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(54) **LEARNING CONTINUOUS CONTROL FOR 3D-AWARE IMAGE GENERATION ON TEXT-TO-IMAGE DIFFUSION MODELS**

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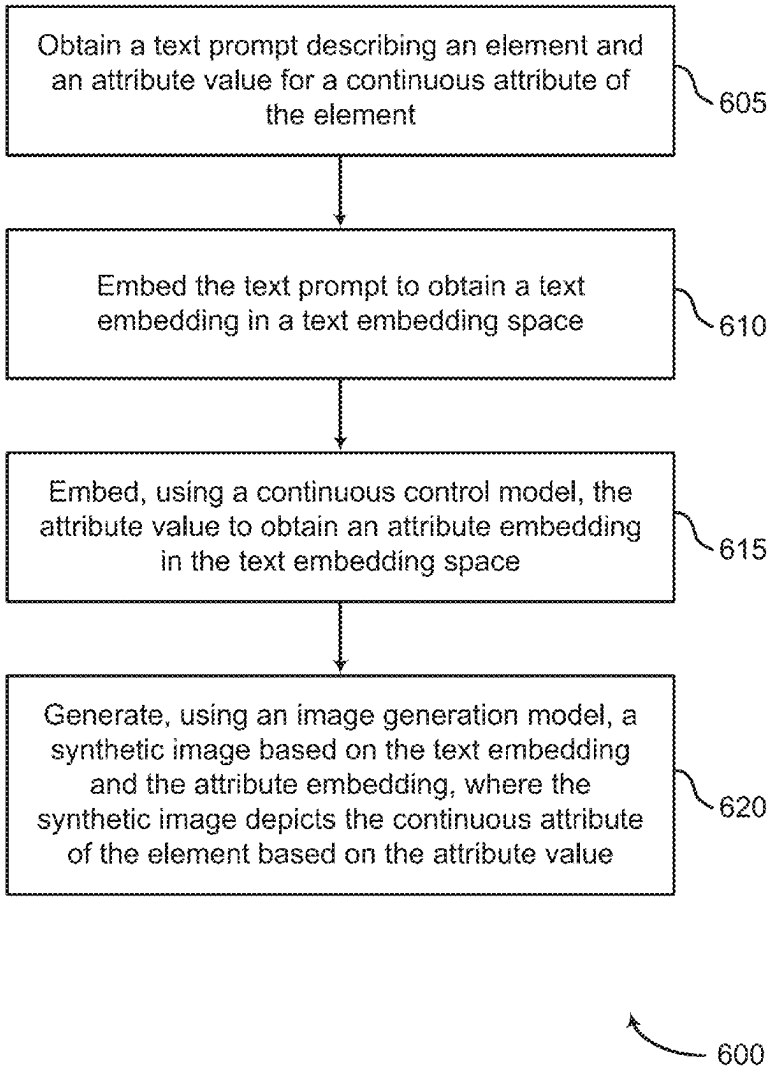
(57) **ABSTRACT**

A method, apparatus, non-transitory computer readable medium, and system for image processing include obtaining a text prompt describing an element and an attribute value for a continuous attribute of the element, embedding the text prompt to obtain a text embedding in a text embedding space, embedding the attribute value to obtain an attribute embedding in the text embedding space, and generating a synthetic image based on the text embedding and the attribute embedding, where the synthetic image depicts the continuous attribute of the element based on the attribute value.



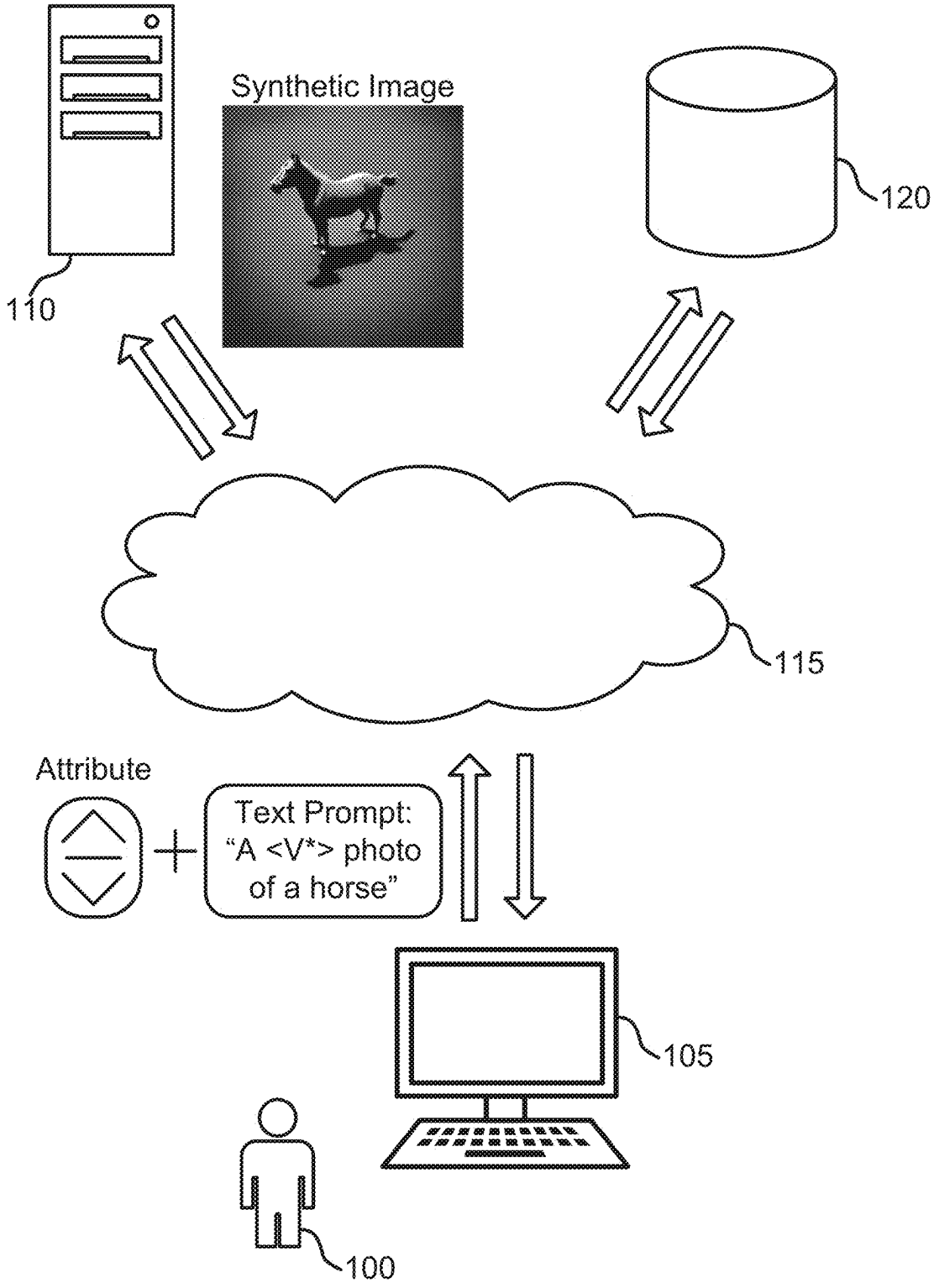

Synthetic Image
110
120
115
Attribute
Text Prompt:
"A <V*> photo
of a horse"
105
100

