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Chandran et al.

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(54) **SEMANTIC DEEP FACE MODELS**

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G06T 13/40	(2011.01)

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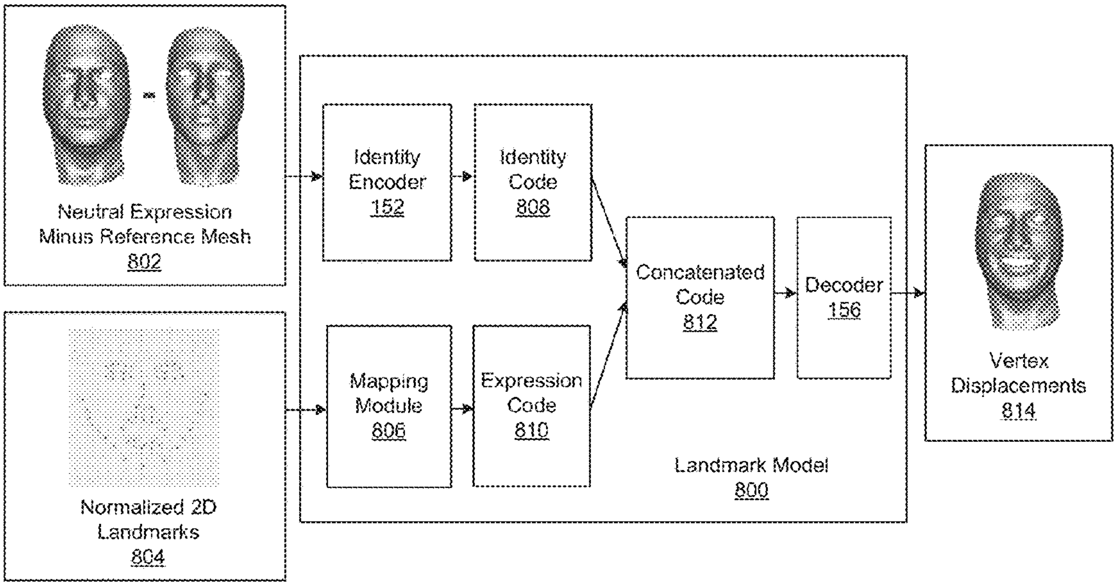
(57) **ABSTRACT**

Techniques are disclosed for training and applying nonlinear face models. In embodiments, a nonlinear face model includes an identity encoder, an expression encoder, and a decoder. The identity encoder takes as input a representation of a facial identity, such as a neutral face mesh minus a reference mesh, and outputs a code associated with the facial identity. The expression encoder takes as input a representation of a target expression, such as a set of blendweight values, and outputs a code associated with the target expression. The codes associated with the facial identity and the facial expression can be concatenated and input into the decoder, which outputs a representation of a face having the facial identity and expression. The representation of the face can include vertex displacements for deforming the reference mesh.

21 Claims, 15 Drawing Sheets



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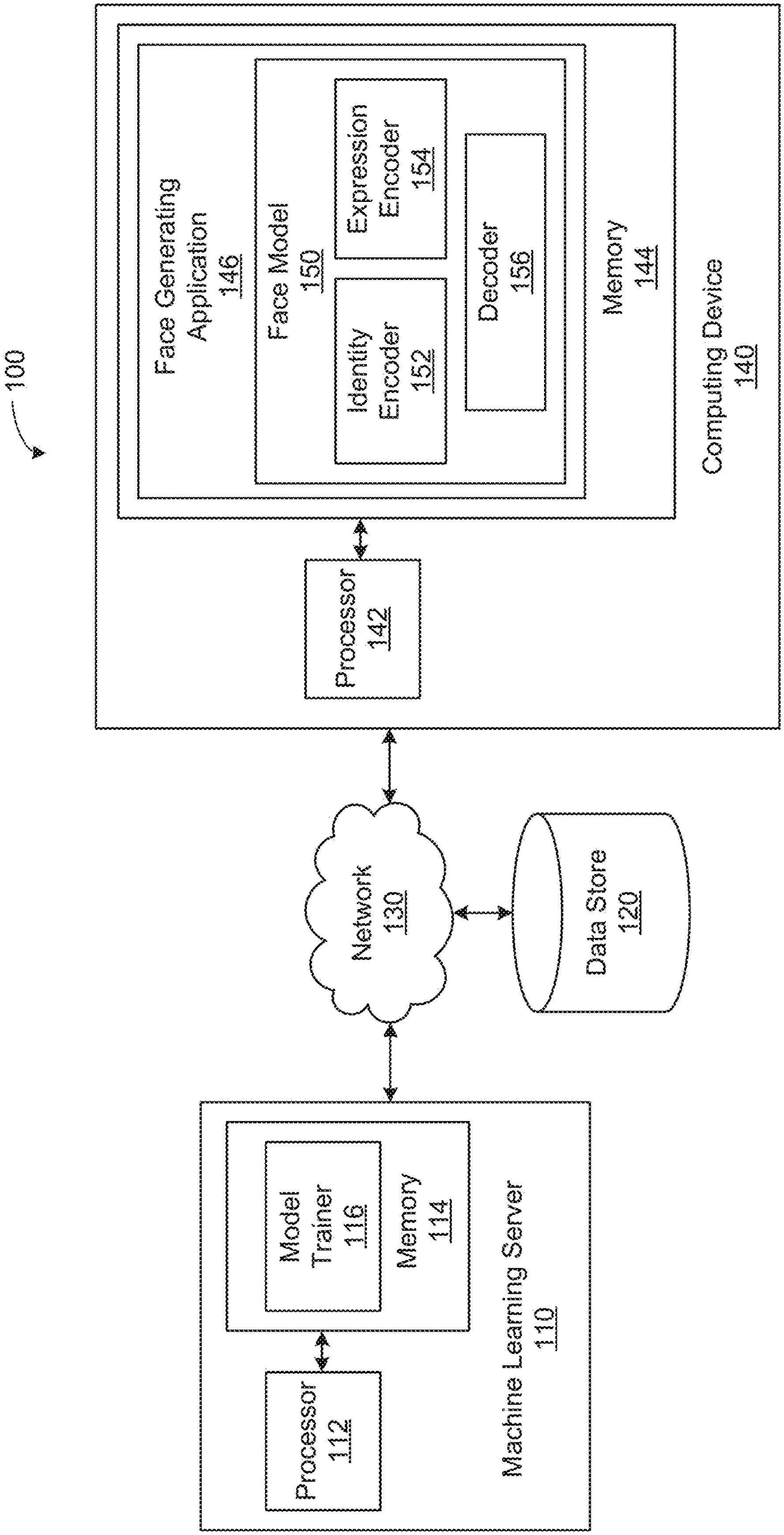
100
Face Generating Application
146
Face Model
150
Identity Encoder
152
Expression Encoder
154
Decoder
156
Memory
144
Processor
142
Computing Device
140
Network
130
Data Store
120
Model Trainer
116
Memory
114
Processor
112
Machine Learning Server
110

FIG. 1

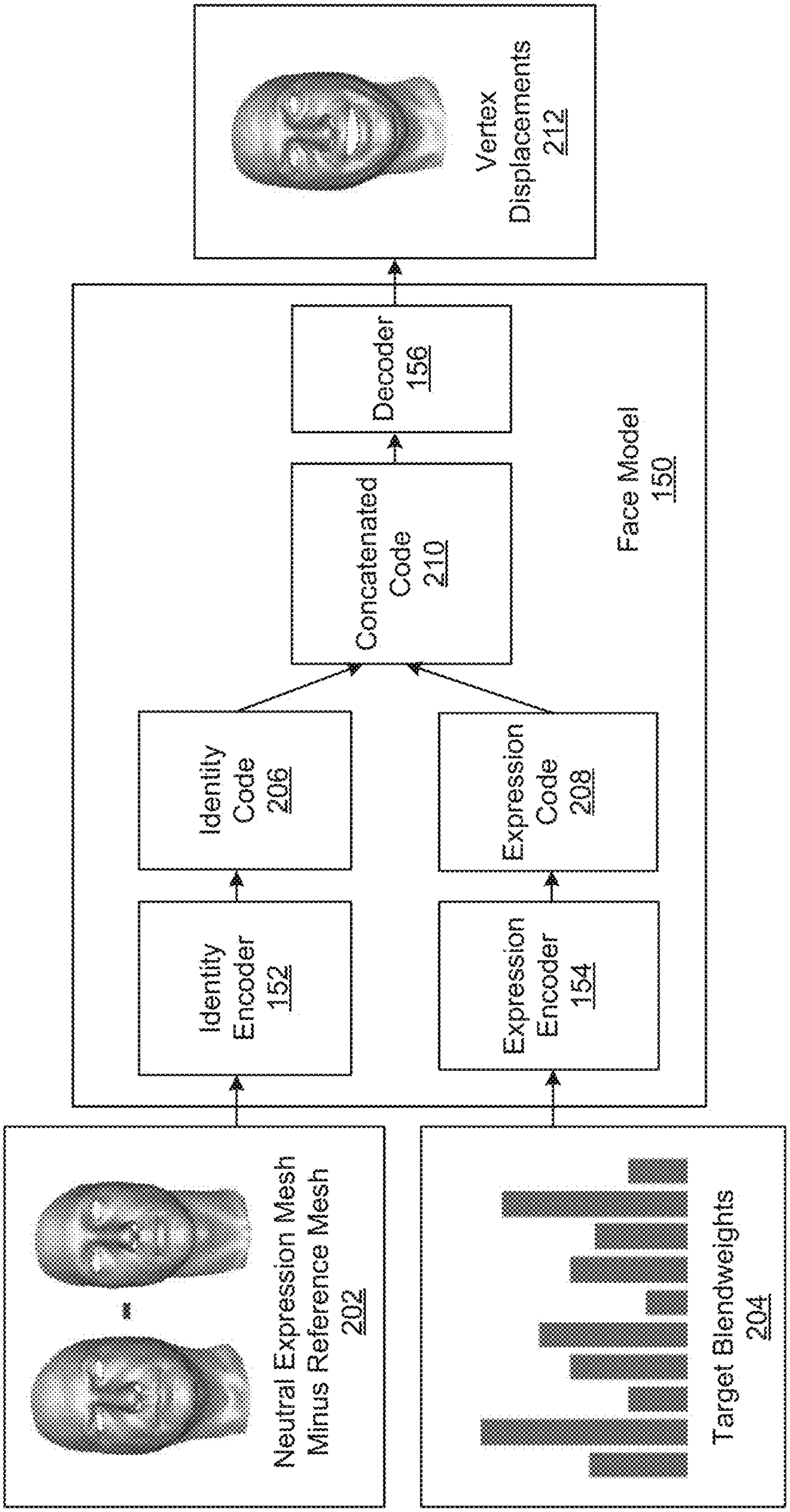
-
Neutral Expression Mesh
Minus Reference Mesh
202
Target Blendweights
204
Identity
Encoder
152
Expression
Encoder
154
Identity
Code
206
Expression
Code
208
Concatenated
Code
210
Decoder
156
Face Model
150
Vertex
Displacements
212

