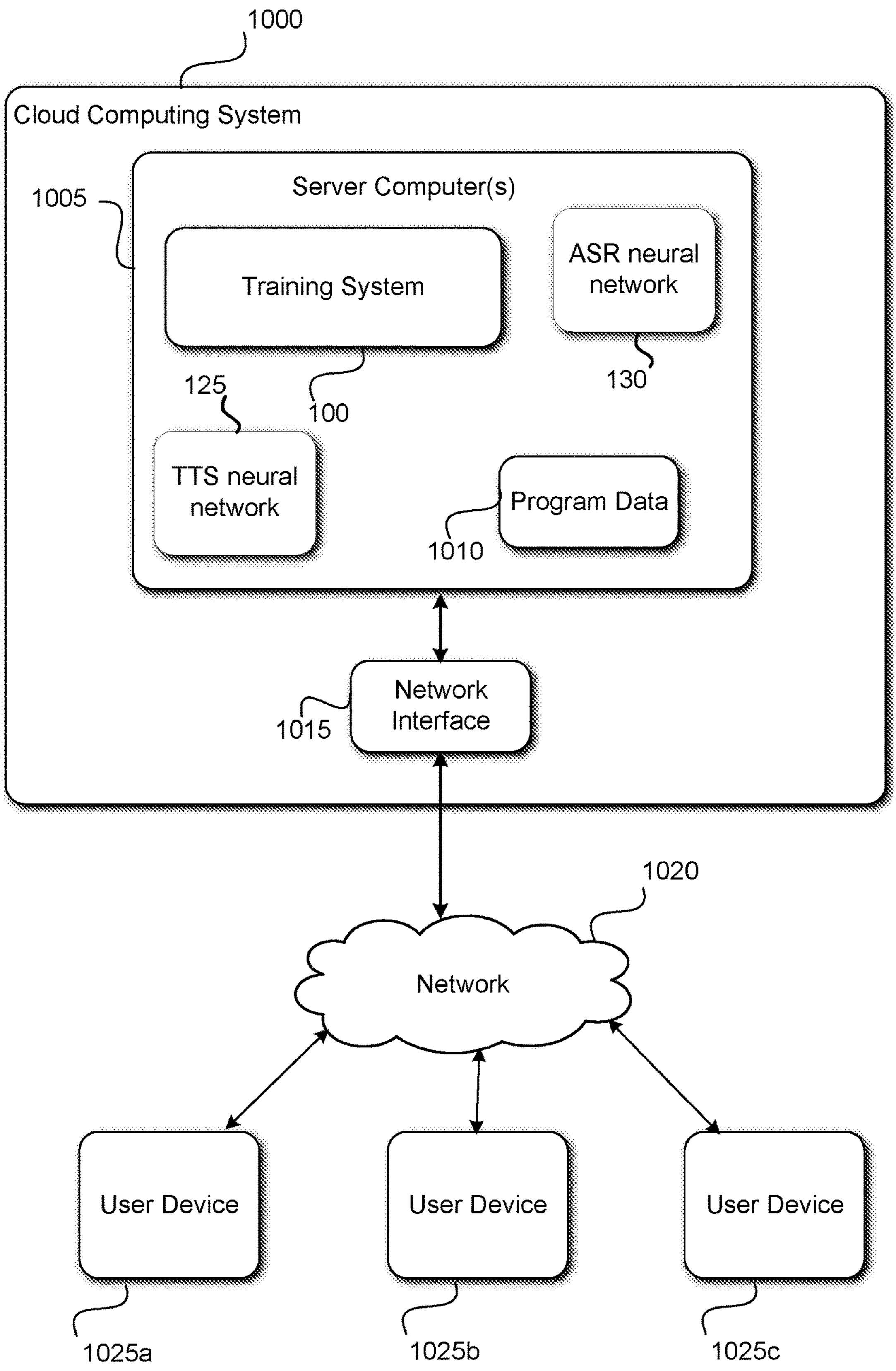

1000
Cloud Computing System
1005
Server Computer(s)
Training System
ASR neural network
125
100
130
TTS neural network
Program Data
1010
Network Interface
1015
1020
Network
User Device
User Device
User Device
1025a
1025b
1025c

FIG. 10

JOINT AUTOMATIC SPEECH RECOGNITION AND TEXT TO SPEECH CONVERSION USING ADVERSARIAL NEURAL NETWORKS

BACKGROUND

[0001] Two common and widely deployed technologies in computational linguistics are Automatic Speech Recognition (ASR) and Text-to-speech (TTS) conversion. However, there is not a common system for training and/or deploying both systems simultaneously. Current end-to-end deep learning-based ASR and TTS systems require paired (text and audio) samples, which are difficult to obtain in significant amounts for proper training of either system.

SUMMARY

[0002] In some embodiments, a solution to the above problems are disclosed herein using an end-to-end deep-learning-based system that can solve both ASR and TTS problems jointly using unpaired text and audio samples. The system includes an adversarially-trained approach to generate a more robust independent TTS neural network and an ASR neural network that can be deployed individually or simultaneously.

[0003] A system of one or more computers can be configured to perform particular operations or actions by virtue of having software, firmware, hardware, or a combination of them installed on the system that in operation causes or cause the system to perform the actions. One or more computer programs can be configured to perform particular operations or actions by virtue of including instructions that, when executed by data processing apparatus, cause the apparatus to perform the actions. One general aspect includes a method for training a text-to-speech (TTS) neural network and an automatic speech recognition (ASR) neural network. The method may include receiving a first text sample as input to the TTS neural network, and generating, using the TTS neural network, a first audio sample representing the first text sample. The first audio sample output by the TTS neural network may be fed into the ASR neural network, which may generate a second text sample representing the first audio sample. The loss based on the difference between the first text sample (fed into the TTS neural network) and the second text sample (output by the ASR neural network) is calculated. A second audio sample is input to the ASR neural network, and a third text sample representing the second audio sample is generated by the ASR neural network. The third text sample generated by the ASR neural network is input into the TTS neural network, which generates a third audio sample representing the third text sample. A second loss based on the difference between the second audio sample (input into the ASR neural network) and the third audio sample (output by the TTS neural network) is calculated. The TTS neural network and ASR neural network are trained by adjusting parameters of each neural network based on the calculated losses. Other embodiments of this aspect include corresponding computer systems, apparatus, and computer programs recorded on one or more computer storage devices, each configured to perform the actions of the methods.