FIG. 1

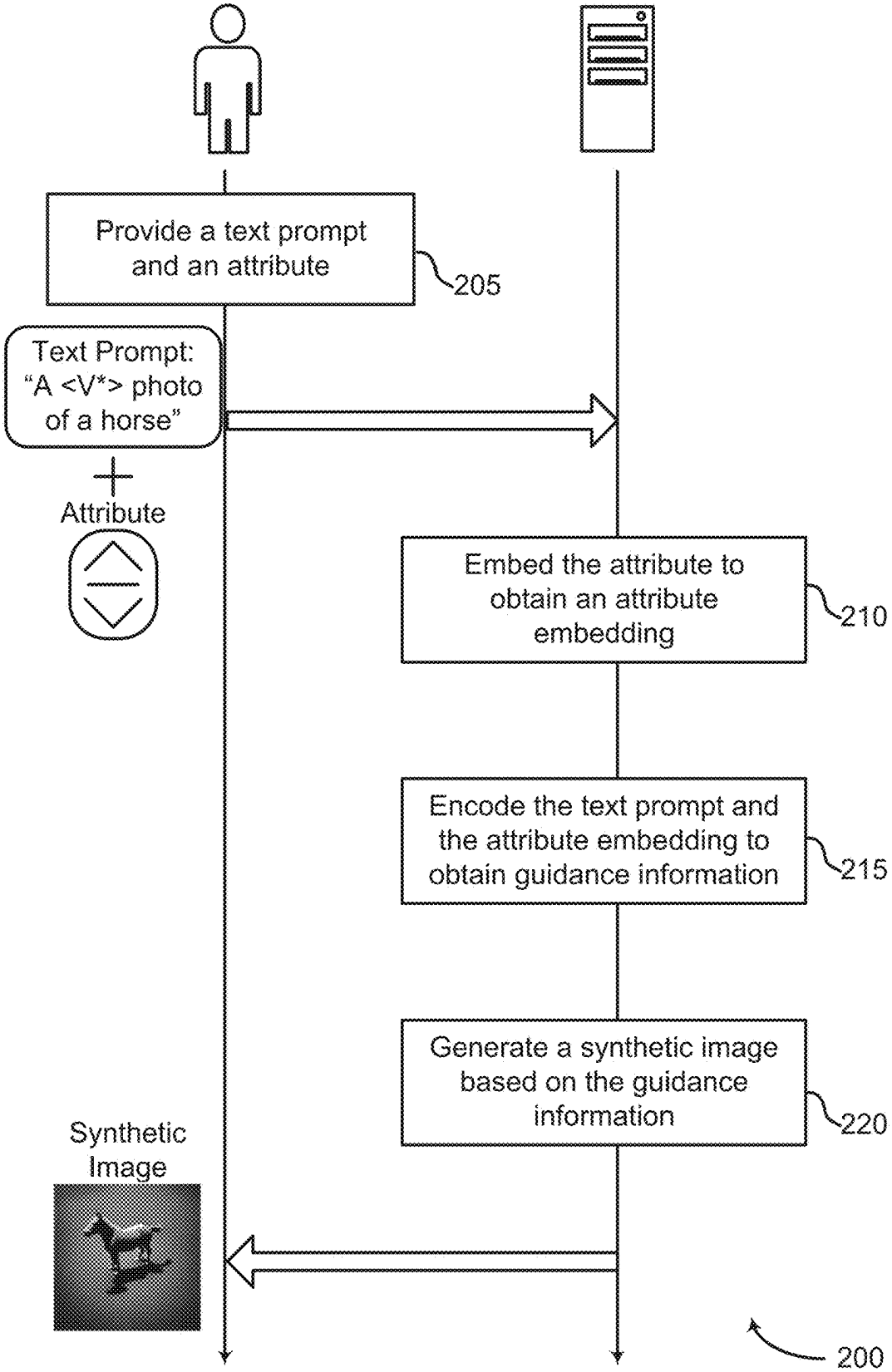

Provide a text prompt and an attribute
205
Text Prompt: "A <V*> photo of a horse"
Attribute
Embed the attribute to obtain an attribute embedding
210
Encode the text prompt and the attribute embedding to obtain guidance information
215
Generate a synthetic image based on the guidance information
220
Synthetic Image
200

FIG. 2

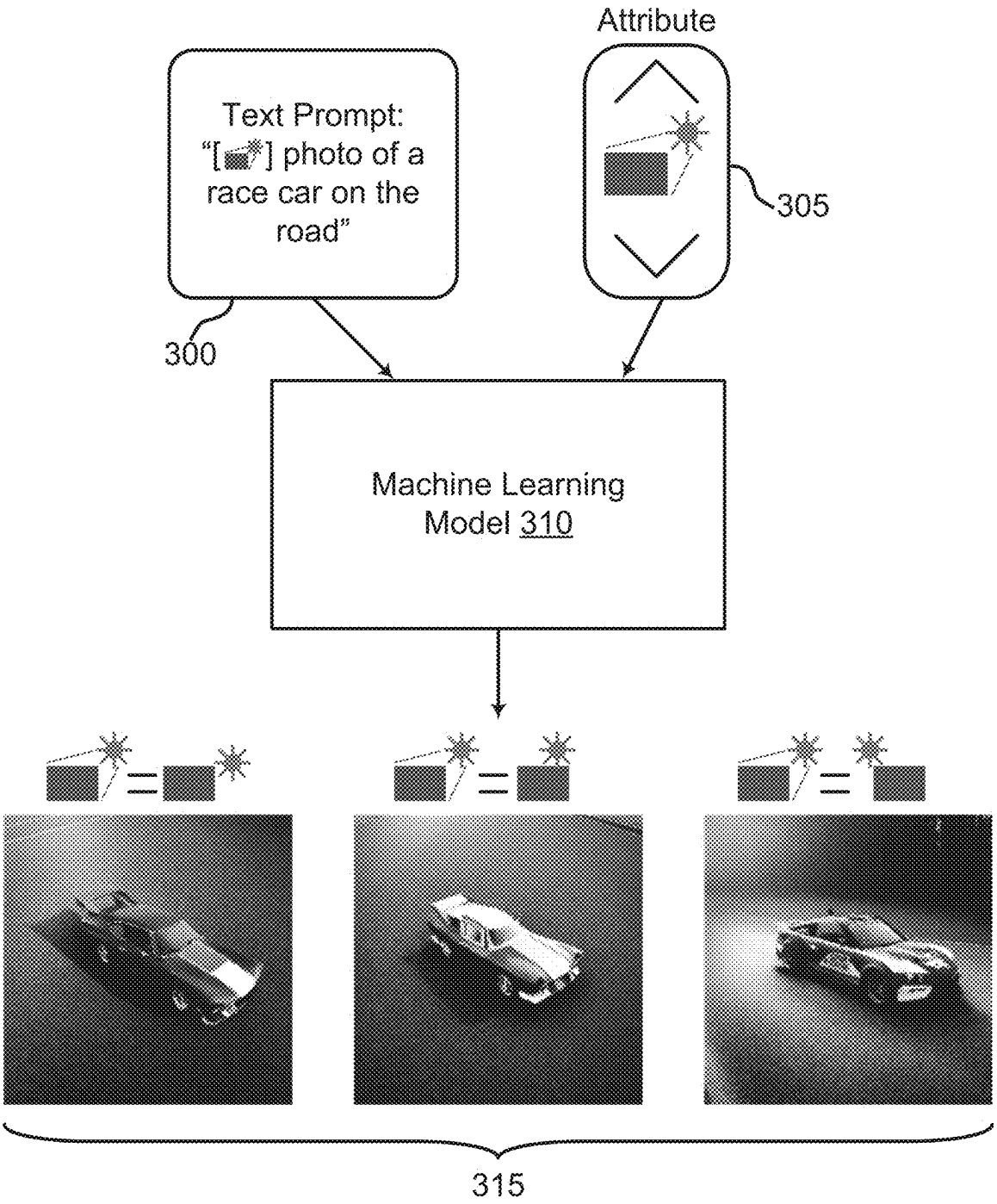

Attribute
Text Prompt: "[*] photo of a race car on the road"
305
300
Machine Learning Model 310
315