FIG. 2

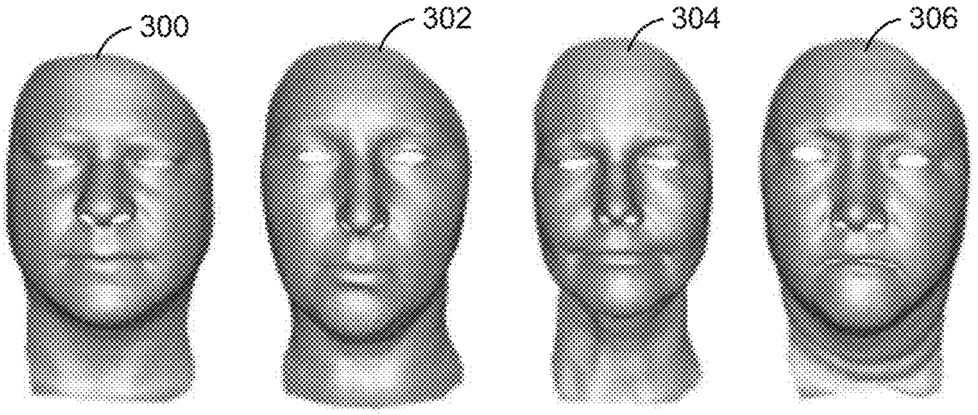

FIG. 3A

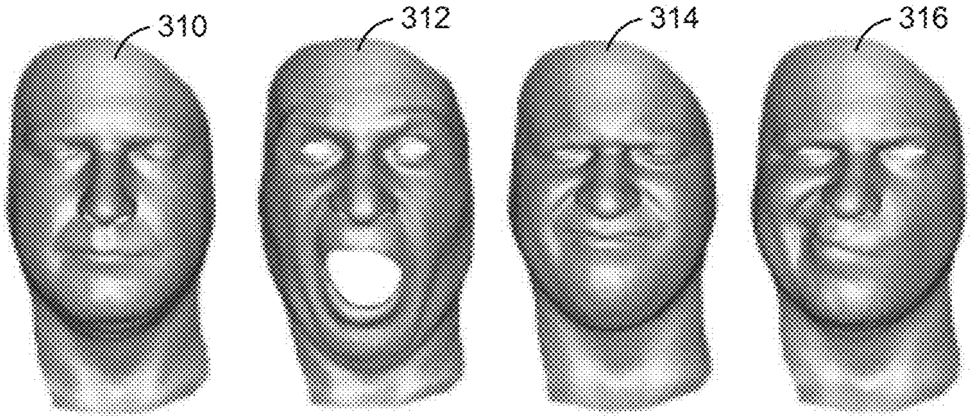

FIG. 3B

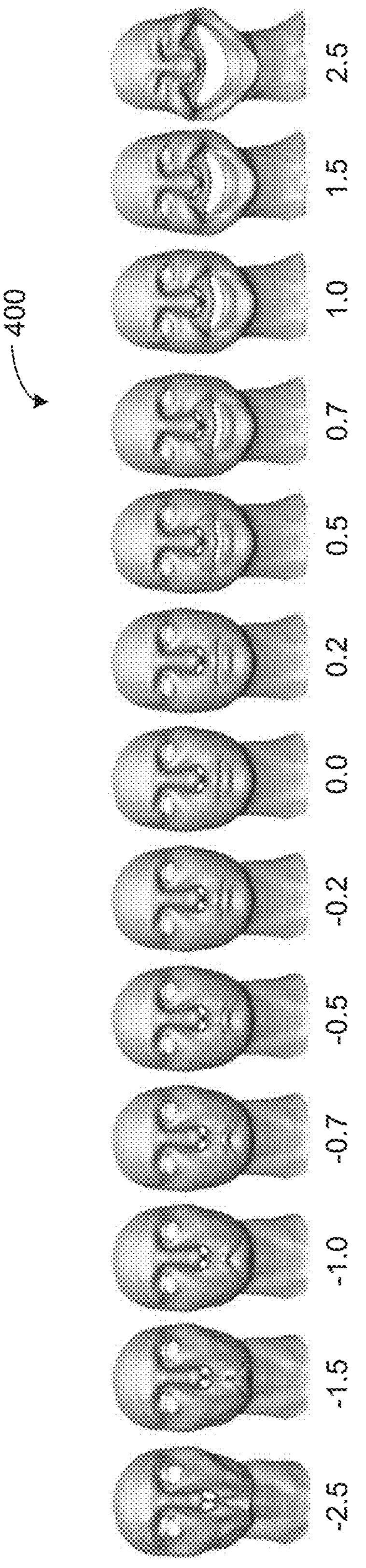

FIG. 4A (Prior Art)

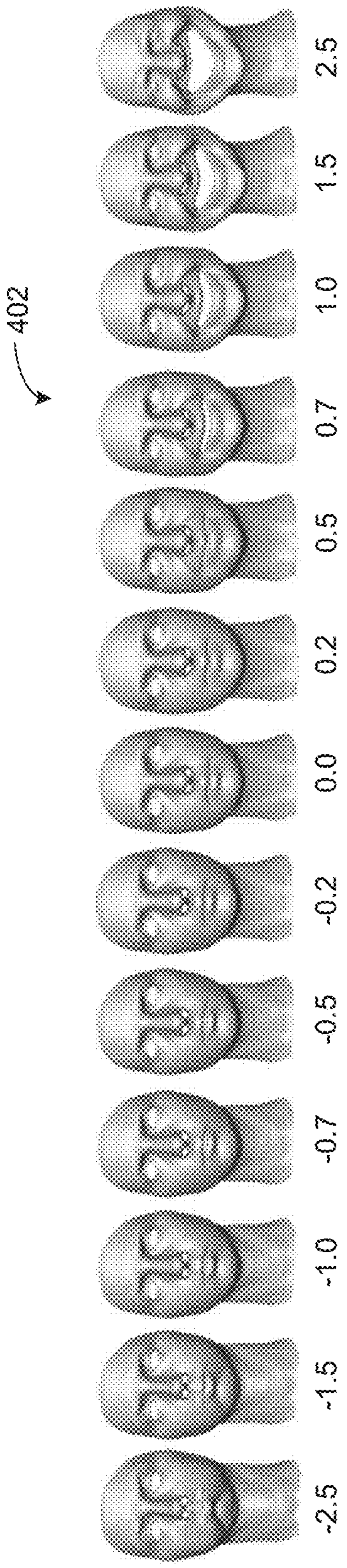

FIG. 4B

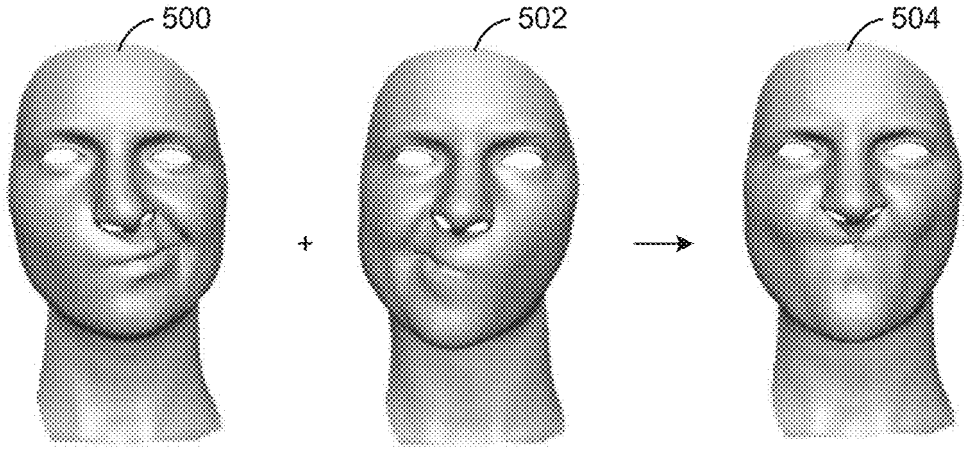

FIG. 5A (Prior Art)