[0004] Implementations may include one or more of the following features. In some embodiments, the TTS neural network includes a text encoder and an audio decoder, and training the TTS neural network includes adjusting one or more parameters of the text encoder or one or more parameters of the audio decoder. In some embodiments, the ASR neural network includes an audio encoder and a text decoder, and training the ASR neural network includes adjusting one or more parameters of the audio encoder or one or more parameters of the text decoder.

[0005] In some embodiments, the ASR neural network may generate a fourth text sample representing a fourth audio sample received as input to the ASR neural network. The fourth text sample output by the ASR and a fifth text sample from a textual source are provided to a text discriminator. The text discriminator may generate a third loss based on the fourth text sample and the fifth text sample. The ASR and/or TTS neural networks may be trained based at least in part on the third loss calculated by the text discriminator. In some embodiments, the text discriminator outputs a first value for a fake text sample (generated from an audio sample by the ASR neural network) and outputs a second value for a real text sample (generated from a textual source).

[0006] In some embodiments, the TTS neural network may generate a fourth audio sample representing a fourth text sample received as input to the TTS neural network. The fourth audio sample output by the TTS neural network and a fifth audio sample from an audio source are provided to an audio discriminator. The audio discriminator may generate a third loss based on the fourth audio sample and the fifth audio sample. The ASR and/or TTS neural networks may be trained based at least in part on the third loss. In some embodiments, the audio discriminator is trained to output a first value for a fake audio sample (generated from a text sample by the TTS neural network) and to output a second value for a real audio sample (generated from an audio source).

[0007] In some embodiments, the trained TTS neural network is deployed independently from the trained ASR neural network. In some embodiments, the trained TTS and ASR neural networks are deployed together to a single device. Implementations of the described techniques may include hardware, a method or process, or computer software on a computer-accessible medium.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] A further understanding of the nature and advantages of various embodiments may be realized by reference to the following figures. In the appended figures, similar components or features may have the same reference label. Further, various components of the same type may be distinguished by following the reference label by a dash and a second label that distinguishes among the similar components. If only the first reference label is used in the specification, the description is applicable to any one of the similar components having the same first reference label irrespective of the second reference label.

[0009] FIG. **1** illustrates a training system, according to some embodiments.

[0010] FIG. **2** illustrates a user device with a deployed TTS neural network, according to some embodiments.

[0011] FIG. **3** illustrates a user device with a deployed ASR neural network, according to some embodiments.

[0012] FIG. **4** illustrates the training system during a first cycle of training, according to some embodiments.

[0013] FIG. **5** illustrates the training system during a second cycle of training, according to some embodiments.

[0014] FIG. **6** illustrates the training system during a third cycle of training, according to some embodiments.

[0015] FIG. **7** illustrates the training system during a fourth cycle of training, according to some embodiments.

[0016] FIG. **8** illustrates a method for adversarially-training ASR and TTS neural networks simultaneously, according to some embodiments.

[0017] FIG. **9** illustrates a computer system, according to some embodiments.

[0018] FIG. **10** illustrates a cloud computing system, according to some embodiments.

DETAILED DESCRIPTION

[0019] As discussed above, disclosed herein is a system and methods for jointly training a text-to-speech (TTS) system (e.g., neural network) and an automatic speech recognition (ASR) system (e.g., neural network). The system does not require paired text and audio samples for training, and the result is a robust ASR and TTS system that can be deployed jointly or separately. The process for training includes four cycles to train a total of 6 components (i.e., a text encoder, a text decoder, an audio encoder, an audio decoder, a text discriminator, and an audio discriminator). Using a generative adversarial network technique, the output from the ASR and the output from the TTS systems can be used as inputs to each other and discriminators to teach the ASR and TTS neural networks to perform robustly without the need for paired samples.

[0020] Turning now to FIG. **1**, a training system **100** is depicted. The training system **100** includes a text corpus **105**, an audio corpus **110**, a text embedder **115**, an audio embedder **120**, a TTS neural network **125**, an ASR neural network **130**, an audio discriminator **135**, a text discriminator **140**, a text loss cycle 1 subsystem **145**, an audio GAN loss subsystem **150**, a text GAN loss subsystem **155**, and an audio loss cycle 2 subsystem **160**. While certain components are depicted and described within training system **100**, more or fewer components may exist in training system **100** to perform operations such as, for example, processors and memory. These components are omitted for ease of description. Further, some components may be merged or separated into more components without departing from the scope of this disclosure.

[0021] The text corpus **105** includes samples of text taken from textual sources. For example, portions or entire books may be included, such as, for example, War and Peace by Leo Tolstoy and Angels and Demons by Dan Brown. The literary types of these samples may include all genres and writing types. Further, samples of text including postings on internet sites may be included and other modern textual communications may be included.

[0022] The audio corpus **110** includes samples of audio taken from audio sources. For example, portions or entire audio books may be included, such as, for example, Anna Karenina by Leo Tolstoy and Origins by Dan Brown. The audio samples may include musical samples, however spoken samples may be preferred.

[0023] Text embedder **115** receives a text sample and embeds the text sample into a known vector space such that the output of the text embedder **115** is a text embedding. The text embedding may be a vector representing the text sample in the known vector space, for example.

[0024] Audio embedder **120** receives an audio sample and embeds the audio sample into a known vector space such that the output of the audio embedder **120** is an audio embedding. The audio embedding may be a mel spectrogram representing the audio sample.

[0025] TTS neural network **125** is a text-to-speech network that receives a text embedding as input and outputs a decoded mel spectrogram representing the text embedding. The TTS neural network **125** includes a text encoder and an audio decoder as will be explained further with respect to FIG. **2**.

[0026] ASR neural network **130** is an automatic speech recognition network (also known as an automatic voice recognition system) that receives an audio embedding (e.g., mel spectrogram) as input and outputs a decoded text embedding representing the audio embedding. The ASR neural network **130** includes an audio encoder and a text decoder as will be explained further with respect to FIG. **3**.

[0027] The audio discriminator **135** is a discrimination system that takes mel spectrograms as input. It is trained to output a first value (e.g., "real," "1," or the like) for a mel spectrogram that was generated from an audio sample. The audio discriminator **135** is further trained to output a second value (e.g., "fake," "0," or the like) for a mel spectrogram that was generated from text via the TTS neural network **125**.