FIG. 3

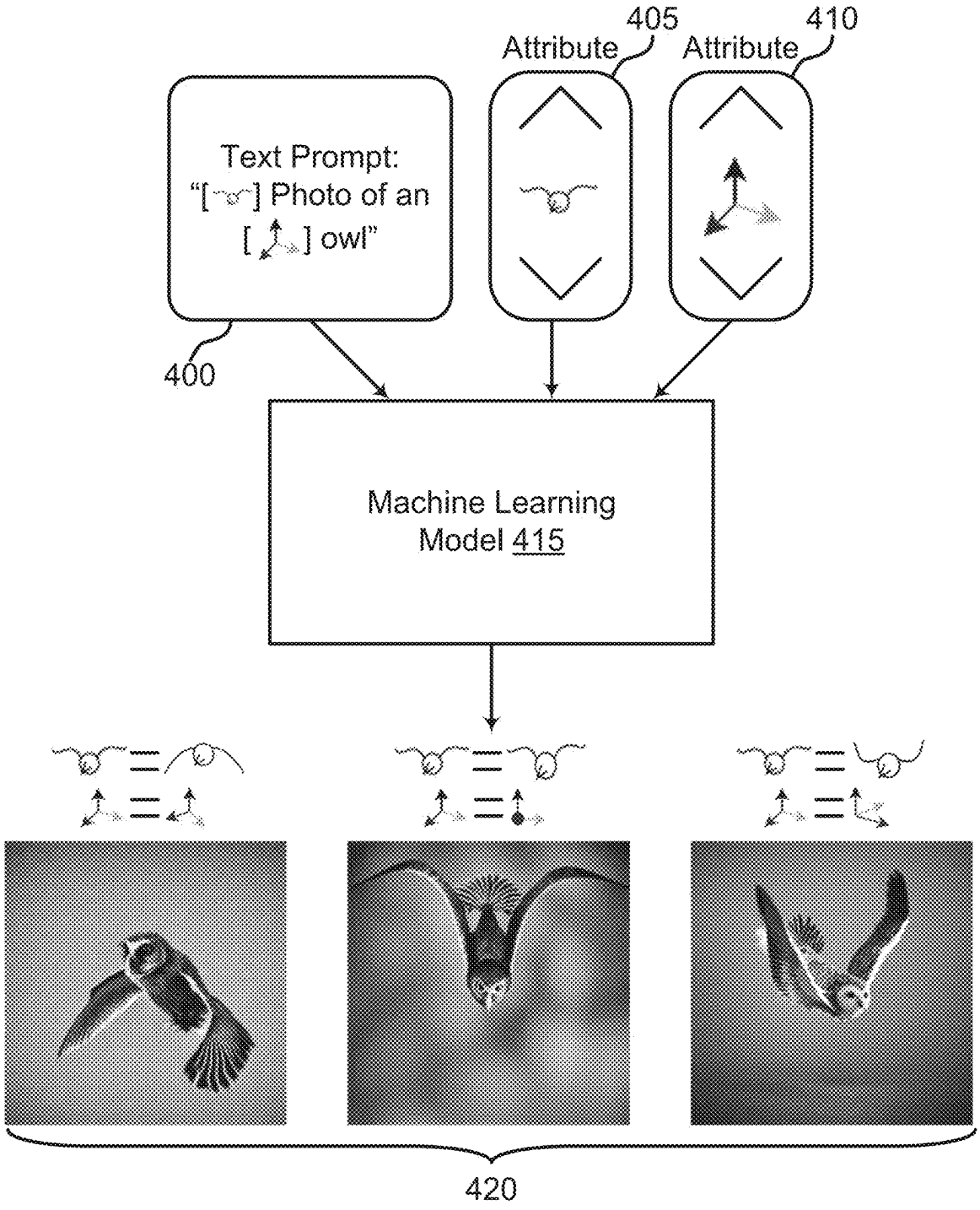

405
Attribute
410
Attribute
Text Prompt:
"[ ] Photo of an
[ ] owl"
400
Machine Learning
Model 415
420

FIG. 4

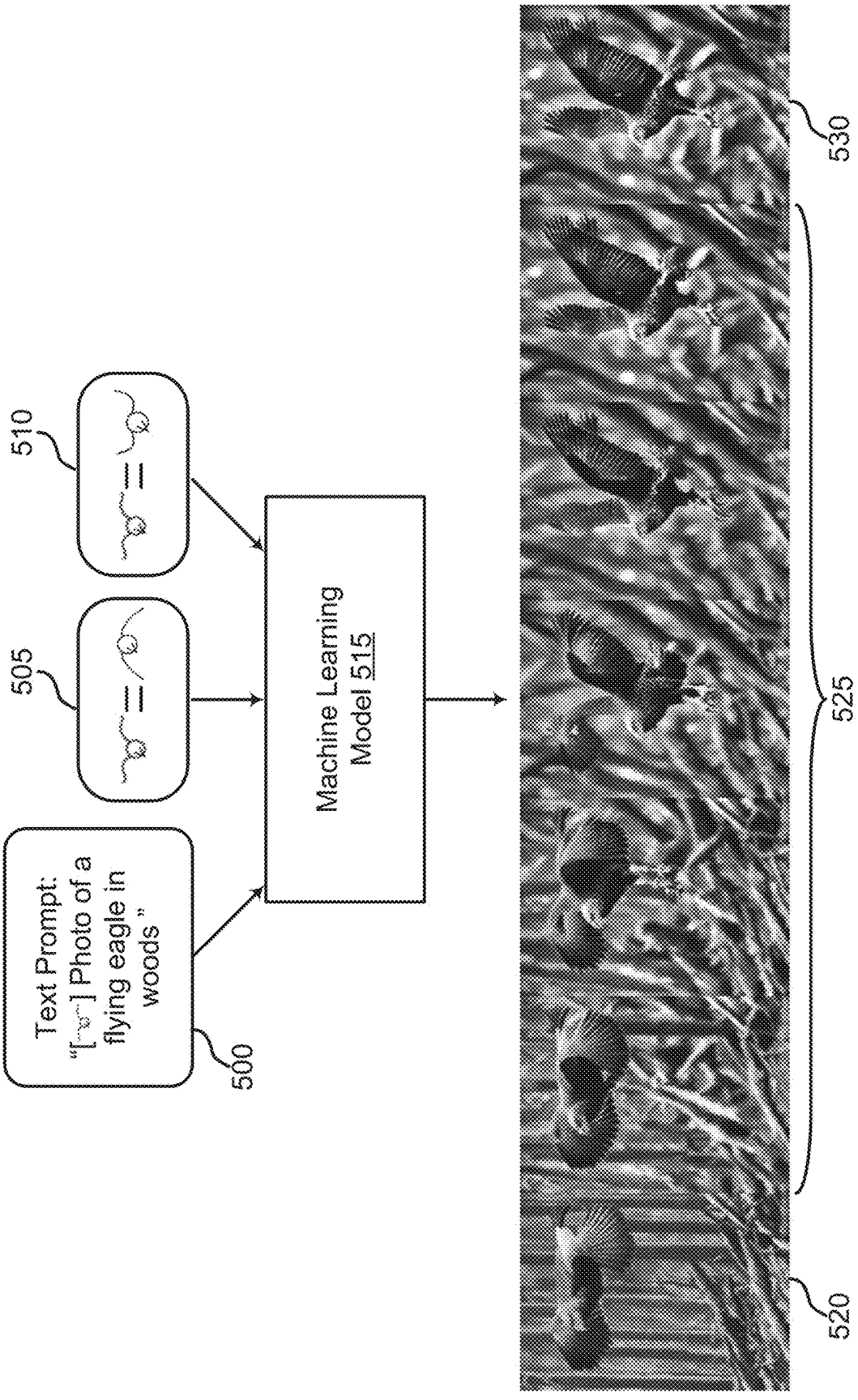

Text Prompt: "[ ] Photo of a flying eagle in woods"
500
505
510
Machine Learning Model 515
520
525
530

FIG. 5

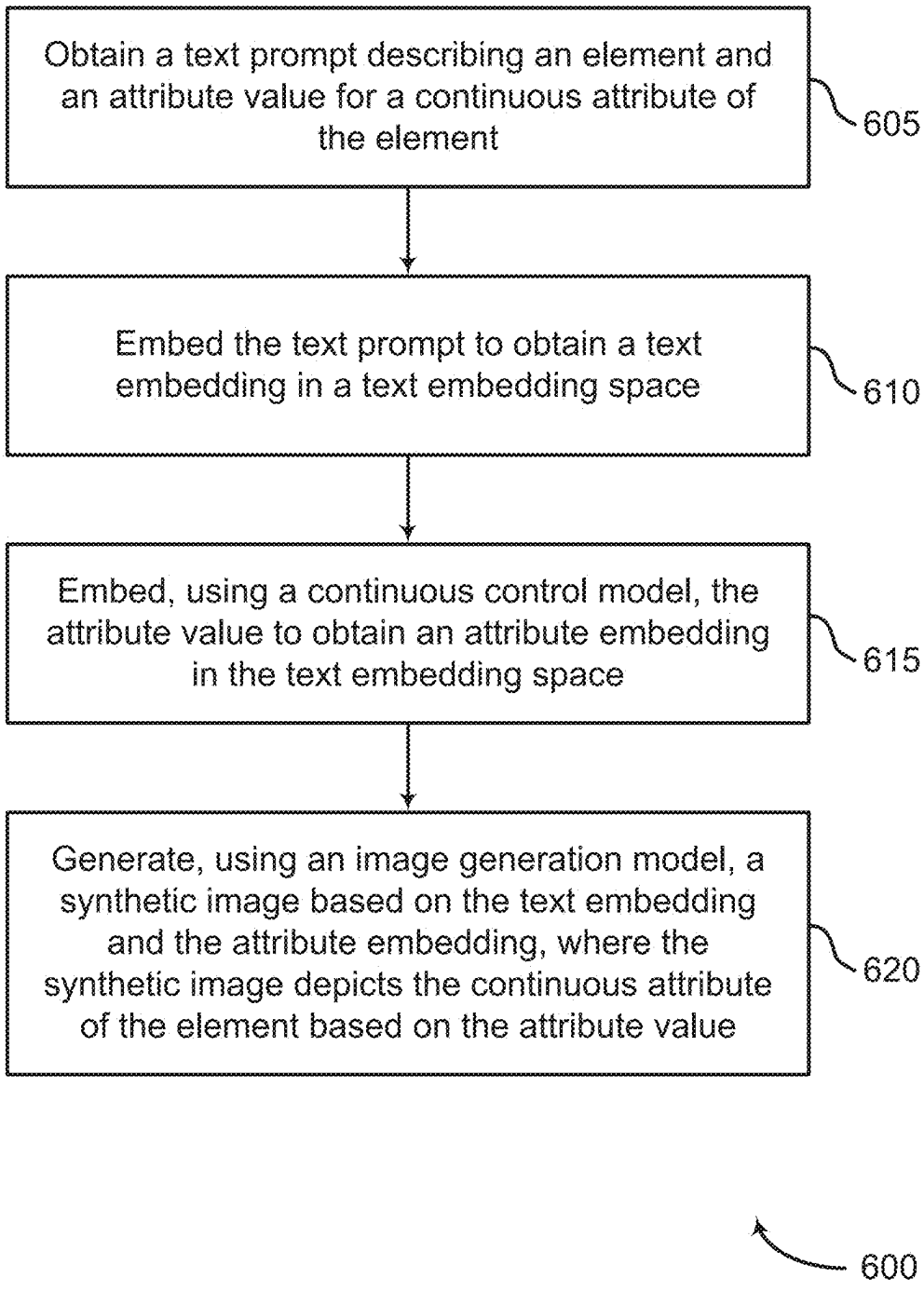

Obtain a text prompt describing an element and an attribute value for a continuous attribute of the element
605
Embed the text prompt to obtain a text embedding in a text embedding space
610
Embed, using a continuous control model, the attribute value to obtain an attribute embedding in the text embedding space
615
Generate, using an image generation model, a synthetic image based on the text embedding and the attribute embedding, where the synthetic image depicts the continuous attribute of the element based on the attribute value
620
600