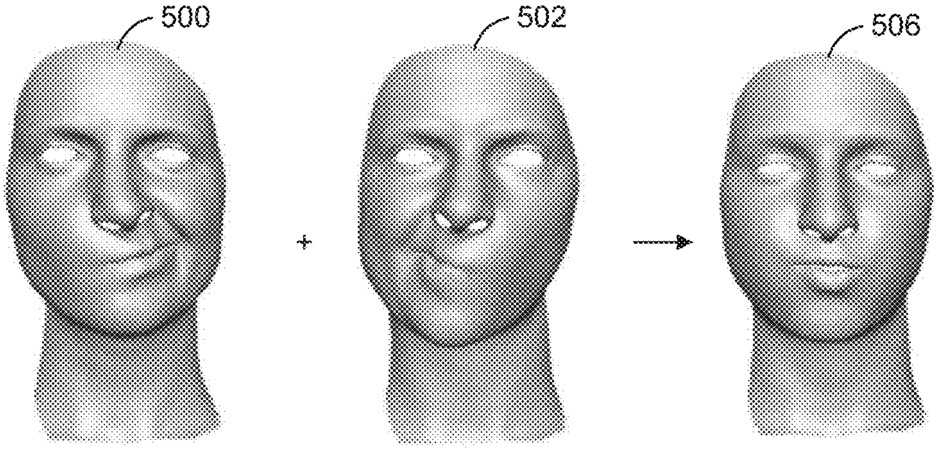

FIG. 5B

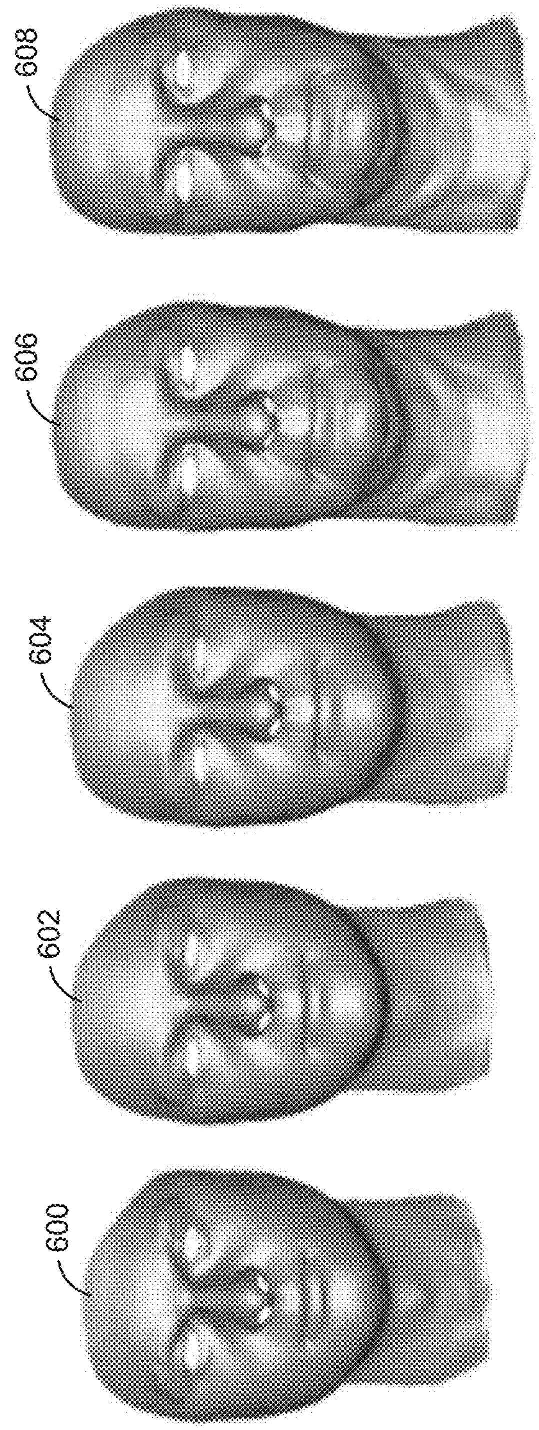

FIG. 6

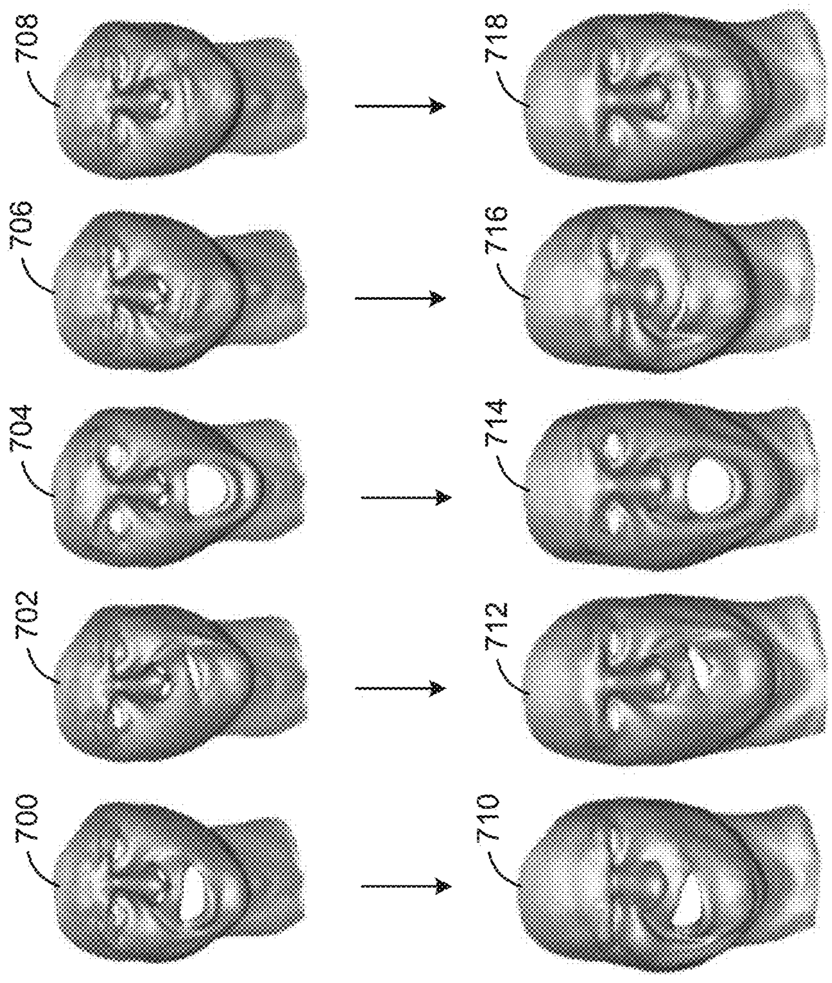

FIG. 7

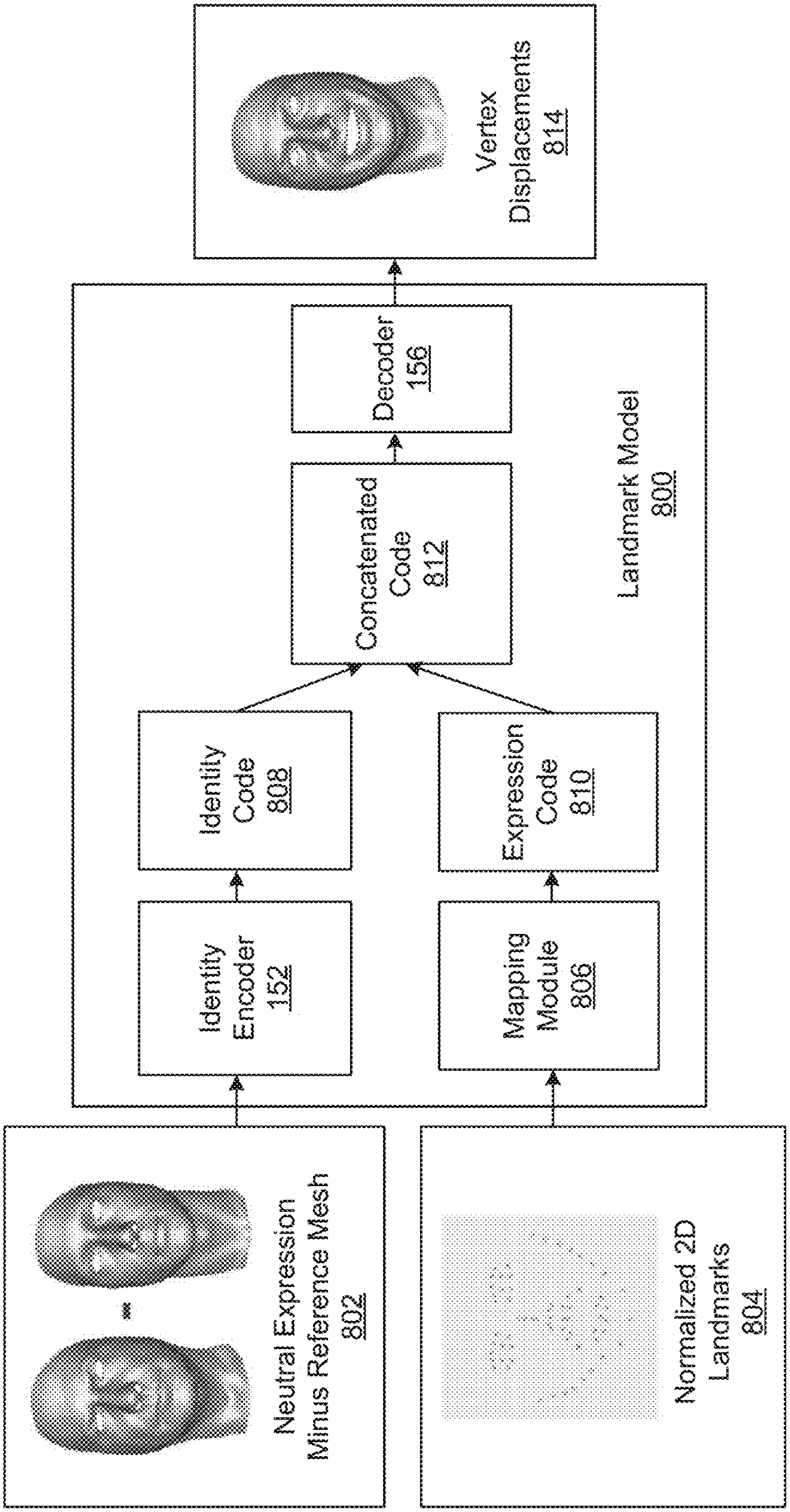
Neutral Expression
Minus Reference Mesh
802
-
Normalized 2D
Landmarks
804
Identity
Encoder
152
Mapping
Module
806
Identity
Code
808
Expression
Code
810
Concatenated
Code
812
Decoder
156
Landmark Model
800
Vertex
Displacements
814

FIG. 8

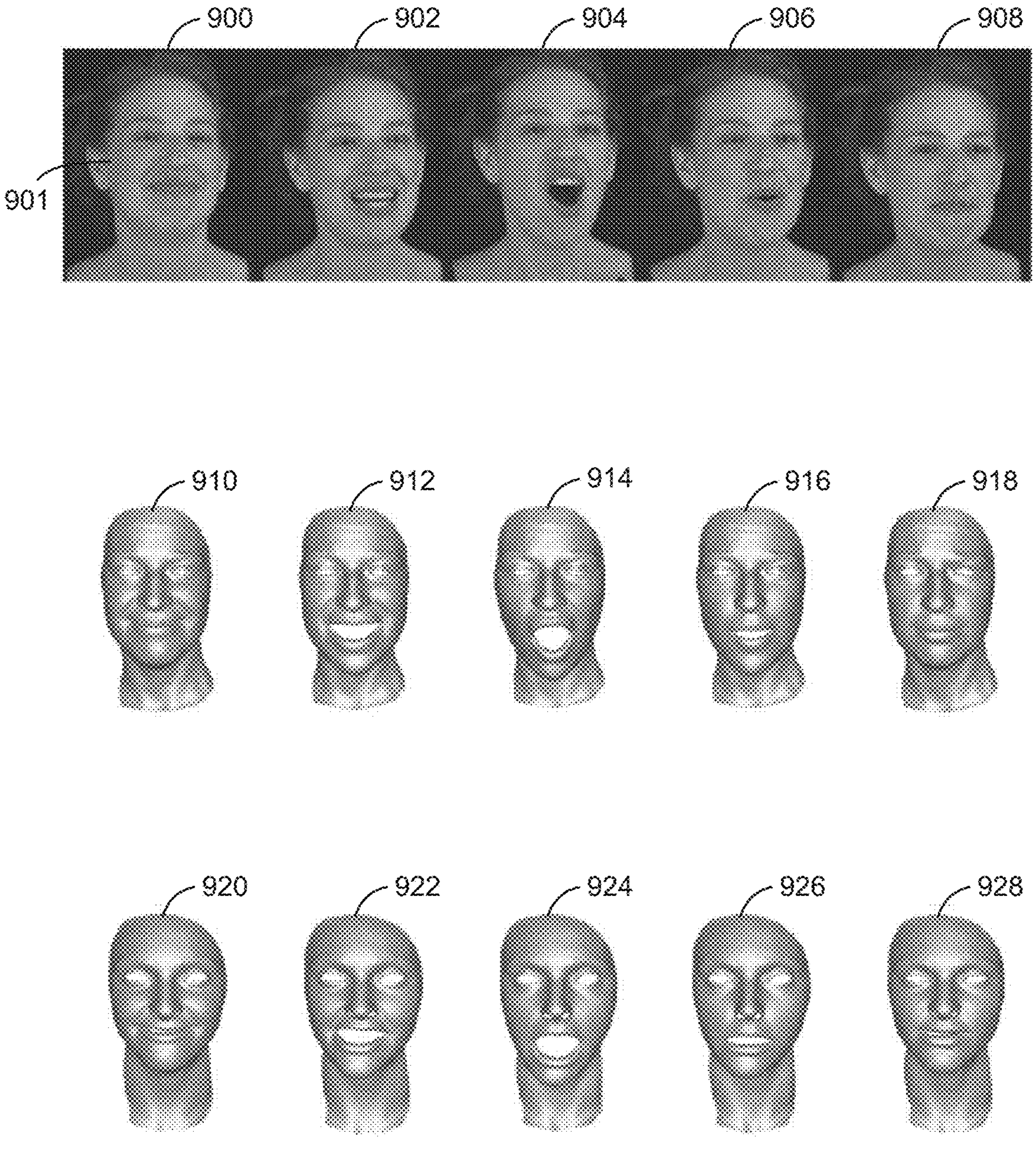

FIG. 9

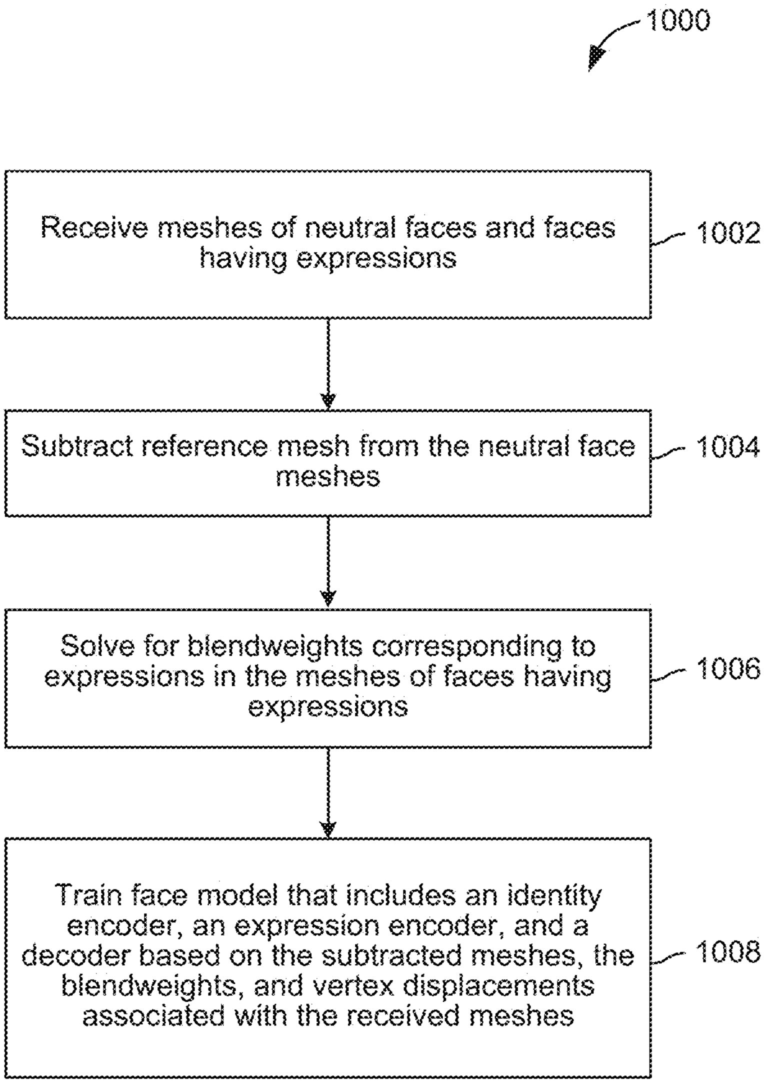
1000
Receive meshes of neutral faces and faces having expressions
1002
Subtract reference mesh from the neutral face meshes
1004
Solve for blendweights corresponding to expressions in the meshes of faces having expressions
1006
Train face model that includes an identity encoder, an expression encoder, and a decoder based on the subtracted meshes, the blendweights, and vertex displacements associated with the received meshes
1008

FIG. 10

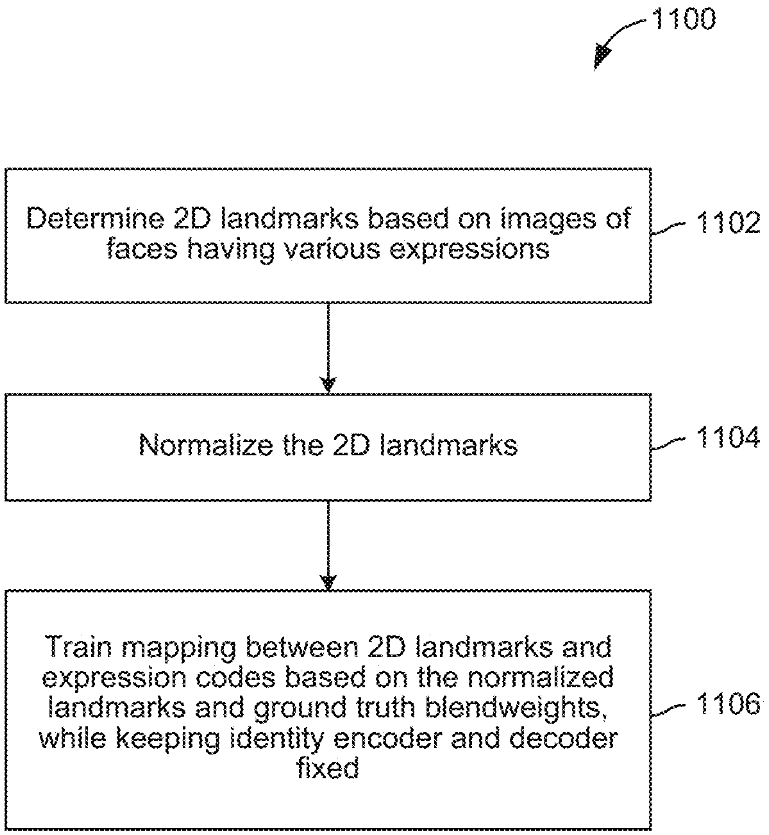
1100
Determine 2D landmarks based on images of faces having various expressions
1102
Normalize the 2D landmarks
1104
Train mapping between 2D landmarks and expression codes based on the normalized landmarks and ground truth blendweights, while keeping identity encoder and decoder fixed
1106

FIG. 11

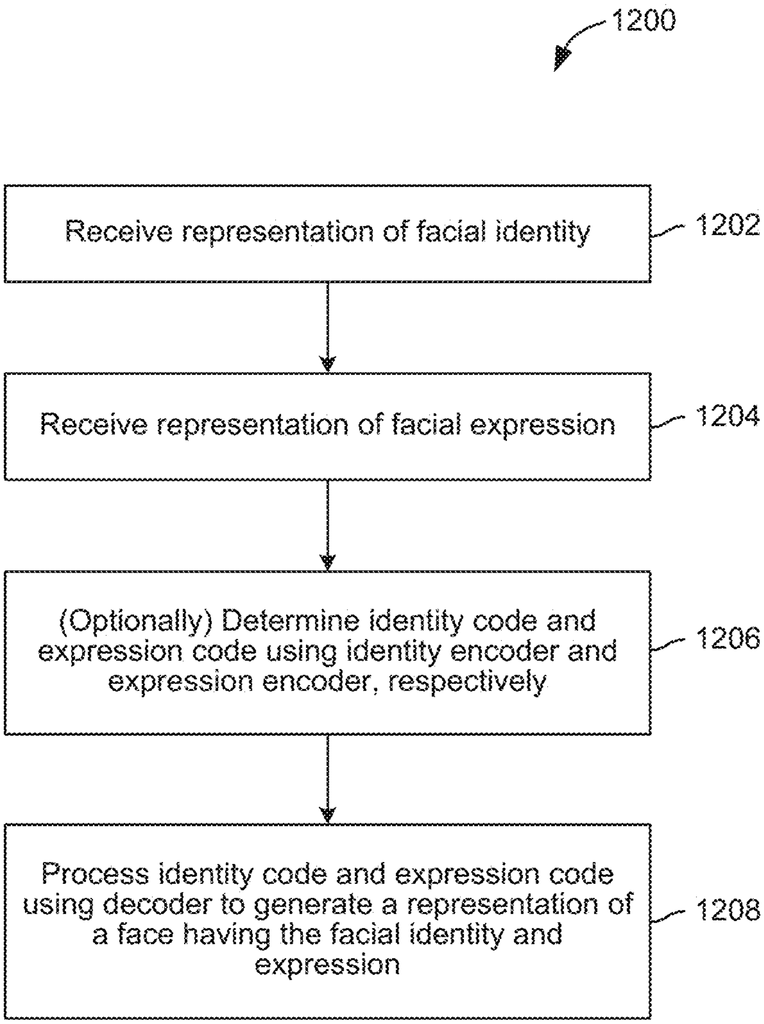
1200
Receive representation of facial identity
1202
Receive representation of facial expression
1204
(Optionally) Determine identity code and expression code using identity encoder and expression encoder, respectively
1206
Process identity code and expression code using decoder to generate a representation of a face having the facial identity and expression
1208