[0028] The text discriminator **140** is a discrimination system that takes text embeddings as input. It is trained to output a first value (e.g., "real," "1," or the like) for a text embedding that was generated from a textual sample. The text discriminator **140** is further trained to output a second value (e.g., "fake," "0," or the like) for a text embedding that was generated from audio via the ASR neural network **130**.

[0029] The text loss cycle 1 subsystem **145** is a first loss calculation subsystem that is used in the first training cycle. As described in more detail with respect to FIG. **4**, the text loss cycle 1 subsystem **145** receives a text embedding from a text sample generated by the text embedder **115** as well as a text embedding that was generated from the text sample after passing the text sample through the text embedder **115**, the TTS neural network **125**, and the ASR neural network **130**. The text loss cycle 1 subsystem **145** calculates the loss between the text embeddings and uses the result to train the components of the TTS neural network **125** and the ASR neural network **130**. This process is described in more detail with respect to FIG. **4**.

[0030] The audio loss cycle 2 subsystem **160** is a second loss calculation subsystem that is used in the second training cycle. As described in more detail with respect to FIG. **5**, the audio loss cycle 2 subsystem **160** receives a mel spectrogram from an audio sample generated by the audio embedder **120** as well as a mel spectrogram that was generated from the audio sample after passing the audio sample through the audio embedder **120**, the ASR neural network **130**, and the TTS neural network **125**. The audio loss cycle 2 subsystem **160** calculates the loss between the mel spectrograms and uses the result to train the components of the TTS neural network **125** and the ASR neural network **130**. This process is described in more detail with respect to FIG. **5**.

[0031] The text GAN loss subsystem **155** is a third loss calculation subsystem that is used in the third training cycle. As described in more detail with respect to FIG. **6**, the text GAN loss subsystem **155** receives the output from the text discriminator **140** and the text embedding from the text embedder **115** that is the "real" text embedding. The text

GAN loss subsystem **155** then uses the difference between the text discriminator **140** results and the text embedding to generate a loss used to train the text discriminator **140** and the ASR neural network **130** components.

[0032] The audio GAN loss subsystem **150** is a fourth loss calculation subsystem that is used in the fourth training cycle. As described in more detail with respect to FIG. **7**, the audio GAN loss subsystem **150** receives the output from the audio discriminator **135** and the mel spectrogram from the audio embedder **120** that is the "real" mel spectrogram. The audio GAN loss subsystem **150** then uses the difference between the audio discriminator **135** results and the mel spectrogram to generate a loss used to train the audio discriminator **135** and the TTS neural network **125** components.

[0033] A more detailed description of how all the components of training system **100** are used together are provided in the descriptions of the following figures.

[0034] FIG. **2** illustrates an example user device **200**. The user device **200** may be a user's computer, smartphone, tablet, or the like. User device **200** may be computing device **900** as described with respect to FIG. **9**. The user device **200** includes the TTS neural network **125** after training that has been deployed to provide text to speech functionality. The user device **200** includes a text input subsystem **205**, a UI subsystem **210**, a speaker **225**, the text embedder **115**, and the TTS neural network **125**.

[0035] The text input subsystem **205** may be any input device including, for example, a keyboard, a screen-based keyboard, or the like. Additionally, the user may select text from a textual source to provide as input via the text input subsystem **205**. The UI subsystem **210** provides an interface for the user to provide and receive information from the TTS neural network **125**. The speaker **225** may be any suitable audio output device from which the user may hear sounds.

[0036] The TTS neural network **125** includes a text encoder **215** that takes a text embedding as input and outputs text latent code. The TTS neural network **125** further includes an audio decoder **220** that takes the text latent code as input and outputs a decoded mel spectrogram. While the two components of a text encoder **215** and audio decoder **220** are described within TTS neural network **125**, the TTS neural network **125** may include many layers, including hidden layers, in which the text encoder **215** and audio decoder **220** are included. For example, TTS neural network **125** may include an input layer, an output layer, and one or more hidden layers. In the described configuration, the TTS neural network **125** receives a text embedding as input and outputs a decoded mel spectrogram representing the text embedding as output.

[0037] Accordingly, the user may enter text into the text input subsystem **205**. The UI subsystem **210** may receive the text input and provide it to the text embedder **115**. The text embedder **115** may generate a text embedding and provide the text embedding as input to the TTS neural network **125**. The text encoder **215** generates text latent code from the text embedding, and the audio decoder **220** generates the decoded mel spectrogram from the text latent code. The decoded mel spectrogram is output to the UI subsystem **210**, which turns the decoded mel spectrogram into an audio sample that can be output by the speaker **225** for the user to hear. In some embodiments, a conversion mechanism (not shown) converts the decoded mel spectrogram into an audio sample used by UI subsystem **210** to output using speaker **225**.

[0038] FIG. **3** illustrates an example user device **300**. The user device **300** may be the same as user device **200** in some examples, and the user device **200** or **300** may include both the ASR neural network **130** and the TTS neural network **125**. The user device **300** may be a user's computer, smartphone, tablet, or the like. User device **300** may be computing device **900** as described with respect to FIG. **9**. The user device **300** includes the ASR neural network **130** after training that has been deployed to provide automatic speech recognition functionality. The user device **300** includes an audio input subsystem **305**, a UI subsystem **310**, a display **325**, the audio embedder **120**, and the ASR neural network **130**.

[0039] The audio input subsystem **305** may be any input device including, for example, a microphone, an audio selection system, or the like. For example, the user may select audio from an audio source to provide as input via the audio input subsystem **305**. The UI subsystem **310** provides an interface for the user to provide and receive information from the ASR neural network **130**. The display **325** may be any suitable textual output device on which the user may view text.

[0040] The ASR neural network **130** includes an audio encoder **315** that takes a mel spectrogram as input and outputs audio latent code. The ASR neural network **130** further includes a text decoder **320** that takes the audio latent code as input and outputs a decoded text embedding. While the two components of an audio encoder **315** and text decoder **320** are described within ASR neural network **130**, the ASR neural network **130** may include many layers, including hidden layers, in which the audio encoder **315** and text decoder **320** are included. For example, ASR neural network **130** may include an input layer, an output layer, and one or more hidden layers. In the described configuration, the ASR neural network **130** receives a mel spectrogram as input and outputs a decoded text embedding representing the mel spectrogram as output.