FIG. 6

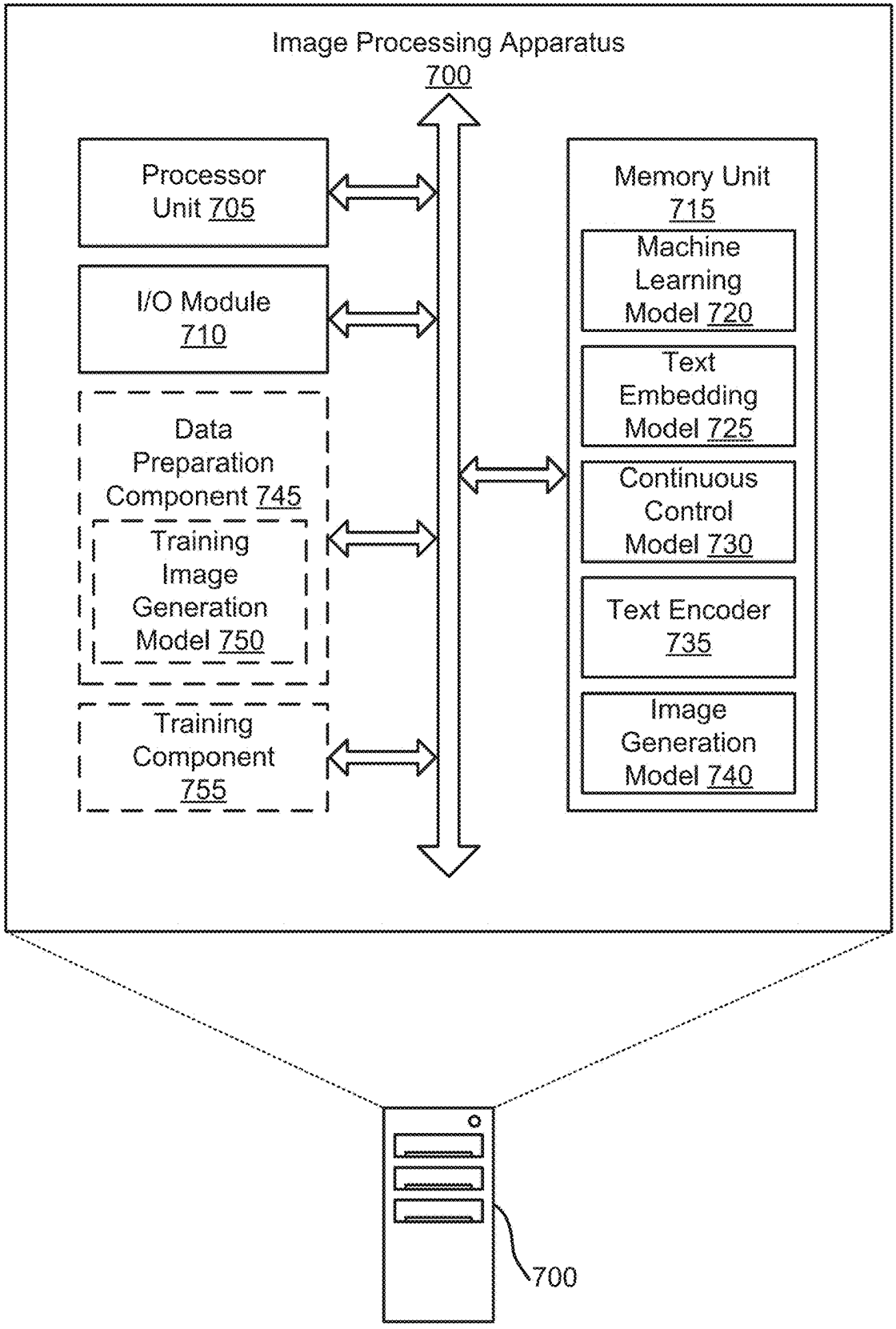


Image Processing Apparatus
700
Processor Unit 705
I/O Module 710
Data Preparation Component 745
Training Image Generation Model 750
Training Component 755
Memory Unit 715
Machine Learning Model 720
Text Embedding Model 725
Continuous Control Model 730
Text Encoder 735
Image Generation Model 740
700

FIG. 7

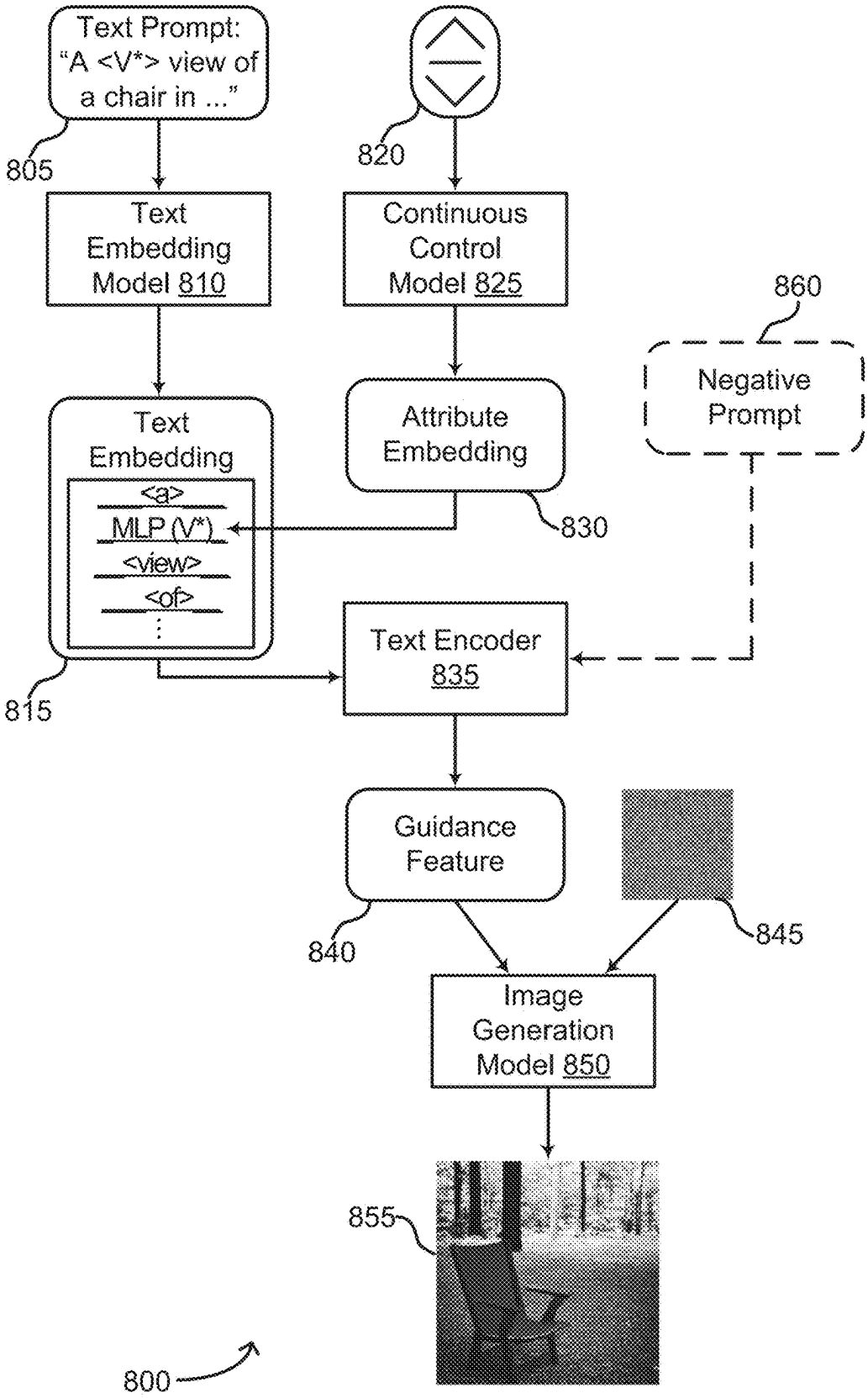

Text Prompt: "A <V*> view of a chair in ..."
805
820
Text Embedding Model 810
Continuous Control Model 825
860
Negative Prompt
Text Embedding
<a>
MLP (V*)
<view>
<of>
Attribute Embedding
830
815
Text Encoder 835
Guidance Feature
840
845
Image Generation Model 850
855
800