FIG. 12

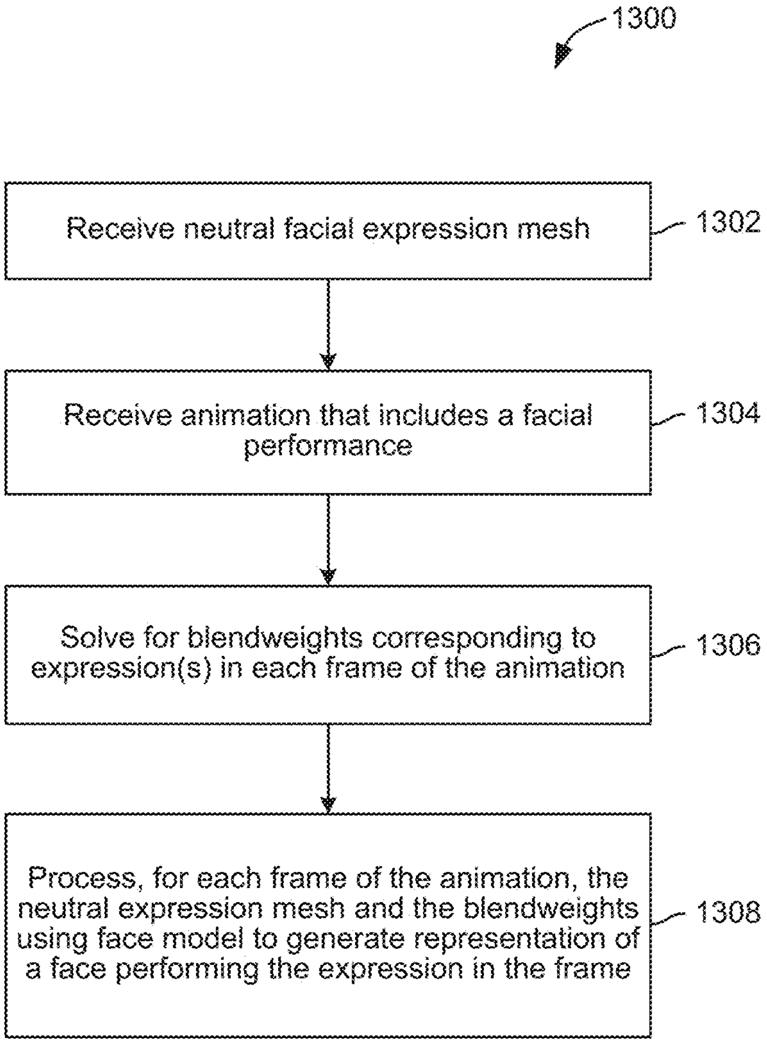
1300
Receive neutral facial expression mesh
1302
Receive animation that includes a facial performance
1304
Solve for blendweights corresponding to expression(s) in each frame of the animation
1306
Process, for each frame of the animation, the neutral expression mesh and the blendweights using face model to generate representation of a face performing the expression in the frame
1308

FIG. 13

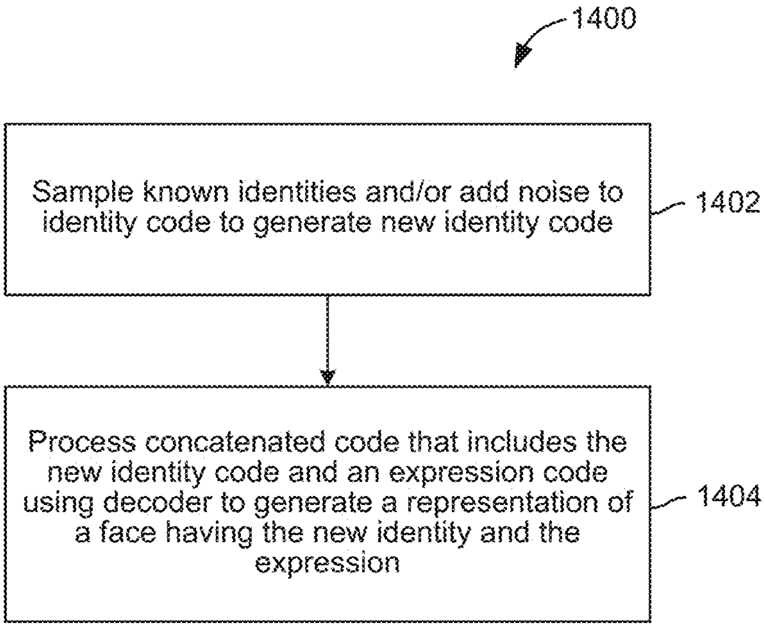
1400
Sample known identities and/or add noise to identity code to generate new identity code
1402
Process concatenated code that includes the new identity code and an expression code using decoder to generate a representation of a face having the new identity and the expression
1404

FIG. 14

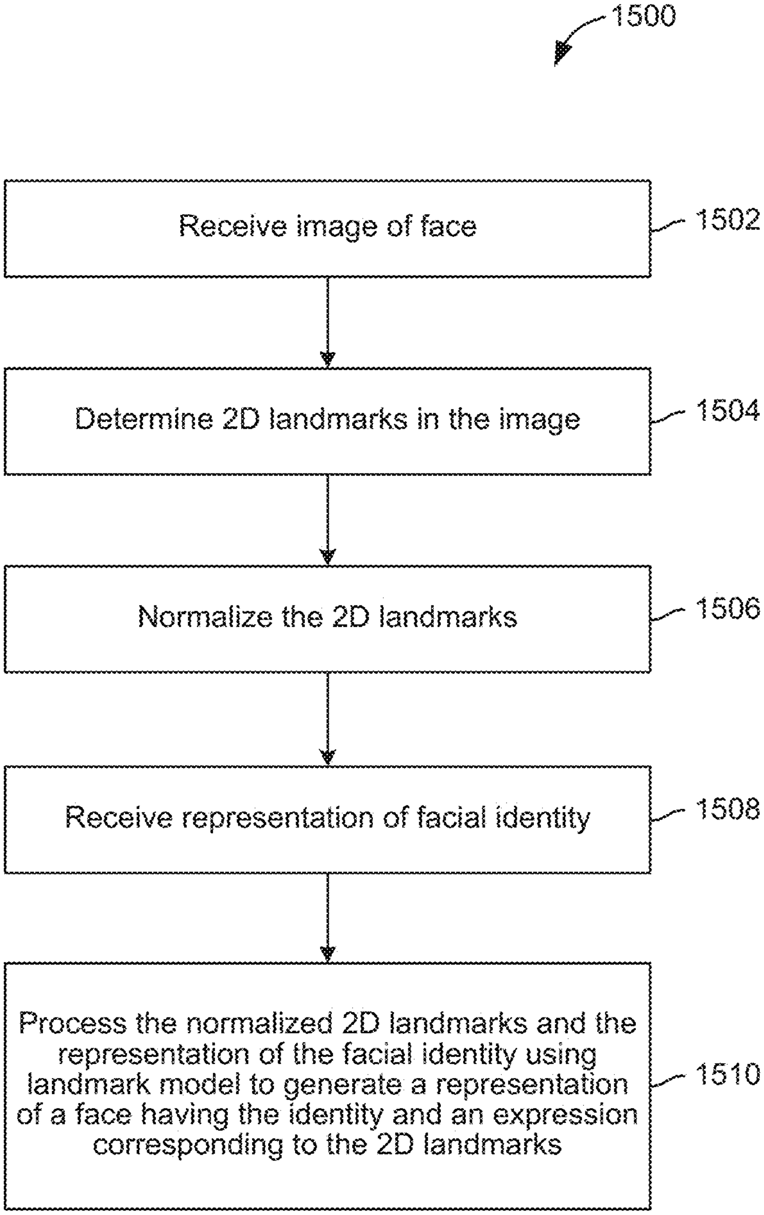
1500
Receive image of face
1502
Determine 2D landmarks in the image
1504
Normalize the 2D landmarks
1506
Receive representation of facial identity
1508
Process the normalized 2D landmarks and the representation of the facial identity using landmark model to generate a representation of a face having the identity and an expression corresponding to the 2D landmarks
1510

FIG. 15

SEMANTIC DEEP FACE MODELS

BACKGROUND

Technical Field

Embodiments of the present disclosure relate generally to computer vision and computer graphics and, more specifically, to semantic deep face models.

Description of the Related Art

Multi-linear morphable models that are built from three-dimensional (3D) face databases are commonly used to generate virtual 3D geometry representing human faces, which are also referred to herein as "faces." Such models typically generate a tensor of different dimensions that a user is permitted to control, such as the identity and expressions of faces that are being generated. User control over the identity and expressions of faces is oftentimes referred to as having "semantic control" of those facial dimensions. One drawback of multi-linear morphable models is that these models rely on linear combinations of different dataset shapes to generate faces, which can limit the quality and expressiveness of the generated faces. For example, the linear blending of facial shapes can result in an unrealistic-looking facial expression or unwanted artifacts, because human faces are highly nonlinear in their deformations.

Non-linear face models, including those based on deep neural networks, have been used to generate more realistic-looking facial images. However, typical non-linear face models do not produce 3D geometry and do not have any notion of semantic control. In particular, such models cannot be used to generate faces having user-controllable identities and expressions.

Currently, there are few, if any, techniques that can generate realistic-looking faces while providing user control of facial identities and expressions.

As the foregoing illustrates, what is needed in the art are more effective techniques for generating faces.

SUMMARY

One embodiment of the present application sets forth a computer-implemented method for generating a representation of a face. The method includes receiving a representation of a facial identity and a representation of a facial expression. The method further includes performing one or more decoding operations based on an encoded representation of the facial identity and an encoded representation of the facial expression to generate a representation of a face having the facial identity and the facial expression.

Another embodiment of the present application sets forth a non-transitory computer-readable storage medium including instructions that, when executed by a processing unit, cause the processing unit to perform steps for generating a representation of a face. The steps include receiving a representation of a facial identity and a representation of a facial expression. The steps further include processing an encoded representation of the facial identity and an encoded representation of the facial expression using a decoder to generate a representation of a face having the facial identity and the facial expression.

Another embodiment of the present application sets forth a computer-implemented method of training a model for generating faces. The method includes receiving a data set that includes meshes of neutral faces and meshes of faces

having expressions. The method further includes training a model based on the data set. The model includes a first encoder that maps representations of neutral faces to encoded representations of facial identities, a second encoder that maps representations of facial expressions to encoded representations of the facial expressions, and a decoder that maps encoded representations of facial identities and encoded representations of facial expressions to representations of faces.

Other embodiments of the present disclosure include, without limitation, a computer-readable medium including instructions for performing one or more aspects of the disclosed techniques as well as a computing device for performing one or more aspects of the disclosed techniques.

At least one technical advantage of the disclosed techniques relative to the prior art is that the disclosed techniques disentangle the notions of facial identity and facial expression using separate facial identity and expression encoders. This architectural approach allows facial identities and expressions to be separately controlled by a user when generating faces using a nonlinear model that includes the facial identity and expression encoders. In addition, the disclosed techniques can be used to generate faces that are more realistic-looking than faces generated by conventional approaches that implement linear-based techniques. These technical advantages represent one or more technological improvements over prior art approaches.

BRIEF DESCRIPTION OF THE DRAWINGS

So that the manner in which the above recited features of the disclosure can be understood in detail, a more particular description of the disclosure, briefly summarized above, may be had by reference to embodiments, some of which are illustrated in the appended drawings. It is to be noted, however, that the appended drawings illustrate only typical embodiments of this disclosure and are therefore not to be considered limiting of its scope, for the disclosure may admit to other equally effective embodiments.