[0041] Accordingly, the user may enter audio into the audio input subsystem **305**. The UI subsystem **310** may receive the audio input and provide it to the audio embedder **120**. The audio embedder **120** may generate a mel spectrogram and provide the mel spectrogram as input to the ASR neural network **130**. The audio encoder **315** generates audio latent code from the mel spectrogram, and the text decoder **320** generates the decoded text embedding from the audio latent code. The decoded text embedding is output to the UI subsystem **310**, which turns the decoded text embedding into a text sample that can be output by the display **325** for the user to view. In some embodiments, a conversion mechanism (not shown) is used to convert the text embedding into a text sample that is provided to the UI subsystem **310** for output by display **325**.

[0042] While the ASR neural network **130** is shown deployed independently from the TTS neural network **125** in FIGS. **2** and **3**, the ASR neural network **130** and TTS neural network **125** may be deployed onto a single device for use simultaneously to provide both TTS services and ASR services.

[0043] FIG. **4** illustrates the first cycle of the training of the TTS neural network **125** and the ASR neural network **130** in training system **100**. A text sample is selected from the text corpus **105**, and the text embedder **115** generates a text embedding representing the text sample. The text embedding is provided to the text loss cycle 1 subsystem **145** and to the TTS neural network **125**.

[0044] The first portion of the first training cycle is to generate a decoded mel spectrogram representing the text embedding by the TTS neural network **125**. The text encoder **215** generates text latent code from the text embedding, and the audio decoder **220** generates the decoded mel spectrogram from the text latent code.

[0045] The second portion of the first training cycle is to generate a decoded text embedding representing the decoded mel spectrogram by the ASR neural network **130**. This is accomplished by feeding the output of the TTS neural network **125** into the input of the ASR neural network **130**. Accordingly, the decoded mel spectrogram from the TTS neural network **125** is fed into the ASR neural network **130**. The audio encoder **315** generates audio latent code from the decoded mel spectrogram, and the text decoder **320** generates a decoded text embedding from the audio latent code. The decoded text embedding is fed into the text loss cycle 1 subsystem **145**.

[0046] The decoded text embedding generated by passing the text sample through the TTS neural network **125** and the ASR neural network **130** would match the text embedding from the text embedder **115** if the TTS neural network **125** and the ASR neural network **130** were functioning perfectly. However, the result is a bit like the "telephone game" of youth. After the same information is passed from one person to the next by whispering it in the ear of the next person in line, some of the details may be lost, and the end result may be a garbled non-sensical sentence. Accordingly, the text loss cycle 1 subsystem compares the decoded text embedding to the text embedding from text embedder **115** to generate a first cycle loss. This cycle may be performed many times during training. The first cycle loss may be:

$$L^{cycle1}=E[|X^{text}-P^{text}|]$$

[0047] In the equation above, X^{text} is a sample from a textual source such as a text sample from the text corpus **105**. P^{text} is the output obtained after X^{text} is processed through a full cycle of the system including the TTS neural network **125** and the ASR neural network **130**.

[0048] FIG. **5** illustrates the second cycle of the training of the TTS neural network **125** and the ASR neural network **130** in training system **100**. The second cycle is much like the first cycle, but instead begins with an audio sample. An audio sample is selected from the audio corpus **110**, and the audio embedder **120** generates a mel spectrogram representing the audio sample. The mel spectrogram is provided to the audio loss cycle 2 subsystem **160** and to the ASR neural network **130**.

[0049] The first portion of the second training cycle is to generate a decoded text embedding representing the mel spectrogram by the ASR neural network **130**. The audio encoder **315** generates audio latent code from the mel spectrogram, and the text decoder **320** generates the decoded text embedding from the audio latent code.

[0050] The second portion of the second training cycle is to generate a decoded mel spectrogram representing the decoded text embedding by the TTS neural network **125**. This is accomplished by feeding the output of the ASR neural network **130** into the input of the TTS neural network **125**. Accordingly, the decoded text embedding from the ASR neural network **130** is fed into the TTS neural network **125**. The text encoder **215** generates text latent code from the decoded text embedding, and the audio decoder **220** generates a decoded mel spectrogram from the text latent code. The decoded mel spectrogram is fed into the audio loss cycle 2 subsystem **160**.

[0051] The decoded mel spectrogram generated by passing the audio sample through the ASR neural network **130** and the TTS neural network **125** would match the mel spectrogram from the audio embedder **120** if the TTS neural network **125** and the ASR neural network **130** were functioning perfectly. However, as in cycle 1, the end result may be a garbled non-sensical sample. Accordingly, the audio loss cycle 2 subsystem **160** compares the decoded mel spectrogram to the mel spectrogram from audio embedder **120** to generate a second cycle loss. This cycle may also be performed many times during training. The second cycle loss may be:

$$L^{cycle2}=E[|X^{audio}-P^{audio}|]$$

[0052] In the equation above, X^{audio} is a sample from an audio source such as an audio sample from the audio corpus **110**. P^{audio} is the output obtained after X^{audio} is processed through a full cycle of the system including the ASR neural network **130** and the TTS neural network **125**.

[0053] FIG. **6** illustrates the third cycle of the training of the TTS neural network **125** and the ASR neural network **130** in training system **100**. In the third cycle, a text sample from the text corpus **105** and an audio sample from the audio corpus **110** are selected. The samples need not be related to each other.

[0054] The audio sample is provided to the audio embedder **120** to generate a mel spectrogram for input to the ASR neural network **130**. The audio encoder **315** generates audio latent code representing the mel spectrogram, and the text decoder **320** generates the decoded text embedding from the audio latent code. The decoded text embedding is fed into the text discriminator **140**.

[0055] The text sample from the text corpus **105** is provided to the text embedder **115**. The text embedder **115** generates a text embedding and provides the text embedding to the text discriminator **140** and the text GAN loss subsystem **155**.

[0056] The text discriminator **140** is trained to output a first value (e.g., "real," "1," or the like) for text embeddings that were generated from the text embedder **115** from a textual source. The text discriminator **140** is also trained to output a second value (e.g., "fake," "0," or the like) for decoded text embeddings generated by the ASR neural network **130**. The text discriminator **140** generates an output value associated with the text embedding from text embedder **115** and for the decoded text embedding. The output values are provided to the text GAN loss subsystem **155**.