FIG. 8

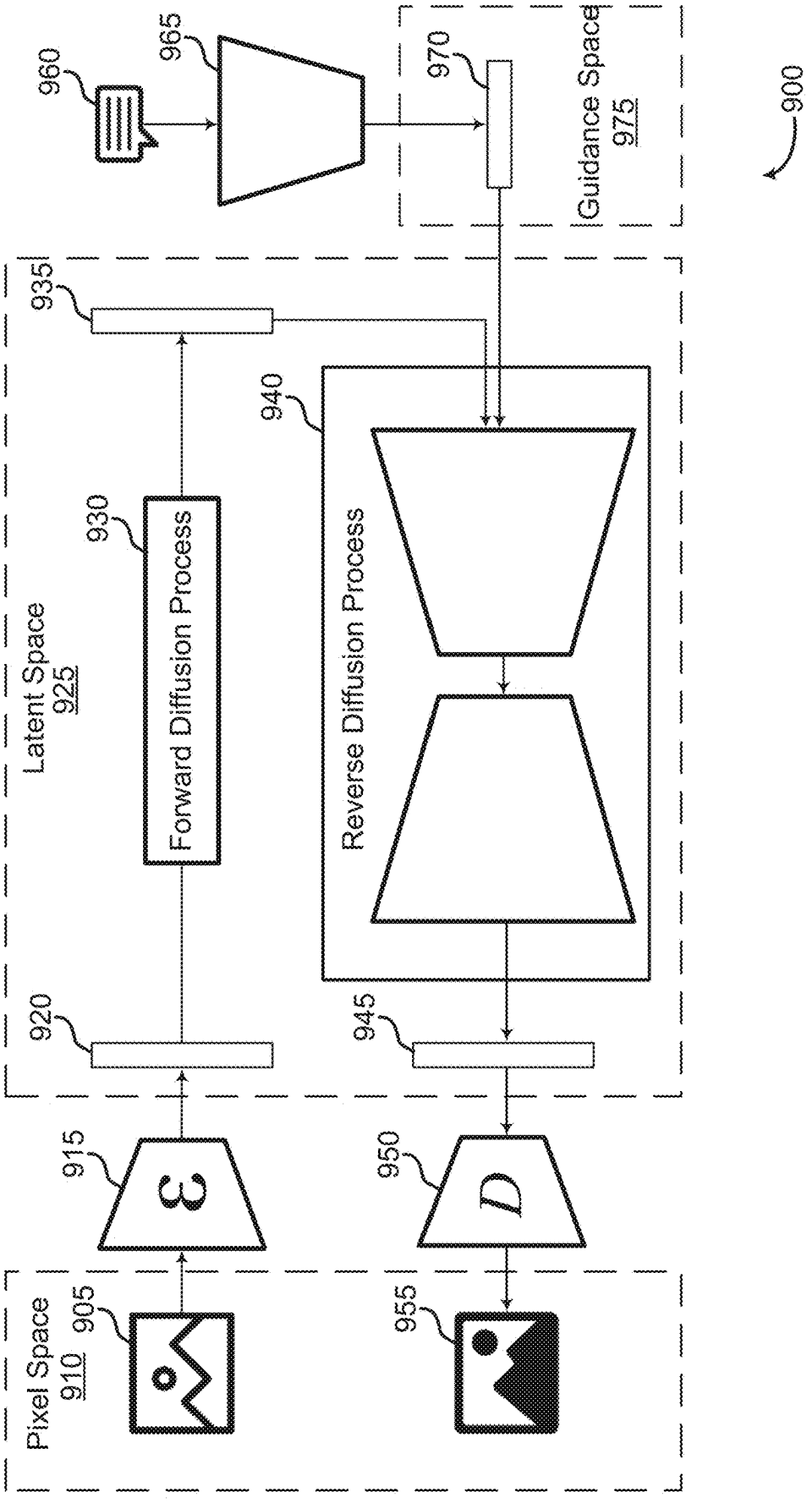

900
960
965
970
Guidance Space
975
935
940
930
Forward Diffusion Process
Reverse Diffusion Process
Latent Space
925
920
945
915
950
Pixel Space
910
905
955

FIG. 9

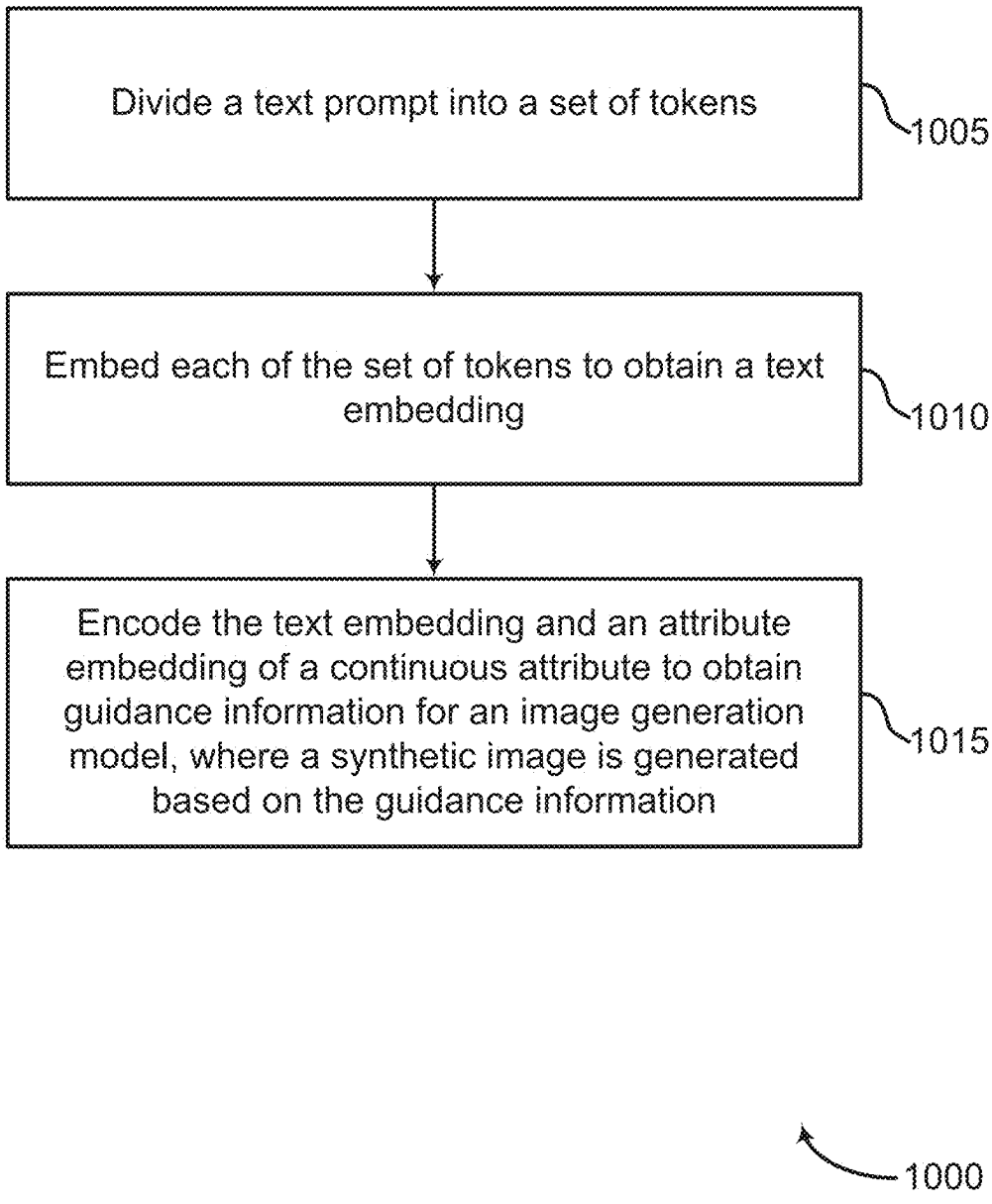

Divide a text prompt into a set of tokens
1005
Embed each of the set of tokens to obtain a text embedding
1010
Encode the text embedding and an attribute embedding of a continuous attribute to obtain guidance information for an image generation model, where a synthetic image is generated based on the guidance information
1015
1000