FIG. **1** illustrates a system configured to implement one or more aspects of the various embodiments;

FIG. **2** is a more detailed illustration of the face model of FIG. **1**, according to various embodiments;

FIG. **3**A illustrates exemplar identities generated using the face model of FIG. **1**, according to various embodiments;

FIG. **3**B illustrates exemplar facial expressions generated for the facial identity of FIG. **3**A using the face model of FIG. **1**, according to various embodiments;

FIG. **4**A illustrates exemplar facial expressions along an expression dimension generated using a conventional linear model, according to the prior art;

FIG. **4**B illustrates exemplar facial expressions along an expression dimension generated using the face model of FIG. **1**, according to various embodiments;

FIG. **5**A illustrates an exemplar superimposing of facial expressions generated using a linear blending technique, according to the prior art;

FIG. **5**B illustrates an exemplar superimposing of facial expressions generated using the face model of FIG. **1**, according to various embodiments;

FIG. **6** illustrates an exemplar interpolation between identities generated using the face model of FIG. **1**, according to various embodiments;

FIG. **7** illustrates an exemplar retargeting of a facial performance from one facial identity to another facial identity using the face model of FIG. **1**, according to various embodiments;

FIG. **8** illustrates a landmark model that includes a mapping between two-dimensional (2D) facial landmarks and expression codes, according to various embodiments;

FIG. **9** illustrates an exemplar facial performance retargeting based on 2D facial landmarks detected in a video, according to various embodiments;

FIG. **10** sets forth a flow diagram of method steps for training a model to generate faces, according to various embodiments;

FIG. **11** sets forth a flow diagram of method steps for training a mapping between 2D facial landmarks and expression codes, according to various embodiments;

FIG. **12** sets forth a flow diagram of method steps for generating faces, according to various embodiments;

FIG. **13** sets forth a flow diagram of method steps for retargeting a facial performance on a new facial identity, according to various embodiments;

FIG. **14** sets forth a flow diagram of method steps for generating new facial identities, according to various embodiments; and

FIG. **15** sets forth a flow diagram of method steps for 2D landmark-based retargeting, according to various embodiments.

DETAILED DESCRIPTION

In the following description, numerous specific details are set forth to provide a more thorough understanding of the present invention. However, it will be apparent to one of skill in the art that embodiments of the present invention may be practiced without one or more of these specific details.

System Overview

FIG. **1** illustrates a system **100** configured to implement one or more aspects of the various embodiments. As shown, the system **100** includes a machine learning server **110**, a data store **120**, and a computing device **140** in communication over a network **130**, which may be a wide area network (WAN) such as the Internet, a local area network (LAN), or any other suitable network.

As shown, a model trainer **116** executes on a processor **112** of the machine learning server **110** and is stored in a system memory **114** of the machine learning server **110**. The processor **112** receives user input from input devices, such as a keyboard or a mouse. In operation, the processor **112** is the master processor of the machine learning server **110**, controlling and coordinating operations of other system components. In particular, the processor **112** may issue commands that control the operation of a graphics processing unit (GPU) that incorporates circuitry optimized for graphics and video processing, including, for example, video output circuitry. The GPU may deliver pixels to a display device that may be any conventional cathode ray tube, liquid crystal display, light-emitting diode display, or the like.

The system memory **114** of the machine learning server **110** stores content, such as software applications and data, for use by the processor **112** and the GPU. The system memory **114** may be any type of memory capable of storing data and software applications, such as a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash ROM), or any suitable combination of the foregoing. In some embodiments, a storage (not shown) may supplement or replace the system memory **114**. The storage may include any number and type of external memories that are accessible to the processor **112** and/or the GPU. For example, and without limitation, the storage may include a Secure Digital Card, an external Flash memory, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any suitable combination of the foregoing.

It will be appreciated that the machine learning server **110** shown herein is illustrative and that variations and modifications are possible. For example, the number of processors **112**, the number of GPUs, the number of system memories **114**, and the number of applications included in the system memory **114** may be modified as desired. Further, the connection topology between the various units in FIG. **1** may be modified as desired. In some embodiments, any combination of the processor **112**, the system memory **114**, and a GPU may be replaced with any type of virtual computing system, distributed computing system, or cloud computing environment, such as a public, private, or a hybrid cloud.

The model trainer **116** is configured to train machine learning models, including a non-linear model for generating faces **150**, which is also referred to herein as a "face model." As shown, the face model **150** includes an identity encoder **152**, an expression encoder **154**, and a decoder **156**. Any technically feasible types of encoders and decoders may be used. In some embodiments, each of the identity encoder **152** and the expression encoder **154** may include a deep neural network, such as an encoder from a variational autoencoder (VAE). Similarly, the decoder **156** may also include a deep neural network in some embodiments. Operation(s) performed to encode representations of facial identities using the identity encoder **152**, or to encode representations of facial expressions using the expression encoder **154** (or another mapping), are also referred to herein as "encoding operation(s)." Operation(s) performed to generate a representation of a face using the decoder **156**, based on an encoded representation of a facial identity and an encoded representation of a facial expression, are also referred to herein as "decoding operation(s)."

As discussed in greater detail below, the identity encoder **152** takes as input a representation of a facial identity and outputs an encoded representation of the facial identity, which is also referred to herein as an "identity code." In some embodiments, the representation of the facial identity that is input into the identity encoder is the difference between a three-dimensional (3D) mesh (e.g., a triangle mesh) of a particular face with a neutral expression and a reference mesh. As used herein, a "neutral" expression refers to a facial expression with neutral positioning of facial features, which is in contrast to other expressions that show stronger emotions such as smiling, crying, etc. The reference mesh can be an average of multiple meshes of faces with neutral expressions, and the difference between the mesh of a particular face and the reference mesh can include displacements between vertices of the two meshes. In some embodiments in which the identity encoder **152** includes a VAE encoder, an identity code can be obtained by compressing such displacements into a mean and a standard deviation using the VAE encoder. Thereafter, a normal distribution can be sampled based on the mean and standard deviation using a re-parameterization technique, and the sampled result can be used as the identity code. In some embodiments, the re-parameterization is performed during training to make the network differentiable, but subsequent to training when the identity encoder **152** is deployed, the re-parameterization may (or may not) be omitted, as experience has shown that similar results are produced regardless of whether re-parameterization is performed. In such cases, the identity encoder **152** may be considered to include the re-parameterization that is used during training, even if re-parameterization is not performed thereafter.

In parallel to the identity encoder **152**, the expression encoder **154** takes as input a representation of a facial expression and outputs an encoded representation of the facial expression, which is also referred to herein as an "expression code." In other embodiments, operations of the identity encoder **152** and the expression encoder **154** may not all be performed in parallel. In some embodiments, the facial expression may be represented as blendweight values, such as a blendweight vector, corresponding to a target expression. Blendweight values, also referred herein as "blendweights," specify how different shapes, such as a shape of a smiling face and a shape of a crying face, should be blended together. For example, a user could specify the blendweight corresponding to a desired facial expression (i.e., the target expression) by adjusting sliders for the blendweights on a user interface (UI). Although discussed herein primarily with respect to blendweights, facial expressions can be represented using other types of control structures for animating faces, which are commonly referred to as "rigs," in alternative embodiments. Similar to the identity encoder **152**, in some embodiments, the expression encoder **154** includes a VAE that outputs a mean and a standard deviation that are used to sample from a normal distribution using a re-parameterization technique, in order to determine an expression code, although the re-parameterization may (or may not) be omitted after the expression encoder **154** is trained and deployed.

As described, the identity encoder **152** in the face model **150** only sees the geometry of a neutral mesh (minus a reference mesh) that represents a facial identity, without knowing about any facial expressions. On the other hand, the expression encoder **154** only sees blendweights that represent a facial expression, without having any notion of facial identity. A joint decoder **156** fuses information relating to a facial identity that is output by the identity encoder **152** together with information relating to a facial expression that is output by the expression encoder **154**, producing geometry having the facial identity as well as the facial expression. Specifically, the identity and expression codes generated by the identity encoder **152** and the expression encoder **154**, respectively, can be concatenated together and input into the decoder **156**, which outputs a representation of a face having a facial identity and expression corresponding to the input identity and expression codes. In some embodiments, the representation of the face that is output by the decoder **156** includes vertex displacements for deforming the reference mesh into the face having the facial identity and expression.

Example architectures of the identity encoder **152**, the expression encoder **154**, and the decoder **156**, as well as techniques for training the same, are discussed in greater detail below. In some embodiments, the identity encoder **152**, the expression encoder **154**, and the decoder **156** are trained by the model trainer **116** in an end-to-end and fully supervised manner, discussed below in conjunction with FIG. **10**. In such cases, the training data set may include 3D meshes of neutral faces for different facial identities, as well as meshes for the same facial identities and a number of predefined expressions. All of the meshes have vertex correspondence with each other, i.e., the same mesh topology is used to fit all of the facial identities and expressions in the data set. Such meshes may be obtained from standalone images and/or the image frames of a video. To train the face model **150**, the model trainer **116** solves for blendweights based on the meshes of faces with expressions (or obtains the blendweights from elsewhere), and the model trainer **116** then trains the identity encoder **152**, the expression encoder **154**, and the decoder **156** using the neutral face meshes minus a reference mesh, as well as the blendweights, as inputs into the identity encoder **152** and the expression encoder **154**, respectively, and vertex displacements for corresponding meshes of faces with expressions as expected outputs of the decoder **156**.

Training data and/or trained machine learning models, including the face model **150**, may be stored in the data store **120**. In some embodiments, the data store **120** may include any storage device or devices, such as fixed disc drive(s), flash drive(s), optical storage, network attached storage (NAS), and/or a storage area-network (SAN). Although shown as accessible over the network **130**, in some embodiments the machine learning server **110** may include the data store **120**.

In some embodiments, the model trainer **116** may also train a mapping between two-dimensional (2D) facial landmarks and expression codes. As discussed in greater detail below in conjunction with FIG. **8**, such a mapping may be included in a model that also includes the previously trained identity encoder **152** and decoder **156**. In such cases, the mapping replaces the expression encoder **154**, permitting expression codes to be generated based on 2D facial landmarks determined from captured images of human faces, rather than blendweights. A model in which the expression encoder **154** is replaced by the mapping between 2D facial landmarks and expression codes is also referred to herein as a "landmark model."

The trained face model **150** and/or the landmark model may be deployed to any suitable applications that generate faces and use the same. Illustratively, a face generating application **146** is stored in a memory **144**, and executes on a processor **142** of the computing device **140**. Components of the computing device **140**, including the memory **144** and the processor **142** may be similar to corresponding components of the machine learning server **110**.

As shown, the application **146** includes the face model **150**, which itself includes the identity encoder **152**, the expression encoder **154**, and the decoder **156**. In other embodiments, the application **146** may include a landmark model in addition to, or in lieu of, the face model **150**. The face model **150** and/or the landmark model may be employed in any technically feasible use cases, including face fitting (e.g., fitting to a facial identity while constraining to the neutral expression, or fitting to a facial expression once a facial identity is known), performance animation (e.g., modifying only the expression space of the face model **150**), and performance transfer or retargeting (e.g., modifying only the identity space of the face model **150**). For example, the application **146** could use the decoder **156** to generate novel faces by sampling from identities represented by meshes in the data set that is used to train the face model **150**, which are also referred to herein as "known identities," or adding random noise to an identity code associated with a known identity. As another example, the application **146** could receive a new identity that is not one of the known identities and use the face model **150** to generate a face having the new identity and a target expression. As another example, the application **146** could perform blendweight retargeting in which the face model **150** is used to transfer facial expression(s) from an image or video to a new facial identity by determining blendweights associated with the facial expression(s) in the image or video, inputting the blendweights into the expression encoder **154**, and inputting a representation of the new facial identity into the identity encoder **152**. As a further example, the application **146** could perform 2D landmark-based capture and retargeting by determining 2D facial landmarks from a facial performance in a video, mapping the facial landmarks to expression codes that are then input, along with an identity code associated with a new identity, into the decoder **156** to generate faces having the new identity and the expressions in the facial performance. As used herein, a "facial performance" refers to a series of facial expressions, such as the facial expressions in successive frames of a video.

The number of machine learning servers and application servers may be modified as desired. Further, the functionality included in any of the applications may be divided across any number of applications or other software that are stored and execute via any number of devices that are located in any number of physical locations.

Non-Linear Face Models

FIG. **2** is a more detailed illustration of the non-linear face model **150** of FIG. **1**, according to various embodiments. As described, the face model **150** includes the identity encoder **152**, the expression encoder **154**, and the decoder **156**. Identity and expression are disentangled through the separate identity and expression encoders **152** and **154**, which may include VAE encoders in some embodiments. In particular, this model architecture disentangles the nonlinear variational latent space of facial identities, which is the face model's **150** internal representation of facial identities, from the nonlinear variational latent space of facial expressions, which is the face model's **150** internal representation of facial expressions. Doing so enables semantic control of facial identities and expressions. In addition, the non-linear nature of the model architecture permits more realistic-looking faces to be generated than conventional multi-linear face models.

As shown, the identity encoder **152** takes as input a neutral expression mesh minus a reference mesh **202**, which represents a facial identity. Given such an input, the identity encoder **152** outputs an identity code **206**. As described, the reference mesh **202** can be a mean of all meshes having a neutral expression in a training data set, the neutral expression mesh and the reference mesh share the same set of vertices, and subtracting the reference mesh from the neutral expression mesh can produce per-vertex displacements associated with the neutral expression mesh.

In some embodiments, the identity encoder **152** includes a VAE encoder in the form of a fully-connected network with residual blocks that compress input displacements into a mean and standard deviation:

$$\mu_{id},\sigma_{id}\leftarrow E_{id}(d_{id}^{N}), \tag{1}$$

where d_{id}^{N} is the mean-subtracted neutral displacements that are fed as input into the VAE encoder, which is denoted by E_{id}; μ_{id} and σ_{id} are the mean and standard deviation, respectively, output by the VAE encoder; the subscript id is used for the facial identity; and the superscript N corresponds to the neutral expression shape.