[0057] The text GAN loss subsystem **155** uses the text embedding information from the text embedder **115** to determine which text embedding is "real" (i.e., from the text embedder **115**) and which is "fake" (i.e., from the ASR neural network **130**). The text GAN loss subsystem **155** can determine whether the text discriminator **140** made correct determinations. The calculated losses by the text GAN loss subsystem **155** can be used to train the text discriminator **140** and the ASR neural network **130**.

[0058] The first loss for the text discriminator **140** is used to train the text discriminator **140**. The first loss can be described as:

$$L^{Text\ Discriminator}=-E_{real}[\log D(X^{real\ text})]-E_{fake}[\log(1-D(X^{fake\ text}))]$$

[0059] In the equation above, $X^{real\ text}$ is a sample from a textual source such as a text sample from the text corpus **105**. $X^{fake\ text}$ is the output obtained after an audio sample (e.g., from audio corpus **110**) is processed through ASR neural network **130**.

[0060] The second loss calculated by the text GAN loss subsystem **155** is used to train the ASR neural network **130**. The second loss can be described as:

$$L^{Text\ Generator}=E_{fake}[\log(1-D(X^{fake\ text}))]$$

[0061] FIG. **7** illustrates the fourth cycle of the training of the TTS neural network **125** and the ASR neural network **130** in training system **100**. In the fourth cycle, a text sample from the text corpus **105** and an audio sample from the audio corpus **110** are selected. The samples need not be related to each other.

[0062] The audio sample is provided to the audio embedder **120** to generate a mel spectrogram for input to the audio discriminator **135** and the audio GAN loss subsystem **150**.

[0063] The text sample from the text corpus **105** is provided to the text embedder **115**. The text embedder **115** generates a text embedding and provides the text embedding to the TTS neural network **125**. The text encoder **215** generates text latent code representing the text embedding, and the audio decoder **220** generates the decoded mel spectrogram from the text latent code. The decoded mel spectrogram is fed into the audio discriminator **135**.

[0064] The audio discriminator **135** is trained to output a first value (e.g., "real," "1," or the like) for mel spectrograms that were generated from the audio embedder **120** from an audio source. The audio discriminator **135** is also trained to output a second value (e.g., "fake," "0," or the like) for decoded mel spectrograms generated by the TTS neural network **125**. The audio discriminator **135** generates an output value associated with the mel spectrogram from audio embedder **120** and for the decoded mel spectrogram. The output values are provided to the audio GAN loss subsystem **150**.

[0065] The audio GAN loss subsystem **150** uses the mel spectrogram information from the audio embedder **120** to determine which mel spectrogram is "real" (i.e., from the audio embedder **120**) and which is "fake" (i.e., from the TTS neural network **125**). The audio GAN loss subsystem **150** can determine whether the audio discriminator **135** made correct determinations. The calculated losses by the audio GAN loss subsystem **150** can be used to train the audio discriminator **135** and the TTS neural network **125**.

[0066] The first loss for the audio discriminator **135** is used to train the audio discriminator **135**. The first loss can be described as:

$$L^{Audio\ Discriminator}=-E_{real}[\log D(X^{real\ audio})]-E_{fake}[\log(1-D(X^{fake\ audio}))]$$

[0067] In the equation above, $X^{real\ audio}$ is a sample from an audio source such as an audio sample from the audio corpus **110**. $X^{fake\ audio}$ is the output obtained after a text sample (e.g., from text corpus **105**) is processed through TTS neural network **125**.

[0068] The second loss calculated by the audio GAN loss subsystem **150** is used to train the TTS neural network **125**. The second loss can be described as:

$$L^{Audio\ Generator}=E_{fake}[\log(1-D(X^{fake\ audio}))]$$

[0069] The text discriminator **140** is trained by minimizing $L^{Text\ Discriminator}$ loss function. The loss function is minimized by providing the loss value into the text discriminator **140** and adjusting output parameters of the text discriminator **140** based on the loss value such that the loss function is minimized on future executions of the text discriminator **140**. Likewise, the audio discriminator **135** is trained by minimizing the $L^{Audio\ Discriminator}$ loss function. The loss function for the audio discriminator **135** is minimized by providing the loss value into the audio discriminator **135** and adjusting output parameters of the audio discriminator **135** based on the loss value such that the loss function is minimized on future executions of the audio discriminator **135**. The text encoder **215**, text decoder **320**, audio encoder **315**, and audio decoder **220** are trained by minimizing the total generative and cycle losses:

$$L^{Total}=L^{cycle1}+L^{cycle2}+L^{Text\ Generator}+L^{Audio\ Generator}$$

[0070] The total generative losses and cycle losses are minimized by feeding the loss values back into the respective neural networks and used to adjust output parameters so that future executions of the neural networks minimize the loss value. For example, L^{cycle1} and L^{cycle2} are provided to the TTS neural network **125** (i.e., text encoder **215** and audio decoder **220**) and ASR neural network **130** (i.e., audio encoder **315** and text decoder **320**) to adjust output parameters of each neural network for minimizing the losses in future executions of the neural networks. $L^{Text\ Generator}$ is also fed back into the ASR neural network **130**, and $L^{Audio\ Generator}$ is fed back in to the TTS neural network **125** to adjust output parameters for minimizing the loss.

[0071] The GAN losses help in improving the overall generative ability of the text encoder **215**, audio encoder **315**, text decoder **320**, and audio decoder **220**. This is because the TTS neural network **125** and ASR neural network **130** must not only produce realistic text embeddings and mel spectrograms but they must also try to fool the respective discriminators as constructed in the loss functions. Thus, we do not rely on only the cycle losses, but also the generative losses ($L^{Text\ Generator}$ and $L^{Audio\ Generator}$) to train the text encoder **215**, audio encoder **315**, text decoder **320**, and audio decoder **220**. This improves the overall output quality of both the ASR neural network **130** and TTS neural network **125**.

[0072] FIG. **8** illustrates a method **800** for training a TTS neural network and ASR neural network. The method **800** may be performed by a computing system such as training system **100** described with respect to FIG. **1**. The method **800** begins at step **805** with the training system receiving a first text sample as input to a TTS neural network. For example, a text sample may be obtained from the text corpus **105**. The text embedder **115** may generate a text embedding of the text sample and provide the text embedding to the TTS neural network **125**.