FIG. 10

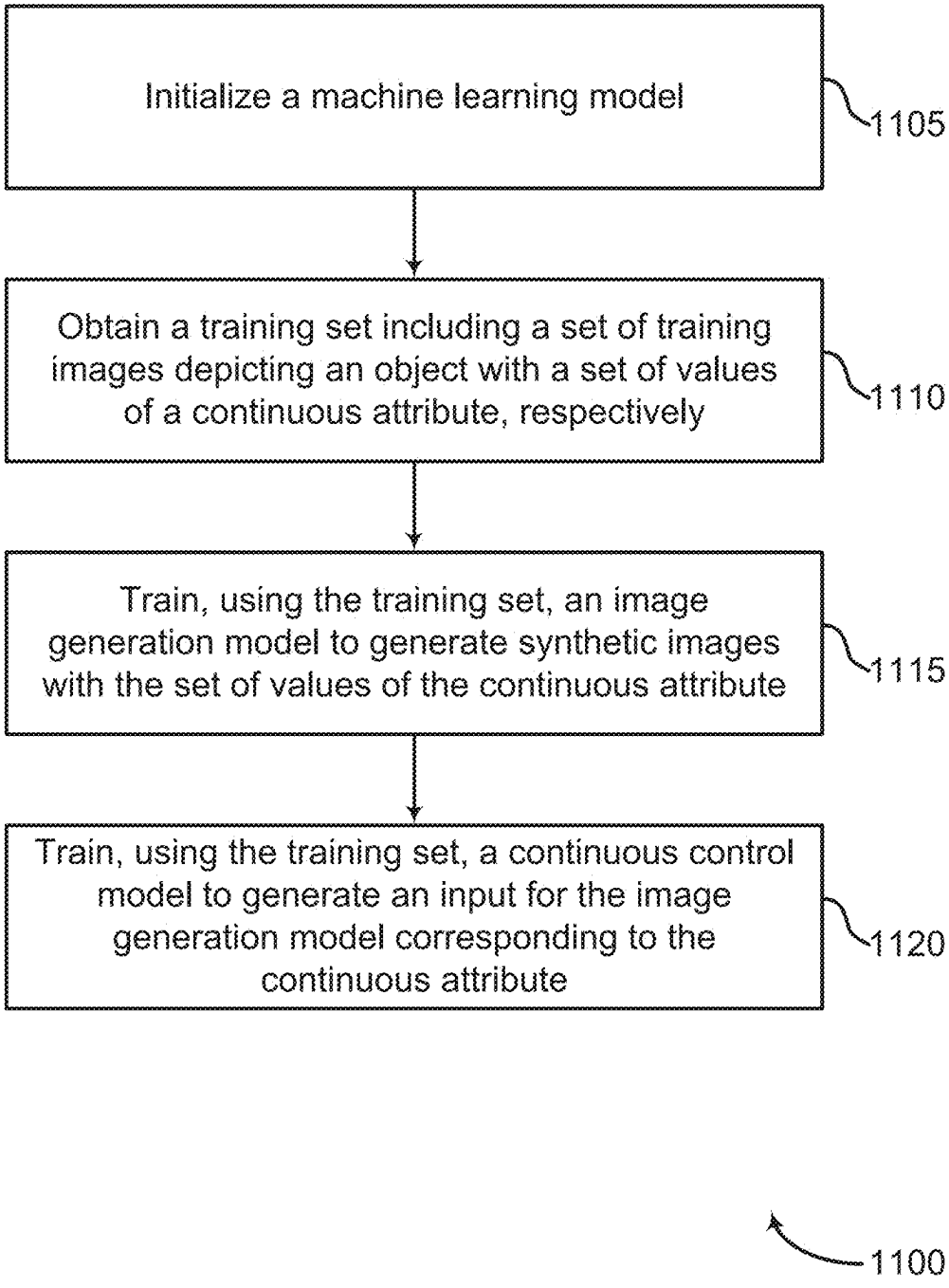

Initialize a machine learning model
1105
Obtain a training set including a set of training images depicting an object with a set of values of a continuous attribute, respectively
1110
Train, using the training set, an image generation model to generate synthetic images with the set of values of the continuous attribute
1115
Train, using the training set, a continuous control model to generate an input for the image generation model corresponding to the continuous attribute
1120
1100

FIG. 11

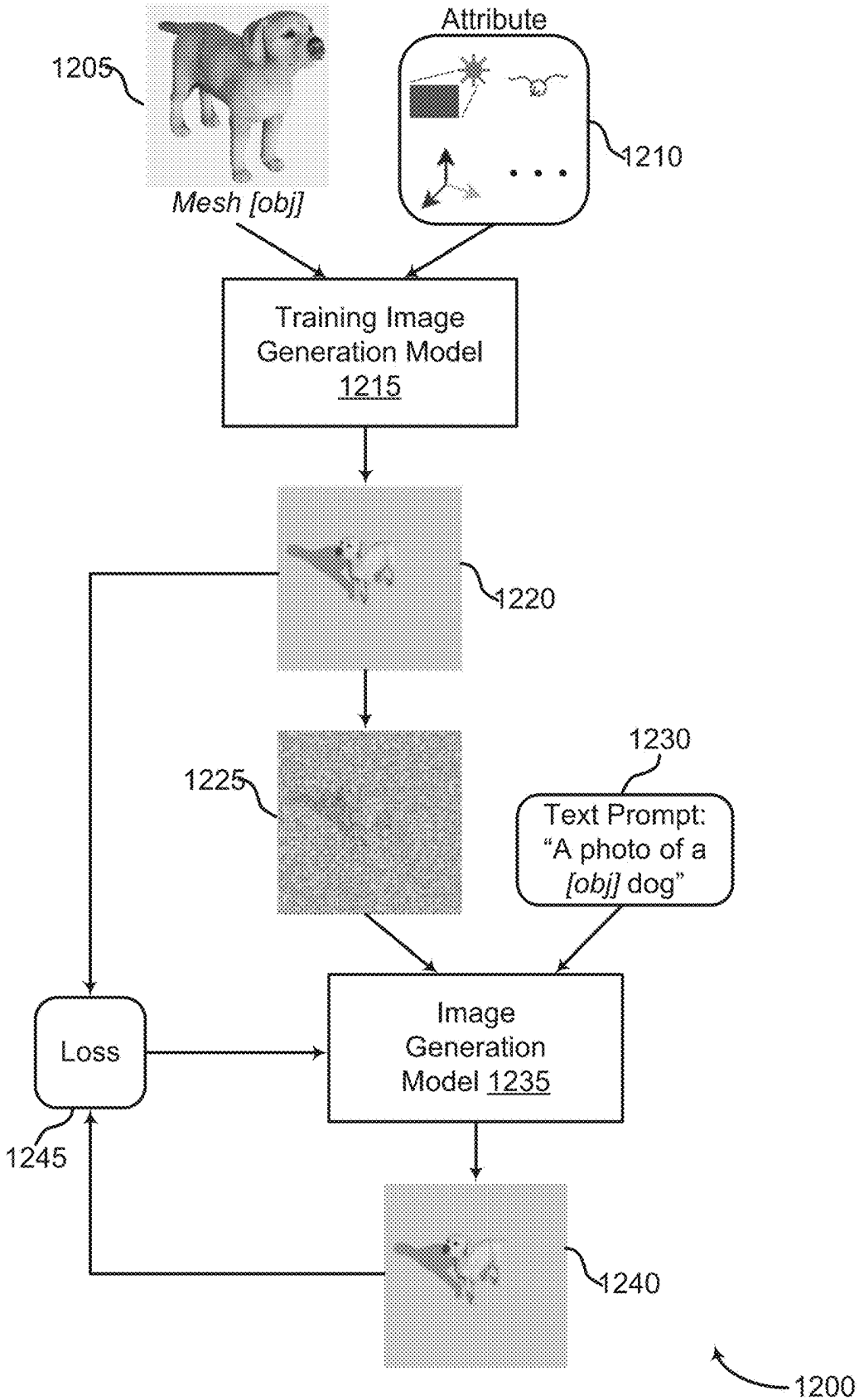

1205
Mesh [obj]
Attribute
1210
Training Image Generation Model 1215
1220
1225
1230
Text Prompt: "A photo of a [obj] dog"
Loss
Image Generation Model 1235
1245
1240
1200