In parallel to the identity encoder **152**, the expression encoder **154** takes a vector of blendweights **204** that corresponds to a target expression as input and compresses or expands the vector of target blendweights **204** into a variational latent space of n_{exp} dimensions, outputting a facial expression code **208**. Similar to the identity encoder **152**, in some embodiments the expression encoder **154** includes a VAE encoder in the form of a fully-connected network with residual blocks and leaky ReLU activations. Such a VAE outputs a mean and standard deviation vector that can be fused into the expression code z_{exp} using a re-parameterization technique that samples a normal distribution based on the mean and standard deviation:

$$\mu_{exp},\sigma_{exp}\leftarrow E_{exp}(b^{T}) \tag{3}$$

$$z_{exp}\leftarrow \mathcal{N}(\mu_{exp},\sigma_{exp}), \tag{4}$$

where the subscript exp is used for facial expression components, the subscript T refers to a target expression shape, b^T is a blendweight vector that corresponds to a target expression shape T that is input into the VAE encoder, which is denoted by E_{exp}, and μ_{exp} and σ_{exp} are the mean and standard deviation, respectively, output by the VAE encoder. As described, in some embodiment, the re-parameterization may be performed during training and omitted (or not) thereafter. Blendweights are used to condition the decoder for two reasons. First, blendweights provide a semantic point of entry into the network and can be manipulated by a user. Second, blendweights are a meaningful representation that can be used to disentangle the notions of facial identity and facial expression, as blendweights contain no notion of identity and are purely descriptive of expression.

As shown, the facial identity code **206** and the facial expression code **208** are concatenated together into a concatenated code **210** that is fed to the decoder **156**. The concatenated code **210** can be in the form of a vector having dimension $n_{id}+n_{exp}$. The decoder **156** is trained to reconstruct a given identity in a desired expression. In some embodiments, the decoder **156** is a fully connected network that outputs vertex displacements d^T with respect to the reference mesh:

$$d^{T}\leftarrow D(z_{id},z_{exp}). \tag{5}$$

Once again, the subscript exp is used for facial expression components, and the subscript T corresponds to a target expression shape. It should be understood that the vertex displacements of equation (5) may be used to deform the reference mesh to generate a mesh having the given identity and desired expression, which can further be rendered to one or more images, such as a standalone image or the frames of a video.

In some embodiments, each of the identity and expression encoders **152** and **154** includes four residual layers. The dimensions of the residual layers of the identity and the expression encoders **152** and **154** are fixed to the dimension of the identity code n_{id} and the dimension of the expression code n_{exp}, respectively. For example, the dimensions of the identity code and the expression code could be set to $n_{id}=32$ and $n_{exp}=256$, respectively.

As described, facial identity and expression are separated in the internal representation of the face model **150**, which permits semantic control of identities and expressions of faces generated by the face model **150**. Experience has shown that the face model **150** is capable of learning to generate more realistic-looking faces than conventional linear-based models. As discussed in greater detail below in conjunction with FIG. **10**, in some embodiments the identity encoder **152**, the expression encoder **154**, and the decoder **156** are trained in an end-to-end and fully supervised manner using a L1 loss function, with the identity and expression latent spaces being constrained using Kullback-Leibler (KL) divergence losses, a fixed learning rate, and the Adaptive Moment Estimation (ADAM) optimizer. That is, three loss functions are used, the L1 loss on reconstruction, which is the mesh prediction output by the decoder **156**, and two KL divergence losses on the identity and expression encoders **152** and **154**, respectively.

FIG. **3**A illustrates exemplar facial identities **300**, **302**, **304**, and **306** generated using the face model **150** of FIG. **1**, according to various embodiments. As shown, the facial identities **300**, **302**, **304**, and **306** have a neutral facial expression and are different from the facial identities used to train the identity encoder **152**, i.e., the "known identities." In embodiments, the known identities may include any suitable identities and be represented in any technically feasible form. In the illustrated example, the facial identities **300**, **302**, **304**, and **306** were generated by randomly sampling the identity latent space.

To generate new facial identities such as the facial identities **300**, **302**, **304**, and **306**, the application **146** can generate an identity code that represents a combination of known identities. For example, assume a user wishes to generate a new facial identity that is similar to one of the known identities. In such a case, the application **146** could generate an identity code for the new facial identity by adding random noise to an identity code associated with the known identity. As another example, a user could manually input an identity code associated with a desired facial identity. In other embodiments, the application **146** may generate the identity code in any technically feasible manner, such as based on user input received via a UI. Then, the application **146** can input a concatenated code that includes the identity code and an expression code into the decoder **156** to determine vertex displacements that will deform a reference mesh into a mesh of a face having the new facial identity and the expression.

FIG. **3**B illustrates exemplar facial expressions **310**, **312**, **314**, and **316** generated for the identity of FIG. **3**A using the face model **150** of FIG. **1**, according to various embodiments. As shown, the facial expressions **310**, **312**, **314**, and **316**, which represent an eyes closed expression, a mouth open expression, a grimacing expression, and a mouth left expression, respectively, are different from the expressions used to train the expression encoder **154**, which are also referred to herein as "known expressions." In embodiments, the known expressions may include any suitable expressions and be represented in any technically feasible form. In the illustrated example, the facial expressions **310**, **312**, **314**, and **316** were generated by randomly sampling the expression latent space.

To generate new facial expressions such as the expressions **310**, **312**, **314**, and **316**, the expression encoder **154** can be used to generate an expression code that represents a combination of known expressions. For example, the application **146** may provide a UI that includes sliders for selecting blendweights that indicate the intensity of shapes representing the known expressions to be included in the new facial expression. In such a case, the application **146** could generate an expression code for the new facial expression by processing the blendweights using the expression encoder **154**. Then, the application **146** can input a concatenated code that includes the identity code and the expression code into the decoder **156** to determine vertex displacements that will deform a reference mesh into a mesh of a face having the facial identity and the new facial expression.

FIG. **4**A illustrates exemplar facial expressions along an expression dimension generated using a conventional linear model, according to the prior art. Illustratively, a blendweight associated with a smile expression shape has been varied between −2.5 and 2.5 to generate a set of facial expressions **400** using a linear blendshape model. As shown, the linear blendshape model can produce exaggerated and physically infeasible expressions. This is particularly the case outside the range of blendweight values [−1, 1].

FIG. **4**B illustrates exemplar facial expressions **402** along an expression dimension generated using the face model **150** of FIG. **1**, according to various embodiments. As shown, the blendweight associated with a smile expression shape has been varied between −2.5 and 2.5 to generate a set of facial expressions **402** using the face model **150**. As described, blendweights associated with a desired expression may be input into the expression encoder **154** to generate an expression code, which can then be input into the decoder **156** along with an identity code to determine vertex displacements for deforming a reference mesh into a mesh of a face having the facial identity and expression.

Experience has shown that linearly varying a blendshape blendweight within [0, 1] provides a nonlinear effect on the generated shape. As shown in FIG. **4**B, a generated smile starts off as a closed mouth smile up until 0.6, and then opens up, which appears more natural than the monotonous interpolation generated by the conventional linear blendshape model, shown in FIG. **4**A.

FIG. **5**A illustrates an exemplar superimposing of facial expressions generated using a linear blending technique, according to the prior art. Experience has shown that conventional linear-based models can be used to superimpose expressions that are non-conflicting (ideally orthogonal), but such models produce poor results for many other shape combinations. As shown, an unrealistic-looking facial expression **504** is produced by superimposing a mouth-right expression **500** and a mouth-left expression **502** using a linear-based model.

FIG. **5**B illustrates superimposing the mouth-right expression **500** and the mouth-left expression **502** using the face model **150** of FIG. **1**, according to various embodiments described herein. As shown, a facial expression **506** generated by the face model **150** appears more realistic-looking than the facial expression **504** generated by the conventional linear-based model that is described above in conjunction with FIG. **5**A.

FIG. **6** illustrates an exemplar interpolation between identities generated using the face model **150** of FIG. **1**, according to various embodiments. For example, a female identity could be interpolated with a male identity to determine an appearance of their offspring. As shown, facial identities **600** and **608** have been interpolated in a 128-dimension latent identity space to generate additional facial identities **602**, **604**, and **606** that are between the facial identities **600** and **608**. Illustratively the interpolation produces a smooth and non-linear traversal of geometry that takes the facial identity **600** to the facial identity **608**.

Experience has shown that interpolated facial identities generated using the non-linear face model **150** appear more realistic-looking, and include fewer artifacts such as intersecting geometry, than interpolated identities generated using conventional linear-based models. Realistic-looking faces can be generated because the face model **150** interpolates in a latent code space to generate valid faces, rather than simply (linearly) interpolating the vertices of faces. The degree of nonlinearity reflected in the output shapes varies as a function of the dimensionality of the identity latent space, with a lower dimensionality producing higher nonlinearity. As a result, interpolating between two identities will appear to pass through other identities for lower-dimensional identity latent spaces. On the other hand, a lower-dimensional identity latent space may reduce reconstruction accuracy due to higher compression. However, the representational power of the face model **150** can be significantly higher than linear models, especially at lower dimensions.

FIG. **7** illustrates an exemplar retargeting of a facial performance from one facial identity to another facial identity using the face model **150** of FIG. **1**, according to various embodiments. As shown, facial expressions **700**, **702**, **704**, **706**, and **708** that are associated with one facial identity are retargeted to the same facial expressions **710**, **712**, **714**, **716**, and **718** for a new facial identity in a natural-looking, nonlinear manner. As used herein, "retargeting" refers to transferring the facial expressions associated with one facial identity, which may be represented as blendweights, onto another facial identity. In some embodiments, retargeting is performed by inputting an identity code associated with the new identity and expression codes associated with the facial expressions **700**, **702**, **704**, **706**, and **708** into the decoder **156** to generate vertex displacements for deforming a reference mesh into meshes of faces having the new facial identity and the same expressions **710**, **712**, **714**, **716**, and **718**. As described, the identity code for the new identity may be manually entered by a user, generated by adding random noise to the identity code associated with a known identity, generated by inputting a neutral face mesh associated with the new identity minus the reference mesh into the identity encoder **152**, or in any other technically feasible manner. As described, the expression code may also be manually entered by a user, generated by inputting user-specified or automatically-determined blendweights into the expression encoder **154**, or in any other technically feasible manner.

FIG. **8** illustrates a landmark model **800** that includes a mapping between 2D facial landmarks and expression codes, according to various embodiments. As shown, the landmark model **800** includes the same identity encoder **152** and decoder **156** as the face model **150**. However, the landmark model **800** includes a mapping module **806** that maps between 2D facial landmarks and expression codes, rather than the expression encoder **154**. The mapping module **806** permits expression codes to be generated from 2D facial landmarks detected in images, such as standalone images or the frames of a video. Such 2D facial landmarks may be detected in any technically feasible manner, including using well-known landmark detection techniques. It should be understood that detecting 2D facial landmarks is typically easier than solving for blendweights.

In some embodiments, sets of 2D facial landmarks could be detected in the captured facial performance of an individual in frames of a video, and the sets of landmarks can then be input into the mapping module **806** to generate expression codes, such as the expression code **810**. In such cases, the application **146** can also normalize the sets of 2D landmarks to generate normalized landmarks, such as normalized 2D landmarks **804**, in order to factor out image translation and scale. In such cases, the application **146** may translate the set of landmarks corresponding to an image such that one of the landmarks is at a predefined position, as well as rescale the set of landmarks such that the length between at least two of the landmarks is a predefined value. For example, the application **146** could translate the set of landmarks such that a landmark corresponding to the center of a nose is at (0,0) and rescale the set of landmarks such that the length of the nose is 1. The application **146** then processes the normalized landmarks (as, e.g., a vector in which the normalized landmarks are stacked together) using the mapping module **806** to generate the expression code **810**.

In parallel to processing normalized landmarks using the mapping module **806**, the application **146** may input a representation of a facial identity, which as shown is a mesh of a face having a target identity and a neutral expression minus a reference mesh **802**, into the identity encoder **152** to generate an identity code **808**. The application **146** can then concatenate the expression code **810** and the identity code **808** into a concatenated code, such as the concatenated code **812**. Such a concatenated code is similar to the concatenated code **210** described above in conjunction with FIG. **2**. The application **146** can input the concatenated code into the decoder **156** to generate representations of faces having the target identity and the expressions represented by the 2D facial landmarks. In the case of 2D facial landmarks detected in multiple frames of a video, a concatenated code for each of the multiple frames may be determined and input into the decoder **156**, as discussed in greater detail below in conjunction with FIG. **9**. Illustratively, the concatenated code **812** is input into the decoder **156** to generate vertex displacements **814** that can be used to deform a reference mesh, similar to the vertex displacements **212** described above in conjunction with FIG. **2**.

As discussed in greater detail below in conjunction with FIG. **11**, in some embodiments, the mapping between 2D facial landmarks and expression codes that is applied by the mapping module **806** is trained while keeping the pre-trained identity encoder **152** and decoder **156** fixed. In particular, the mapping may be trained with ground truth blendweights, which permit supervision on the facial expression code, given the pre-trained expression encoder **154**, and the resulting geometry may be included in a loss function during training using the pre-trained decoder **156**, as discussed in greater detail below in conjunction with FIG. **11**.

FIG. **9** illustrates an exemplar facial performance retargeting based on 2D facial landmarks detected in a video, according to various embodiments. As shown, a set of 2D facial landmarks **901** is detected in each of a number of frames **900**, **902**, **904**, **906**, and **908** of a video that depicts an individual performing various expressions. The 2D facial landmarks **901** are referred to herein individually as a facial landmark **901** and collectively as facial landmarks **901**. As described, well-known landmark detection techniques may be used in some embodiments to detect 2D facial landmarks in images and frames of a video.

The application **146** can retarget the expressions of the individual in the video frames to meshes of faces having various identities by processing the detected sets of landmarks using the mapping module **806**, which performs a mapping between 2D facial landmarks and expression codes, and further inputting a representation of a target facial identity into the identity encoder **152** that generates an associated identity code. Thereafter, the application **146** can concatenate the identity code together with the expression codes, and feed the concatenated codes into the decoder **156** to generate representations of faces having the target facial identity and the expressions depicted in the video.