[0073] At step **810** the TTS neural network may generate a first audio sample representing the first text sample. For example, the TTS neural network **125** may receive the text sample from the text embedder **115**. The text encoder **215** of the TTS neural network **125** may generate text latent code from the text embedding, and the audio decoder **220** may generate a decoded mel spectrogram from the text latent code. The decoded mel spectrogram may be the audio sample representing the text sample.

[0074] At step **815** the ASR neural network may generate a second text sample representing the first audio sample. For example, the decoded mel spectrogram from the TTS neural network **125** may be provided to the ASR neural network **130**. The audio encoder **315** may generate audio latent code from the mel spectrogram, and the text decoder **320** may generate a decoded text embedding from the audio latent code. The decoded text embedding may be the second text sample.

[0075] At step **820** the training system may calculate a first loss based on the difference between the first text sample and the second text sample. For example, the text loss cycle 1 subsystem may calculate the first loss based on the difference between the text embedding created by the text embedder **115** from the text sample obtained from the text corpus **105** and the decoded text embedding generated by the ASR neural network **130** from the decoded mel spectrogram generated by the TTS neural network **125** from the original text sample.

[0076] At step **825** the training system may receive a second audio sample as input to the ASR neural network. For example, an audio sample may be obtained from the audio corpus **110**. The audio embedder **120** may generate a mel spectrogram of the audio sample and provide the mel spectrogram to the ASR neural network **130**.

[0077] At step **830** the ASR neural network may generate a third text sample representing the second audio sample. For example, the mel spectrogram from the audio embedder **120** may be used by the audio encoder **315** to generate audio latent code. The text decoder **320** may generate a decoded text embedding of the audio latent code. The decoded text embedding may be the third text sample.

[0078] At step **835** the TTS neural network may generate a third audio sample representing the third text sample. For example, the decoded text embedding may be fed into the TTS neural network **125**. The text encoder **215** may generate text latent code from the decoded text embedding, and the audio decoder **220** may generate a decoded mel spectrogram from the text latent code. The decoded mel spectrogram may be the third audio sample.

[0079] At step **840** the training system may calculate a second loss based on the difference between the second audio sample and the third audio sample. For example, the audio loss cycle 2 subsystem **160** may calculate the second loss based on the difference between the mel spectrogram created by the audio embedder **120** from the audio sample obtained from the audio corpus **110** and the decoded mel spectrogram generated by the TTS neural network **125** from the decoded text embedding generated by the ASR neural network **130** from the original audio sample.

[0080] At step **845** the training system may train the TTS neural network by adjusting parameters of the TTS neural network based at least in part on the first and second losses. For example, the training system may feed the first and second losses back into the TTS neural network **125**. The TTS neural network **125** may adjust parameters of the text encoder **215** and the audio decoder **220** to minimize the loss values from the loss functions on future executions of the TTS neural network **125**.

[0081] At step **850** the training system may train the ASR neural network by adjusting parameters of the ASR neural network based at least in part on the first and second losses. For example, the training system may feed the first and second losses back into the ASR neural network **130**. The ASR neural network **130** may adjust parameters of the audio encoder **315** and the text decoder **320** to minimize the loss values from the loss functions on future executions of the ASR neural network **130**.

Examples of Computing Environments for Implementing Certain Embodiments

[0082] Any suitable computing system or group of computing systems can be used for performing the operations described herein. For example, FIG. **10** illustrates a cloud computing system **1000** by which at least a portion of the functionality of training system **100** may be offered. FIG. **9** depicts an example of a computing device **900** that may be at least a portion of training system **100**. The implementation of the computing device **900** could be used for one or more of the subsystems depicted in FIG. **1**. In an embodiment, a single training system **100** having devices similar to those depicted in FIG. **9** (e.g., a processor, a memory, etc.) combines the one or more operations and data stores depicted as separate subsystems in FIG. **1**.

[0083] FIG. **9** illustrates a block diagram of an example of a computer system **900**. Computer system **900** can be any of the described computers herein including, for example, training system **100**, user device **200**, user device **300**, and the like. The computing device **900** can be or include, for example, an integrated computer, a laptop computer, desktop computer, tablet, server, a smartphone, or other electronic device.

[0084] The computing device **900** can include a processor **940** interfaced with other hardware via a bus **905**. A memory **910**, which can include any suitable tangible (and non-transitory) computer readable medium, such as RAM, ROM, EEPROM, or the like, can embody program components (e.g., program code **915**) that configure operation of the computing device **900**. Memory **910** can store the program code **915**, program data **917**, or both. In some examples, the computing device **900** can include input/output ("I/O") interface components **925** (e.g., for interfacing with a display **945**, keyboard, mouse, and the like) and additional storage **930**.

[0085] The computing device **900** executes program code **915** that configures the processor **940** to perform one or more of the operations described herein. Examples of the program code **915** include, in various embodiments, text embedder **115**, TTS neural network **125**, audio discriminator **135**, audio embedder **120**, ASR neural network **130**, text discriminator **140**, text loss cycle 1 subsystem **145**, audio GAN loss subsystem **150**, Text GAN loss subsystem **155**, audio loss cycle 2 subsystem **160**, or any other suitable systems or subsystems that perform one or more operations described herein (e.g., one or more development systems for configuring an interactive user interface). The program code **915** may be resident in the memory **910** or any suitable computer-readable medium and may be executed by the processor **940** or any other suitable processor.

[0086] The computing device **900** may generate or receive program data **917** by virtue of executing the program code **915**. For example, text samples, audio samples, the data in text corpus **105**, the data in audio corpus **110**, and so forth are all examples of program data **917** that may be used by the computing device **900** during execution of the program code **915**.

[0087] The computing device **900** can include network components **920**. Network components **920** can represent one or more of any components that facilitate a network connection. In some examples, the network components **920** can facilitate a wireless connection and include wireless interfaces such as IEEE 802.11, Bluetooth, or radio interfaces for accessing cellular telephone networks (e.g., a transceiver/antenna for accessing CDMA, GSM, UMTS, or other mobile communications network). In other examples, the network components **920** can be wired and can include interfaces such as Ethernet, USB, or IEEE 1394.