FIG. 12

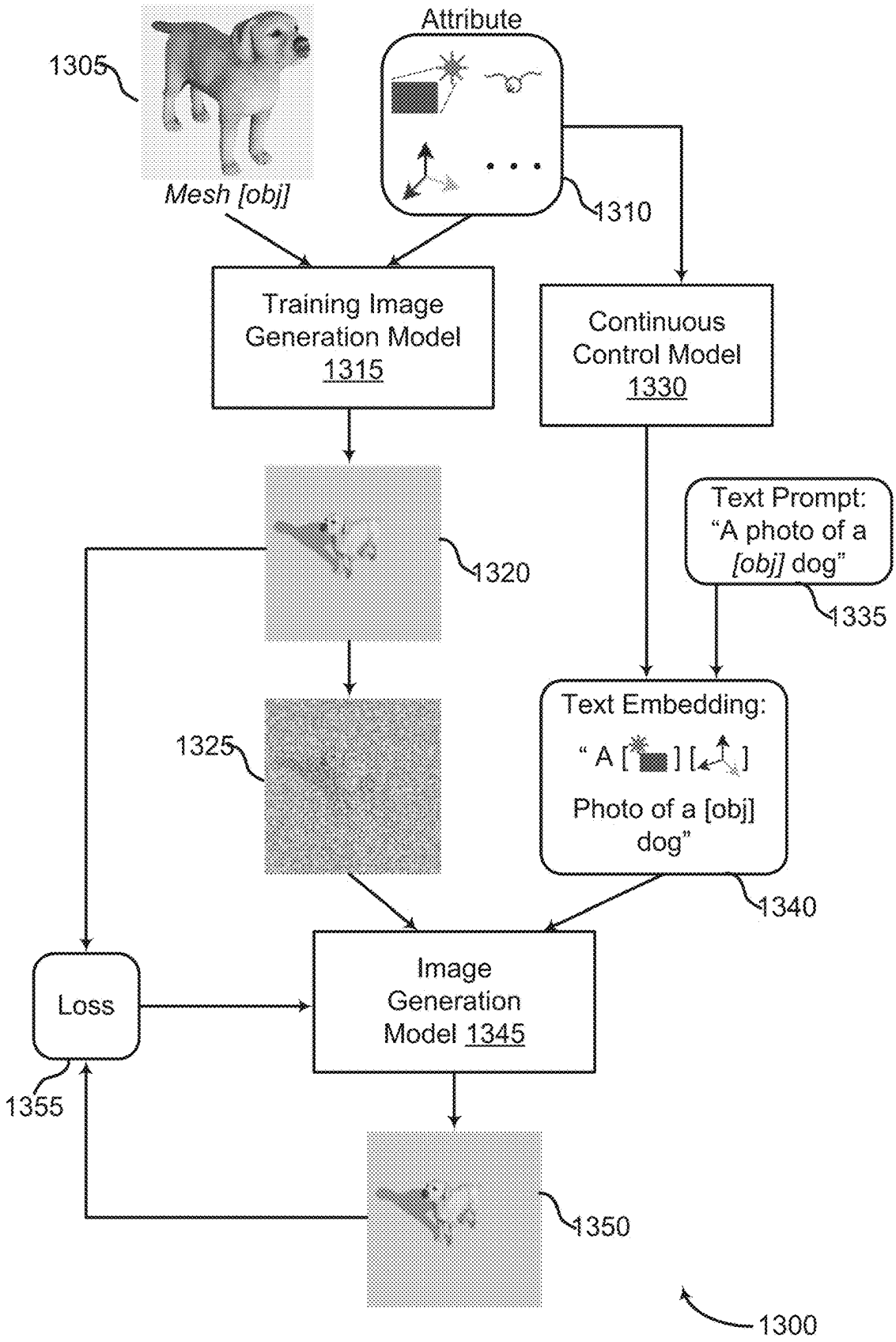

1305
Mesh [obj]
Attribute
1310
Training Image Generation Model 1315
Continuous Control Model 1330
1320
Text Prompt: "A photo of a [obj] dog"
1335
1325
Text Embedding:
" A [ ] [ ]
Photo of a [obj] dog"
1340
Loss
Image Generation Model 1345
1355
1350
1300

FIG. 13

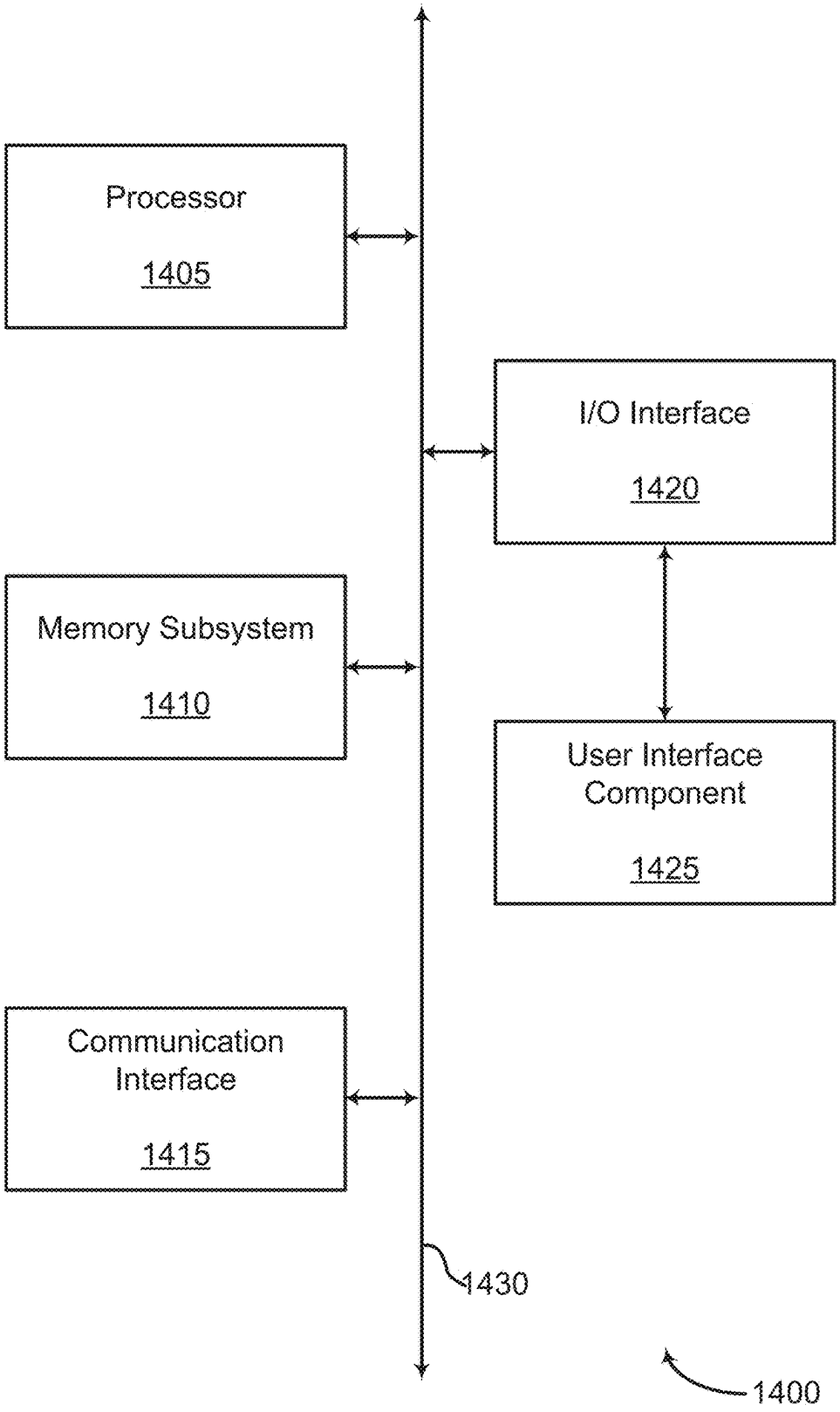

Processor
1405
I/O Interface
1420
Memory Subsystem
1410
User Interface Component
1425
Communication Interface
1415
1430
1400

FIG. 14

LEARNING CONTINUOUS CONTROL FOR 3D-AWARE IMAGE GENERATION ON TEXT-TO-IMAGE DIFFUSION MODELS

BACKGROUND

[0001] The following relates generally to image processing, and more specifically to image generation using a machine learning model. Image processing refers to the use of a computer to edit an image using an algorithm or a processing network. In some cases, image processing software can be used for various image processing tasks, such as image restoration, image detection, image compositing, image editing, and image generation. For example, image generation includes the use of the machine learning model to generate an image based on a text prompt.

[0002] In some cases, image generation models may be used to generate images that have the appearance of depth. That is, two-dimensional (2D) images can have the appearance of three-dimensional (3D) attributes such as depth or perspective.

SUMMARY

[0003] Aspects of the present disclosure provide methods, non-transitory computer readable media, apparatuses, and systems for image processing. Aspects of the present disclosure include a continuous control model trained to generate an attribute embedding based on an input attribute. In one aspect, the input attribute includes a 3-dimensional characteristic of an element described by a text prompt. In some aspects, a text embedding model generates a text embedding based on the text prompt. In some aspects, the text embedding and the attribute embedding are combined as an input embedding to a text encoder to generate a guidance embedding for an image generation model. The image generation model generates a synthetic image based on the guidance feature, where the synthetic image includes the element described by the text prompt and depicts the continuous attribute of the element based on the attribute value.

[0004] A method, apparatus, non-transitory computer readable medium, and system for image processing include obtaining a text prompt describing an element and an attribute value for a continuous attribute of the element, embedding the text prompt to obtain a text embedding in a text embedding space, embedding, using a continuous control model, the attribute value to obtain an attribute embedding in the text embedding space, and generating, using an image generation model, a synthetic image based on the text embedding and the attribute embedding, where the synthetic image depicts the continuous attribute of the element based on the attribute value.

[0005] A method, apparatus, non-transitory computer readable medium, and system for image processing include initializing a machine learning model, obtaining a training set including a plurality of training images depicting an object with a plurality of values of a continuous attribute, respectively, training, using the training set, an image generation model to generate synthetic images with the plurality of values of the continuous attribute, and training, using the training set, a continuous control model to generate an input for the image generation model corresponding to the continuous attribute.

[0006] An apparatus and system for image processing include at least one processor, at least one memory storing instructions executable by the at least one processor, a continuous control model comprising parameters stored in the at least one memory and trained to embed an attribute value of a continuous attribute to obtain an attribute embedding in a text embedding space, and an image generation model comprising parameters stored in the at least one memory and trained to generate a synthetic image based on a text embedding of a text prompt and the attribute embedding, where the synthetic image depicts the continuous attribute based on the attribute value.

BRIEF DESCRIPTION OF THE DRAWINGS

[0007] FIG. **1** shows an example of an image processing system according to aspects of the present disclosure.

[0008] FIG. **2** shows an example of a method for text-to-image generation according to aspects of the present disclosure.

[0009] FIGS. **3** and **4** show examples of a mixed-text to image generation according to aspects of the present disclosure.

[0010] FIG. **5** shows an example of an image interpolation using an attribute value according to aspects of the present disclosure.

[0011] FIG. **6** shows an example of a method for generating a synthetic image based on a text prompt according to aspects of the present disclosure.

[0012] FIG. **7** shows an example of an image processing apparatus according to aspects of the present disclosure.

[0013] FIG. **8** shows an example of a machine learning model according to aspects of the present disclosure.

[0014] FIG. **9** shows an example of a diffusion model according to aspects of the present disclosure.

[0015] FIG. **10** shows an example of a method for generating a synthetic image based on an embedding according to aspects of the present disclosure.

[0016] FIG. **11** shows an example of a method for training a machine learning model according to aspects of the present disclosure.

[0017] FIG. **12** shows an example of a first stage training according to aspects of the present disclosure.