As shown, faces **910**, **912**, **914**, **916**, and **918** are reconstructions of the individual in the frames **900**, **902**, **904**, **906**, and **908**, respectively. In some embodiments, such reconstructions may be generated by inputting the 2D facial landmarks **901** into the mapping module **806** and inputting a mesh associated with the individual (which can be determined from images or videos using well-known techniques) into the identity encoder **152**, as described above in conjunction with FIG. **8**.

As shown, faces **920**, **922**, **924**, **926**, and **928** are retargetings of the expressions in the frames **900**, **902**, **904**, **906**, and **908**, respectively, to a new facial identity. In some embodiments, the faces **920**, **922**, **924**, **926**, and **928** can be generated by inputting the sets of 2D facial landmarks **901** associated with each of the frames **900**, **902**, **904**, **906**, and **908** into the mapping module **806** and inputting a representation of the new facial identity into the identity encoder **152**, as described above in conjunction with FIG. **8**.

FIG. **10** sets forth a flow diagram of method steps for training a model to generate faces, according to various embodiments. Although the method steps are described in conjunction with the systems of FIG. **1-2**, persons of ordinary skill in the art will understand that any system configured to perform the method steps, in any order, is within the scope of the present disclosure.

As shown, a method **1000** begins at step **1002**, where the model trainer **116** receives meshes of neutral faces and meshes of faces having expressions. The meshes may be obtained in any technically feasible manner. In some embodiments, the meshes are extracted, using well-known techniques, from standalone images and/or the frames of videos depicting human faces. For example, a passively-lit, multi-camera setup could be used to capture a number of individuals having different ethnicities, genders, age groups, and body mass index (BMI) in a predefined set of facial expressions, including the neutral expression. The captured images of individuals can then be reconstructed using well-known techniques, and a template mesh including a number of vertices can be semi-automatically registered to the reconstructions of each individual. In addition, facial expressions can be stabilized to remove rigid head motions and align the facial expressions to the same canonical space. Experience has shown that a relatively small number of individuals (e.g., hundreds of individuals) and predefined expressions (e.g., tens of expressions) can be used to train the face model **150**.

In addition to capturing static expressions, dynamic expressions such as sequences of the individuals speaking, may be captured in videos. That is, the face model **150** can be trained using standalone images and/or videos. In some embodiment, the video can depict an individual going through a number of facial expressions, some of which may be linear combinations of a predefined set of facial expressions. In such a case, the model trainer **116** can, using a registered mesh from a static image, perform an optimization to determine a set of blendweights associated with the combination of facial expressions in a given frame of the video. For example, the optimization could be a least squares fitting. The model trainer **116** can then use the set of blendweights during training of the face model **150**, as discussed in greater detail below. It should be noted, however, that the face model **150** is trained to generate realistic-looking faces rather than blendshape fits based on the blendweights, which is what linear-based techniques would generate. That is, the face model **150** actually learns a residual between a linear blendshape model and a true nonlinear shape of 3D faces.

At step **1004**, the model trainer **116** subtracts a reference mesh from each of the received neutral meshes to determine a set of differences between the meshes. As described, in some embodiments, the reference mesh is an average of the meshes of faces with neutral expressions, and the difference between neutral meshes and the reference mesh can include a set of displacements between vertices of the two meshes.

At step **1006**, the model trainer **116** solves for sets of blendweights corresponding to the expressions in each of the meshes of faces having expressions. Any technically feasible technique may be used to solve for the blendweights. For example, the model trainer **116** could use the least squares fitting described above to solve for the blendweights.

At step **1008**, the model trainer **116** trains the face model **150** that includes the identity encoder **152**, the expression encoder **154**, and the decoder **156** based on the sets of differences, the blendweights, and vertex displacements associated with the received meshes. As described, in some embodiments the identity encoder **152**, the expression encoder **154**, and the decoder **156** are trained end-to-end in a fully supervised manner. In such cases, reconstructed geometry is penalized using a L1 loss, and the identity and expression latent spaces are constrained using KL divergence losses. Further, a fixed learning rate and the ADAM optimizer may be used during training.

FIG. **11** sets forth a flow diagram of method steps for training a mapping between 2D facial landmarks and expression codes, according to various embodiments. Although the method steps are described in conjunction with the systems of FIGS. **1** and **8**, persons of ordinary skill in the art will understand that any system configured to perform the method steps, in any order, is within the scope of the present disclosure.

As shown, a method **1100** begins at step **1102**, where the model trainer **116** determines a set of 2D landmarks for each of a number of images depicting human faces with various expressions. The 2D landmarks may be determined in any technically feasible manner, including using well-known landmark detection techniques.

At step **1104**, the model trainer **116** normalizes the sets of 2D landmarks. Such a normalization factors out image translation and scale. In some embodiments, the model trainer **116** may normalize the 2D landmarks by translating the landmarks such that one of the landmarks is at a predefined position and rescaling the landmarks such that the length between at least two of the landmarks is a predefined value, as described above in conjunction with FIG. **8**.

At step **1106**, the model trainer **116** trains the mapping between 2D landmarks and expression codes applied by the mapping module **806** based on the normalized landmarks and ground truth blendweights, while keeping the previously trained identity encoder **152** and the decoder **156** fixed. In some embodiments, the mapping may be trained using the ground truth blendweights, which permit supervision on the facial expression code, given the pre-trained expression encoder **154**, and the resulting geometry may be included in the loss function during training using the pre-trained decoder **156**.

FIG. **12** sets forth a flow diagram of method steps for generating faces, according to various embodiments. Although the method steps are described in conjunction with the system of FIGS. **1-2**, persons of ordinary skill in the art will understand that any system configured to perform the method steps, in any order, is within the scope of the present disclosure.

As shown, a method **1200** begins at step **1202**, where the application **146** receives a representation of a facial identity. The representation of the facial identity may be in any technically feasible form. For example, the representation of the facial identity could be an identity code. As further examples, the representation of the facial identity could be a neutral face mesh that can be converted to an identity code by subtracting a reference mesh and inputting a difference into the identity encoder **152**, a captured image or video frame from which such a neutral face mesh can be determined, etc.

At step **1204**, the application **146** receives a representation of a facial expression. The representation of the facial expression may be in any technically feasible form. For example, the representation of the facial expression could be an expression code. In particular, a user could input a "one-hot" vector that specifies a blendweight of 1 for one blendshape and 0 for other blendshapes, or a vector that specifies blendweights for combining multiple blendshapes. As further examples, the representation of the facial expression could include target blendweights that are specified by a user (e.g., via sliders within a UI) and can be converted to an expression code using the expression encoder **154**, target blendweights determined based on a frame of an animation of a face, etc.

At step **1206**, the application **146** optionally determines an identity code and an expression code using the identity encoder **152** and the expression encoder **152**, respectively. This step assumes that the representations of the facial identity and the facial expression received at steps **1202** and **1204** are not identity and expression codes, respectively, in which case the application **146** may simply concatenate the identity and expression codes together. When the representations of the facial identity and the facial expression are not identity and expression codes, however, the application **146** can input such representations, after any necessary processing (e.g., to subtract a reference mesh from a neutral face mesh or to solve for blendweights based on an image or video frame), into the identity encoder **152** that outputs an identity code and the expression encoder **152** that outputs an expression code, respectively. In some embodiments, the receipt of the representation of the facial identity at step **1202** and the determining of the identity code using the identity encoder **152** can occur in parallel with the receipt of the representation of the facial expression at step **1204** and the determining of the expression code using the expression encoder **152**.

At step **1208**, the application **146** processes the identity code and the expression code using the decoder **156** to generate a representation of a face having the facial identity and expression. In some embodiments, the representation of the face includes vertex displacements that can be used to deform a reference mesh into the face having the facial identity and expression, as described above in conjunction with FIGS. **1-2**.

Thereafter, the application **146** may render one or more images using the representation of the face output by the decoder **156**. For example, the application **146** could deform a reference mesh using vertex displacements output by the decoder **156**, and then render the deformed mesh as a standalone image or one or more frames of a video.

FIG. **13** sets forth a flow diagram of method steps for retargeting a facial performance on a new facial identity, according to various embodiments. Although the method steps are described in conjunction with the system of FIGS. **1-2**, persons of ordinary skill in the art will understand that any system configured to perform the method steps, in any order, is within the scope of the present disclosure.

As shown, a method **1300** begins at step **1302**, where the application **146** receives a neutral facial expression mesh associated with a new identity. The neutral facial expression mesh may be generated in any technically feasible manner. For example, the application **146** (or another application) could use well-known techniques to extract the neutral facial expression mesh from a captured image or video of an individual.

At step **1304**, the application **146** receives an animation that includes a facial performance. In some embodiments, the receipt of the neutral facial expression mesh at step **1302** may occur concurrently with the receipt of the animation at step **1304**. As described, the facial performance includes a series of facial expressions. In some embodiments, the facial performance is a 3D animation of a mesh. In other embodiments, the facial performance may be in any technical feasible form, such as a video, multiple videos taken from different vantage points, an artist-created animation, etc. Although described with respect to an animation, it should be understood that the retargeting of the method **1300** may also be performed for an individual facial expression, such as a facial expression in a standalone image.

At step **1306**, the application **146** solves for blendweights corresponding to expression(s) in each frame of the animation. The application **146** may solve for the blendweights in any technically feasible manner, including using least squares fitting. In particular, solving for the blendweights may include solving to a 3D animation of a mesh, solving to a single video, solving to multiple videos, solving to an artist-created animation, etc., depending on the type of animation that is received at step **1304**.

At step **1308**, the application **146** processes, for each frame of the animation, the neutral expression mesh and the blendweights using the face model **150** to generate a representation of a face performing the expression indicated by the blendweights in the frame. Similar to step **1210** of the method **1200** described above in conjunction with FIG. **12**, the representation of the face can, in some embodiments, include vertex displacements for deforming a reference mesh into a mesh of a face having the target facial identity and the expression in the frame.

FIG. **14** sets forth a flow diagram of method steps for generating new facial identities, according to various embodiments. Although the method steps are described in conjunction with the system of FIGS. **1-2**, persons of ordinary skill in the art will understand that any system configured to perform the method steps, in any order, is within the scope of the present disclosure.

As shown, a method **1400** begins at step **1402**, where the application **146** samples known identities and/or adds noise to an identity code to generate a new identity code. For example, the application **146** could sample the known identities by generating an identity code associated with a facial identity that is a random, or user-specified, combination of the known identities.

At step **1404**, the application **146** processes a concatenated code that includes the new identity code and an expression code using the decoder **156** to generate a representation of a face having a new facial identity associated with the identity code and an expression associated with the expression code. Similar to step **1210** of the method **1200** described above in conjunction with FIG. **12**, the representation of the face can, in some embodiments, include vertex displacements for deforming a reference mesh into the face having the new identity and the expression.

FIG. **15** sets forth a flow diagram of method steps for 2D landmark-based retargeting, according to various embodiments. Although the method steps are described in conjunction with the system of FIG. **8**, persons of ordinary skill in the art will understand that any system configured to perform the method steps, in any order, is within the scope of the present disclosure.

As shown, a method **1500** begins at step **1502**, where the application **146** receives an image of a face. For example, the image could be a standalone image or one of multiple frames of a video. In the case of a video, steps of the method **1500** may be repeated for each frame in the video.

At step **1504**, the application **146** determines 2D landmarks in the received image. Similar to step **1102** of the method **1100** described above in conjunction with FIG. **11**, the 2D landmarks may be determined in any technically feasible manner, including using well-known landmark detection techniques.

At step **1506**, the application **146** normalizes the 2D landmarks. Such a normalization factors out image translation and scale. Similar to step **1104** of the method **1100** described above in conjunction with FIG. **11**, normalizing the 2D landmarks may include translating the landmarks such that one of the landmarks is at a predefined position and rescaling the landmarks such that the length between at least two of the landmarks is a predefined value.

At step **1508**, the application **146** receives a representation of a facial identity. Similar to step **1202** of the method **1200** described above in conjunction with FIG. **12**, the facial identity may be represented in any technically feasible manner, such as an identity code, a neutral face mesh that can be converted to an identity code using the identity encoder **152**, an image or video frame from which a neutral face mesh can be determined, etc.

At step **1510**, the application **146** processes the normalized 2D landmarks and the representation of the facial identity using the landmark model **800** to generate a representation of a face having the identity and an expression corresponding to the normalized 2D landmarks. Similar to step **1210** of the method **1200** described above in conjunction with FIG. **12**, the representation of the face can, in some embodiments, include vertex displacements for deforming a reference mesh into the face having the facial identity and an expression corresponding to the normalized 2D landmarks.

Although discussed herein primarily with respect to human faces, some embodiments may also be used to generate other types of faces, such as animal faces, or even objects other than faces. For example, embodiments could be used in general character rigging. Although discussed herein primarily with respect to the identity encoder **152** and the expression encoder **154**, some embodiments may also include other types of encoders. For example, separate encoders could be trained, in a similar manner as the identity encoder **152** and the expression encoder **154** are trained, to encode different identity characteristics such as ethnicity, age, BMI, etc. Thereafter, such encoders can be used to control the identity characteristics in representations of faces generated by the face model **150**.