[0088] Although FIG. **9** depicts a single computing device **900** with a single processor **940**, the system can include any number of computing devices **900** and any number of processors **940**. For example, multiple computing devices **900** or multiple processors **940** can be distributed over a wired or wireless network (e.g., a Wide Area Network, Local Area Network, or the Internet). The multiple computing devices **900** or multiple processors **940** can perform any of the steps of the present disclosure individually or in coordination with one another.

[0089] In some embodiments, the functionality provided by the training system **100** may be offered as cloud services by a cloud service provider. For example, FIG. **10** depicts an example of a cloud computing system **1000** offering a training service that can be used by a number of user subscribers using user devices **1025***a*, **1025***b*, and **1025***c* across a data network **1020**. User devices **1025***a*, **1025***b*, and **1025***c* could be examples of a vehicle **105** described above. In the example, the training service or the trained TTS or ASR neural networks may be offered under a Software as a Service (SaaS) model. One or more users may subscribe to the training service, the trained ASR neural network, and/or the TTS neural network, and the cloud computing system performs the processing to provide the training service, ASR service, and/or TTS service to subscribers. The cloud computing system may include one or more remote server computers **1005**.

[0090] The remote server computers **1005** include any suitable non-transitory computer-readable medium for storing program code (e.g., training system **100**) and program data **1010**, or both, which is used by the cloud computing system **1000** for providing the cloud services. A computer-readable medium can include any electronic, optical, magnetic, or other storage device capable of providing a processor with computer-readable instructions or other program code. Non-limiting examples of a computer-readable medium include a magnetic disk, a memory chip, a ROM, a RAM, an ASIC, optical storage, magnetic tape or other magnetic storage, or any other medium from which a processing device can read instructions. The instructions may include processor-specific instructions generated by a compiler or an interpreter from code written in any suitable computer-programming language, including, for example, C, C++, C#, Visual Basic, Java, Python, Perl, JavaScript, and ActionScript. In various examples, the server computers **1005** can include volatile memory, non-volatile memory, or a combination thereof

[0091] One or more of the servers **1005** execute the program code **1010** that configures one or more processors of the server computers **1005** to perform one or more of the operations that provide training services, ASR services, and/or TTS services. As depicted in the embodiment in FIG. **10**, the one or more servers **1005** provide the services via the training system **100**, ASR neural network **130**, and/or TTS neural network **125**. Any other suitable systems or subsystems that perform one or more operations described herein (e.g., one or more development systems for configuring an interactive user interface) can also be implemented by the cloud computing system **1000**.

[0092] In certain embodiments, the cloud computing system **1000** may implement the services by executing program code and/or using program data **1010**, which may be resident in a memory device of the server computers **1005** or any suitable computer-readable medium and may be executed by the processors of the server computers **1005** or any other suitable processor.

[0093] In some embodiments, the program data **1010** includes one or more datasets and models described herein. Examples of these datasets include the text corpus **105** and the audio corpus **110**, and so forth. In some embodiments, one or more of data sets, models, and functions are stored in the same memory device. In additional or alternative embodiments, one or more of the programs, data sets, models, and functions described herein are stored in different memory devices accessible via the data network **1015**.

[0094] The cloud computing system **1000** also includes a network interface device **1015** that enable communications to and from cloud computing system **1000**. In certain embodiments, the network interface device **1015** includes any device or group of devices suitable for establishing a wired or wireless data connection to the data networks **1020**. Non-limiting examples of the network interface device **1015** include an Ethernet network adapter, a modem, and/or the like. The training system **100** is able to communicate with the user devices **1025***a*, **1025***b*, and **1025***c* via the data network **1020** using the network interface device **1015**.

General Considerations

[0095] While the present subject matter has been described in detail with respect to specific aspects thereof, it will be appreciated that those skilled in the art, upon attaining an understanding of the foregoing, may readily produce alterations to, variations of, and equivalents to such aspects. Numerous specific details are set forth herein to provide a thorough understanding of the claimed subject matter. However, those skilled in the art will understand that the claimed subject matter may be practiced without these specific details. In other instances, methods, apparatuses, or systems that would be known by one of ordinary skill have not been described in detail so as not to obscure claimed subject matter. Accordingly, the present disclosure has been presented for purposes of example rather than limitation, and does not preclude the inclusion of such modifications, variations, and/or additions to the present subject matter as would be readily apparent to one of ordinary skill in the art

[0096] Unless specifically stated otherwise, it is appreciated that throughout this specification discussions utilizing terms such as "processing," "computing," "calculating," "determining," and "identifying" or the like refer to actions or processes of a computing device, such as one or more computers or a similar electronic computing device or devices, that manipulate or transform data represented as physical electronic or magnetic quantities within memories, registers, or other information storage devices, transmission devices, or display devices of the computing platform. The use of "adapted to" or "configured to" herein is meant as open and inclusive language that does not foreclose devices adapted to or configured to perform additional tasks or steps. Additionally, the use of "based on" is meant to be open and inclusive, in that a process, step, calculation, or other action "based on" one or more recited conditions or values may, in practice, be based on additional conditions or values beyond those recited. Headings, lists, and numbering included herein are for ease of explanation only and are not meant to be limiting.

[0097] Aspects of the methods disclosed herein may be performed in the operation of such computing devices. The system or systems discussed herein are not limited to any particular hardware architecture or configuration. A computing device can include any suitable arrangement of components that provide a result conditioned on one or more inputs. Suitable computing devices include multi-purpose microprocessor-based computer systems accessing stored software that programs or configures the computing system from a general purpose computing apparatus to a specialized computing apparatus implementing one or more aspects of the present subject matter. Any suitable programming, scripting, or other type of language or combinations of languages may be used to implement the teachings contained herein in software to be used in programming or configuring a computing device. The order of the blocks presented in the examples above can be varied—for example, blocks can be re-ordered, combined, and/or broken into sub-blocks. Certain blocks or processes can be performed in parallel.