In sum, techniques are disclosed for training and applying nonlinear face models. In some embodiments, a nonlinear face model includes an identity encoder, an expression encoder, and a decoder. The identity encoder takes as input a representation of a facial identity, such as a neutral face mesh minus a reference mesh, and outputs a code associated with the facial identity. The expression encoder takes as input a representation of a facial expression, such as a set of blendweights, and outputs a code associated with the facial expression. The codes associated with the facial identity and the facial expression can be concatenated and input into the decoder, which outputs a representation of a face having the facial identity and expression. The representation of the face can include vertex displacements for deforming the reference mesh. The nonlinear face model can be used in various applications, including generating novel faces or expressions and facial performance retargeting based on blendweights or 2D facial landmarks.

At least one technical advantage of the disclosed techniques relative to the prior art is that the disclosed techniques disentangle the notions of facial identity and facial expression using separate facial identity and expression encoders. This architectural approach allows facial identities and expressions to be separately controlled by a user when generating faces using a nonlinear model that includes the facial identity and expression encoders. In addition, the disclosed techniques can be used to generate faces that are more realistic-looking than faces generated by conventional approaches that implement linear-based techniques. These technical advantages represent one or more technological improvements over prior art approaches.

1. In some embodiments, a computer-implemented method for generating a representation of a face comprises receiving a representation of a facial identity and a representation of a facial expression, and performing one or more decoding operations based on an encoded representation of the facial identity and an encoded representation of the facial expression to generate a representation of a face having the facial identity and the facial expression.

2. The computer-implemented method of clause 1, wherein the representation of the facial identity includes a mesh of a face having a neutral expression, and the method further comprises generating the encoded representation of the facial identity by subtracting, from the mesh of the face, a reference mesh of a face to determine a set of differences between the mesh of the face and the reference mesh, and encoding the set of differences to generate the encoded representation of the facial identity.

3. The computer-implemented method of clauses 1 or 2, wherein the representation of the facial identity comprises the encoded representation of the facial identity.

4. The computer-implemented method of any of clauses 1-3, further comprising generating the encoded representation of the facial identity by adding noise to an encoded representation of another facial identity.

5. The computer-implemented method of any of clauses 1-4, wherein the representation of the facial expression includes one or more two-dimensional (2D) landmarks of facial features associated with an image depicting a face, and the method further comprises generating the encoded representation of the facial expression by mapping the one or more 2D landmarks to the encoded representation of the facial expression.

6. The computer-implemented method of any of clauses 1-5, wherein the representation of the facial expression includes one or more blendweight values, and the method further comprises performing one or more encoding operations based on the one or more blendweight values to generate the encoded representation of the facial expression.

7. The computer-implemented method of any of clauses 1-6, further comprising determining the one or more blendweight values based on one or more images.

8. The computer-implemented method of any of clauses 1-7, further comprising determining the one or more blendweight values based on one or more three-dimensional meshes.

9. The computer-implemented method of any of clauses 1-8, wherein the representation of the facial expression comprises the encoded representation of the facial expression.

10. The computer-implemented method of any of clauses 1-9, further comprising rendering at least one image based on the representation of the face.

11. In some embodiments, a non-transitory computer-readable storage medium includes instructions that, when executed by a processing unit, cause the processing unit to perform steps for generating a rendering of a face, the steps comprising receiving a representation of a facial identity and a representation of a facial expression, and processing an encoded representation of the facial identity and an encoded representation of the facial expression using a decoder to generate a representation of a face having the facial identity and the facial expression.

12. The computer-readable storage medium of clause 11, the steps further comprising processing the representation of the facial identity using a first variational autoencoder (VAE) encoder to generate the encoded representation of the facial identity, and processing the representation of the facial expression using a second VAE encoder to generate the encoded representation of the facial expression.

13. The computer-readable storage medium of clauses 11 or 12, wherein processing the encoded representation of the facial identity and the encoded representation of the facial expression using the decoder comprises concatenating the encoded representation of the facial identity and the encoded representation of the facial expression to generate an encoded representation of the facial identity and the facial expression, and inputting the encoded representation of the facial identity and the facial expression into the decoder.

14. The computer-readable storage medium of any of clauses 11-13, wherein the representation of the facial identity includes a mesh of a face having a neutral expression, and the steps further comprise generating the encoded representation of the facial identity by subtracting, from the mesh of the face, a reference mesh of a face to determine a set of differences between the mesh of the face and the reference mesh, and encoding the set of differences to generate the encoded representation of the facial identity.

15. The computer-readable storage medium of any of clauses 11-14, wherein the representation of the facial identity comprises the encoded representation of the facial identity, and the encoded representation of the facial identity is generated by adding noise to an encoded representation of another facial identity.

16. The computer-readable storage medium of any of clauses 11-15, wherein the representation of the facial expression includes one or more two-dimensional (2D) landmarks of facial features associated with an image depicting a face, and the steps further comprise generating the encoded representation of the facial expression by mapping the one or more 2D landmarks to the encoded representation of the facial expression.

17. The computer-readable storage medium of any of clauses 11-16, wherein the representation of the facial expression includes one or more blendweight values, and the steps further comprise performing one or more encoding operations based on the one or more blendweight values to generate the encoded representation of the facial expression.

18. The computer-readable storage medium of any of clauses 11-17, the steps further comprising receiving the one or more blendweight values via a user interface, or determining the one or more blendweight values based on at least one image or three-dimensional mesh.

19. The computer-readable storage medium of any of clauses 11-18, the steps further comprising rendering at least one image based on the representation of the face.

20. In some embodiments, a computer-implemented method of training a model for generating faces comprises receiving a data set that includes meshes of neutral faces and meshes of faces having expressions, and training a model based on the data set, wherein the model comprises a first encoder that maps representations of neutral faces to encoded representations of facial identities, a second encoder that maps representations of facial expressions to encoded representations of the facial expressions, and a decoder that maps encoded representations of facial identities and encoded representations of facial expressions to representations of faces.

21. The computer-implemented method of clause 20, wherein training the model based on the data set comprises subtracting each of the meshes of neutral faces from a reference mesh to determine a respective set of differences, and determining a respective set of blendweight values corresponding to a facial expression in each of the meshes of faces having expressions, and the model is trained based on the sets of differences and the sets of blendweight values.

Any and all combinations of any of the claim elements recited in any of the claims and/or any elements described in this application, in any fashion, fall within the contemplated scope of the present invention and protection.

The descriptions of the various embodiments have been presented for purposes of illustration, but are not intended to be exhaustive or limited to the embodiments disclosed. Many modifications and variations will be apparent to those of ordinary skill in the art without departing from the scope and spirit of the described embodiments.

Aspects of the present embodiments may be embodied as a system, method or computer program product. Accordingly, aspects of the present disclosure may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.) or an embodiment combining software and hardware aspects that may all generally be referred to herein as a “module” or “system.” Furthermore, aspects of the present disclosure may take the form of a computer program product embodied in one or more computer readable medium(s) having computer readable program code embodied thereon.

Any combination of one or more computer readable medium(s) may be utilized. The computer readable medium may be a computer readable signal medium or a computer readable storage medium. A computer readable storage medium may be, for example, but not limited to, an electronic, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, or device, or any suitable combination of the foregoing. More specific examples (a non-exhaustive list) of the computer readable storage medium would include the following: an electrical connection having one or more wires, a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), an optical fiber, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any suitable combination of the foregoing. In the context of this document, a computer readable storage medium may be any tangible medium that can contain, or store a program for use by or in connection with an instruction execution system, apparatus, or device.

Aspects of the present disclosure are described above with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems) and computer program products according to embodiments of the disclosure. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer program instructions. These computer program instructions may be provided to a processor of a general purpose computer, special purpose computer, or other programmable data processing apparatus to produce a machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, enable the implementation of the functions/acts specified in the flowchart and/or block diagram block or blocks. Such processors may be, without limitation, general purpose processors, special-purpose processors, application-specific processors, or field-programmable.

The flowchart and block diagrams in the figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods and computer program products according to various embodiments of the present disclosure. In this regard, each block in the flowchart or block diagrams may represent a module, segment, or portion of code, which comprises one or more executable instructions for implementing the specified logical function (s). It should also be noted that, in some alternative implementations, the functions noted in the block may occur out of the order noted in the figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts, or combinations of special purpose hardware and computer instructions.

While the preceding is directed to embodiments of the present disclosure, other and further embodiments of the disclosure may be devised without departing from the basic scope thereof, and the scope thereof is determined by the claims that follow.

What is claimed is:

1. A computer-implemented method for generating a representation of a face, the computer-implemented method comprising:

receiving a representation of a facial identity and a representation of a facial expression;

processing the representation of the facial identity using a first variational autoencoder (VAE) encoder to generate an encoded representation of the facial identity;

processing the representation of the facial expression using a second VAE encoder to generate an encoded representation of the facial expression; and

performing one or more decoding operations based on the encoded representation of the facial identity and the encoded representation of the facial expression to generate the representation of the face having the facial identity and the facial expression.

2. The computer-implemented method of claim **1**, wherein the representation of the facial identity includes a mesh of the face having a neutral expression, and the computer-implemented method further comprises generating the encoded representation of the facial identity by:

subtracting a reference mesh from the mesh of the face to determine a set of differences between the mesh of the face and the reference mesh; and

encoding the set of differences to generate the encoded representation of the facial identity.

3. The computer-implemented method of claim **1**, wherein the representation of the facial identity comprises the encoded representation of the facial identity.

4. The computer-implemented method of claim **1**, further comprising generating the encoded representation of the facial identity by adding noise to an encoded representation of another facial identity.

5. The computer-implemented method of claim **1**, wherein the representation of the facial expression includes one or more two-dimensional (2D) landmarks of facial features associated with an image depicting the face, and

the computer-implemented method further comprises generating the encoded representation of the facial expression by mapping the one or more 2D landmarks to the encoded representation of the facial expression.

6. The computer-implemented method of claim **1**,

wherein the representation of the facial expression includes one or more blendweight values, and the computer-implemented method further comprises performing one or more encoding operations based on the one or more blendweight values to generate the encoded representation of the facial expression.

7. The computer-implemented method of claim **6**, further comprising determining the one or more blendweight values based on one or more images.

8. The computer-implemented method of claim **6**, further comprising:

receiving the one or more blendweight values via a user interface; or

determining the one or more blendweight values based on one or more three-dimensional meshes.

9. The computer-implemented method of claim **1**, wherein the representation of the facial expression comprises the encoded representation of the facial expression.

10. The computer-implemented method of claim **1**, further comprising rendering at least one image based on the representation of the face.

11. A non-transitory computer-readable storage medium including instructions that, when executed by a processing unit, cause the processing unit to perform steps for generating a representation of a face, the steps comprising:

receiving a representation of a facial identity and a representation of a facial expression;

processing the representation of the facial identity using a first variational autoencoder (VAE) encoder to generate an encoded representation of the facial identity; and

processing the representation of the facial expression using a second VAE encoder to generate an encoded representation of the facial expression; and

processing the encoded representation of the facial identity and the encoded representation of the facial expression using a decoder to generate the representation of the face having the facial identity and the facial expression.

12. The non-transitory computer-readable storage medium of claim **11** wherein the representation of the face includes one or more vertex displacements for deforming a reference mesh.

13. The computer-readable storage medium of claim **11**, wherein processing the encoded representation of the facial identity and the encoded representation of the facial expression using the decoder comprises:

concatenating the encoded representation of the facial identity and the encoded representation of the facial expression to generate an encoded representation of the facial identity and the facial expression; and

inputting the encoded representation of the facial identity and the facial expression into the decoder.

14. The computer-readable storage medium of claim **11**, wherein the representation of the facial identity includes a mesh of the face having a neutral expression, and the steps further comprise generating the encoded representation of the facial identity by:

subtracting a reference mesh from the mesh of the face, the to determine a set of differences between the mesh of the face and the reference mesh; and

encoding the set of differences to generate the encoded representation of the facial identity.

15. The computer-readable storage medium of claim **11**, wherein the representation of the facial identity comprises the encoded representation of the facial identity, and the encoded representation of the facial identity is generated by adding noise to an encoded representation of another facial identity.

16. The computer-readable storage medium of claim **11**, wherein the representation of the facial expression includes one or more two-dimensional (2D) landmarks of facial features associated with an image depicting the face, and

the steps further comprise generating the encoded representation of the facial expression by mapping the one or more 2D landmarks to the encoded representation of the facial expression.

17. The computer-readable storage medium of claim **11**, wherein the representation of the facial expression includes one or more blendweight values, and the steps further comprise performing one or more encoding operations based on the one or more blendweight values to generate the encoded representation of the facial expression.

18. The computer-readable storage medium of claim **17**, the steps further comprising:

receiving the one or more blendweight values via a user interface; or

determining the one or more blendweight values based on at least one image or three-dimensional mesh.

19. The computer-readable storage medium of claim **11**, the steps further comprising rendering at least one image based on the representation of the face.

20. A computer-implemented method of training a model for generating a representation of a face, the computer-implemented method comprising:

receiving a data set that includes meshes of neutral faces that respectively represent a face having a neutral expression and meshes of faces that respectively represent a face having a facial expression; and

training a model based on the data set, wherein the model comprises:

a first variational autoencoder (VAE) encoder configured to map representations of neutral faces to encoded representations of facial identities,

a second VAE encoder configured to map representations of faces having facial expressions to encoded representations of the facial expressions, and

a decoder configured to map encoded representations of facial identities and encoded representations of facial expressions to representations of faces.

21. The computer-implemented method of claim **20**, wherein training the model based on the data set comprises:

subtracting a reference mesh from each of the meshes of neutral faces to determine a respective set of differences;

determining a respective set of blendweight values corresponding to a facial expression in each of the meshes of faces having facial expressions; and

training the model based on the sets of differences and the sets of blendweight values.

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