What is claimed is:

1. A method for training a text-to-speech (TTS) neural network and an automatic speech recognition (ASR) neural network, the method comprising:
- receiving a first text sample as input to the TTS neural network;
- generating, using the TTS neural network, a first audio sample representing the first text sample;
- generating, using the ASR neural network, a second text sample representing the first audio sample;
- calculating a first loss based on a first difference between the first text sample and the second text sample;
- receiving a second audio sample as input to the ASR neural network;
- generating, using the ASR neural network, a third text sample representing the second audio sample;
- generating, using the TTS neural network, a third audio sample representing the third text sample;
- calculating a second loss based on a second difference between the second audio sample and the third audio sample;
- training the TTS neural network by adjusting parameters of the TTS neural network based at least in part on the first loss and the second loss; and
- training the ASR neural network by adjusting parameters of the ASR neural network based at least in part on the first loss and the second loss.

2. The method of claim **1**, wherein the TTS neural network comprises a text encoder and an audio decoder, and wherein training the TTS neural network comprises adjusting one or more parameters of the text encoder or one or more parameters of the audio decoder.

3. The method of claim **1**, wherein the ASR neural network comprises an audio encoder and a text decoder, and wherein training the ASR neural network comprises adjusting one or more parameters of the audio encoder or one or more parameters of the text decoder.

4. The method of claim **1**, further comprising:
- generating, using the ASR neural network, a fourth text sample representing a fourth audio sample received as input to the ASR neural network;
- receiving, as input to a text discriminator, the fourth text sample and a fifth text sample from a textual source;
- generating, by the text discriminator, a third loss based on the fourth text sample and the fifth text sample;
- further training the TTS neural network based at least in part on the third loss; and
- further training the ASR neural network based at least in part on the third loss.

5. The method of claim **4**, wherein the text discriminator is trained to output a first value for a fake text sample, wherein the fake text sample is generated from an audio sample, and wherein the text discriminator is trained to output a second value for a real text sample, wherein the real text sample is generated from a textual source.

6. The method of claim **1**, further comprising:
- generating, using the TTS neural network, a fourth audio sample representing a fourth text sample received as input to the TTS neural network;
- receiving, as input to an audio discriminator, the fourth audio sample and a fifth audio sample from an audio source;
- generating, by the audio discriminator, a third loss based on the fourth audio sample and the fifth audio sample;
- further training the TTS neural network based at least in part on the third loss; and
- further training the ASR neural network based at least in part on the third loss.

7. The method of claim **6**, wherein the audio discriminator is trained to output a first value for a fake audio sample, wherein the fake audio sample is generated from a text sample, and wherein the audio discriminator is trained to output a second value for a real audio sample, wherein the real audio sample is generated from an audio source.

8. The method of claim **1**, further comprising:
- deploying the trained TTS neural network.

9. The method of claim **1**, further comprising:
- deploying the trained ASR neural network.

10. A system, comprising:
- a text-to-speech (TTS) neural network;
- an automatic speech recognition (ASR) neural network;
- one or more processors; and
- a memory having stored thereon instructions that, upon execution by the one or more processors, cause the one or more processors to:
  - provide a first text sample as input to the TTS neural network;
  - receive, from the TTS neural network, a first audio sample representing the first text sample;
  - provide the first audio sample as input to the ASR neural network;
  - receive, from the ASR neural network, a second text sample representing the first audio sample;
  - calculate a first loss based on a first difference between the first text sample and the second text sample;

provide a second audio sample as input to the ASR neural network;

receive, from the ASR neural network, a third text sample representing the second audio sample;

provide the third text sample as input to the TTS neural network;

receive, from the TTS neural network, a third audio sample representing the third text sample;

calculate a second loss based on a second difference between the second audio sample and the third audio sample;

train the TTS neural network by adjusting parameters of the TTS neural network based at least in part on the first loss and the second loss; and

train the ASR neural network by adjusting parameters of the ASR neural network based at least in part on the first loss and the second loss.

11. The system of claim **10**, wherein the TTS neural network comprises a text encoder and an audio decoder, and wherein the instructions for training the TTS neural network comprises instructions that, upon execution by the one or more processors, cause the one or more processors to adjust one or more parameters of the text encoder or one or more parameters of the audio decoder.

12. The system of claim **10**, wherein the ASR neural network comprises an audio encoder and a text decoder, and wherein the instructions for training the ASR neural network comprises instructions that, upon execution by the one or more processors, cause the one or more processors to adjust one or more parameters of the audio encoder or one or more parameters of the text decoder.

13. The system of claim **10**, wherein the instructions comprise further instructions that, upon execution by the one or more processors, cause the one or more processors to:

receive, from the ASR neural network, a fourth text sample representing a fourth audio sample provided as input to the ASR neural network;

provide, as input to a text discriminator, the fourth text sample and a fifth text sample from a textual source;

receive, from the text discriminator, a third loss based on the fourth text sample and the fifth text sample;

further train the TTS neural network based at least in part on the third loss; and

further train the ASR neural network based at least in part on the third loss.

14. The system of claim **13**, wherein the text discriminator is trained to output a first value for a fake text sample, wherein the fake text sample is generated from an audio sample, and wherein the text discriminator is trained to output a second value for a real text sample, wherein the real text sample is generated from a textual source.

15. The system of claim **10**, wherein the instructions comprise further instructions that, upon execution by the one or more processors, cause the one or more processors to:

receive, from the TTS neural network, a fourth audio sample representing a fourth text sample provided as input to the TTS neural network;

provide, as input to an audio discriminator, the fourth audio sample and a fifth audio sample from an audio source;

receive, from the audio discriminator, a third loss based on the fourth audio sample and the fifth audio sample;

further train the TTS neural network based at least in part on the third loss; and

further train the ASR neural network based at least in part on the third loss.

16. The system of claim **15**, wherein the audio discriminator is trained to output a first value for a fake audio sample, wherein the fake audio sample is generated from a text sample, and wherein the audio discriminator is trained to output a second value for a real audio sample, wherein the real audio sample is generated from an audio source.

17. The system of claim **10**, wherein the trained TTS neural network and the trained ASR neural network are deployed independently.

18. The system of claim **10**, wherein the trained TTS neural network and the trained ASR neural network are deployed for use on a single device.

19. A system, comprising:

a text-to-speech (TTS) neural network;

an automatic speech recognition (ASR) neural network;

a text discriminator; and

an audio discriminator, wherein the TTS neural network and ASR neural network were trained simultaneously using a generative adversarial network including the text discriminator and audio discriminator.

20. The system of claim **19**, wherein the TTS neural network and the ASR neural network are deployed independently.

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