[0018] FIG. **13** shows an example of a second stage training according to aspects of the present disclosure.

[0019] FIG. **14** shows an example of a computing device according to aspects of the present disclosure.

DETAILED DESCRIPTION

[0020] Aspects of the present disclosure provide methods, non-transitory computer readable media, apparatuses, and systems for image processing. Aspects of the present disclosure include a continuous control model trained to generate an attribute embedding based on an input attribute. In one aspect, the input attribute includes a 3-dimensional characteristic of an element described by a text prompt. In some aspects, a text embedding model generates a text embedding based on the text prompt. In some aspects, the text embedding and the attribute embedding are combined as an input embedding to a text encoder to generate a guidance embedding for an image generation model. The image generation model generates a synthetic image based on the guidance feature, where the synthetic image includes the element described by the text prompt and depicts the continuous attribute of the element based on the attribute value.

[0021] According to some aspects, the input attribute includes a 3-dimensional characteristic of the element described by the text prompt. For example, the input attribute includes orientation, illumination direction, non-rigid shape transformation, zoom effect, or object poses of the element. However, expressing these 3-dimensional characteristics in text descriptions is challenging and laborious. According to some aspects, the input attribute is integrated into a user control to allow a user to easily control a value of the input attribute of the element to be generated in the synthetic image.

[0022] A subfield in image processing relates to text-to-image generation. Text-to-image generation models are capable of generating 2D images that closely resemble authentic photographs. However, the text inputs used to generate these 2D images are inherently limited to high-level descriptions, which are far removed from the detailed controls over actual photography. In some cases, conventional models are trained with limited datasets, for example, limited descriptions of a training image with the precise object movements and camera parameters. In some cases, training images can be rendered with predefined camera parameters, object movements, or non-rigid shape transformations at a fine-grained scale. However, generating these training images can be inefficient and computationally burdensome.

[0023] Conventional text-to-image generation models use large-scale text-image datasets to guide the image generation process. In some cases, conventional models utilize memory-efficient strategies by incorporating latent-space diffusion methods for enhanced performance. In some cases, conventional models use zero-convolution for conditioning on text and image data (e.g., depth map, canny map, and sketch). However, these conventional models fail to control attributes of an element depicted in the image, such as illumination direction or object orientation.

[0024] In some cases, conventional models first generate an image conditioned based on a text input and then perform edits using textual instructions. For example, a user can edit the generated image by amending the text prompt while preserving some aspects of the original image. However, conventional approaches are limited in detailed control over an element depicted in the image because of the limitation on the user's ability to describe the characteristics of the element through text. For example, describing a change in the illumination direction by an angle of 11° in a 3-dimensional space would pose a considerable challenge.

[0025] In some cases, conventional models can be trained on 3D data of an element (e.g., various viewpoints of a 3D rendering). The conventional models enable viewpoint editing given the image depicting the element. In some cases, conventional models rely on extensive 3D datasets to perform edits to an object orientation of the element depicted in the image. However, these edits are performed in a post-processing stage (for example, performing edits to the generated image). As a result, conventional models are inefficient in generating synthetic images having controllable 3-dimensional characteristics.

[0026] Accordingly, the present disclosure describes a method and a system that generates a synthetic image depicting a desired attribute of an element based on a continuous attribute input including an attribute value and a text prompt describing the element. In one aspect, the text prompt and the continuous attribute input are combined and input into an image generation model to generate the synthetic image. In one aspect, the continuous attribute input includes a 3-dimensional characteristic of the element such as orientation, illumination direction, non-rigid shape transformation, object pose, zoom effect, etc. In one aspect, the continuous attribute input is integrated into a user control of a user interface that allows a user to easily input a desired attribute to generate the synthetic image. In one aspect, the continuous attribute input includes a variable input instead of a specific value.

[0027] According to some aspects, the image generation model is trained using a two-stage training process. The first training stage is to train the image generation model to learn the identity of an element described by the text prompt. For example, the image generation model generates a synthetic image based on a training image depicting an element and the text prompt describing the element. The image generation model is then fine-tuned using a reconstruction loss computed based on the training image and the synthetic image. By fine-tuning the image generation model in the first stage using the reconstruction loss, the image generation model can learn the identity of the element described by the text prompt.

[0028] According to some aspects, the second training stage is to train the image generation model to learn the attribute of the element based on the continuous attribute input and the text prompt. For example, a continuous control model receives the continuous attribute input to generate an attribute embedding. The attribute embedding is combined with a text embedding of the text prompt to generate an input embedding for the image generation model. The image generation model generates a synthetic image based on the training image and the input embedding. In one aspect, the training image depicts the element and includes an attribute of the continuous attribute input. The image generation model is fine-tuned using a reconstruction loss computed based on the training image and the synthetic image. By fine-tuning the image generation model in the second stage using the reconstruction loss, the image generation model can learn the attribute of the element from the continuous attribute input.

[0029] According to some aspects, the continuous control model is trained to generate an attribute embedding based on the attribute value. For example, the continuous control model includes a multilayer perceptron (MLP). In one aspect, the MLP is able to receive a continuous input or an input (e.g., the attribute input) and generate a continuous output (e.g., the attribute embedding). Accordingly, the continuous control model can generate an attribute embedding based on an attribute value for a continuous attribute input, where the attribute embedding is used as input to the image generation model.

[0030] According to some aspects, the image generation model is configured to generate the synthetic image based on a negative prompt. In one aspect, the negative prompt is used to guide the image generation model away from generating the element described by the negative prompt. For example, the negative prompt includes elements depicted in the training images. By generating the synthetic image using the negative prompt, the image generation model can be generalized on new, unseen data.

[0031] An example system of the inventive concept in image processing is provided with reference to FIGS. **1** and **14**. An example application of the inventive concept in

image processing is provided with reference to FIGS. **2-5**. Details regarding the architecture of an image processing apparatus are provided with reference to FIGS. **7-9**. An example of a process for image processing is provided with reference to FIGS. **6** and **10**. A description of an example training process is provided with reference to FIGS. **11-13**.

[0032] Embodiments of the present disclosure include systems and methods that improve on conventional image generation models by generating more accurate synthetic images given a target continuous attribute, including 3D attributes such as camera perspective and lighting conditions. For example, an image generation model may be trained to generate a synthetic image with a target perspective based on a text prompt describing the object and an input specifying the target attribute. The improved accuracy may be achieved by training an attribute encoder (i.e., a continuous control model) that converts a continuous attribute into a text embedding space. Furthermore, by combining the output of a continuous control model with a text prompt, the image generation model can generate synthetic images with a target continuous characteristic more efficiently (i.e., in a single generation process).

[0033] In some examples, the image generation model is trained using a two-stage training process. For example, the first training stage enables the image generation model to learn the modify attributes (i.e., a pose or perspective) of a particular object. The second training stage enables the image generation model to learn the continuous attribute of the element from the continuous attribute input. Accordingly, by training the image generation using the two-stage training process, the image generation model is able to disentangle attributes from object identity and thus enhance the quality of image generation.

Image Processing

[0034] In FIGS. **1-6** and **10**, a method, apparatus, non-transitory computer readable medium, and system for image processing include obtaining a text prompt describing an element and an attribute value for a continuous attribute of the element, embedding the text prompt to obtain a text embedding in a text embedding space, embedding, using a continuous control model, the attribute value to obtain an attribute embedding in the text embedding space, and generating, using an image generation model, a synthetic image based on the text embedding and the attribute embedding. In some cases, the synthetic image depicts the continuous attribute of the element based on the attribute value.

[0035] In some aspects, the continuous attribute comprises a 3-dimensional characteristic of the element. Some examples of the method, apparatus, non-transitory computer readable medium, and system further include dividing the text prompt into a plurality of tokens. Some examples further include embedding each of the plurality of tokens using a text embedding model. In some aspects, the text prompt includes a nonce token corresponding to the attribute value. In some aspects, the text prompt includes a word corresponding to the continuous attribute.

[0036] Some examples of the method, apparatus, non-transitory computer readable medium, and system further include encoding the text embedding and the attribute embedding to obtain guidance information for the image generation model. In some cases, the synthetic image is generated based on the guidance information. Some examples of the method, apparatus, non-transitory computer readable medium, and system further include performing a diffusion process on a noise input to obtain the synthetic image.

[0037] In some aspects, the image generation model is trained using a training set including a plurality of training images depicting an object with a plurality of values of the continuous attribute, respectively. Some examples of the method, apparatus, non-transitory computer readable medium, and system further include identifying a negative prompt based on the object from the plurality of training images. In some cases, the synthetic image is generated based on the negative prompt.

[0038] Some examples of the method, apparatus, non-transitory computer readable medium, and system further include obtaining an additional attribute value corresponding to an additional continuous attribute. In some cases, the synthetic image is generated to depict the additional attribute value.

[0039] Some examples of the method, apparatus, non-transitory computer readable medium, and system further include obtaining a plurality of attribute values for the continuous attribute. Some examples further include generating, using the image generation model, a plurality of synthetic images based on a same random input and the plurality of attribute values, respectively.

[0040] FIG. **1** shows an example of an image processing system according to aspects of the present disclosure. The example shown includes user **100**, user device **105**, image processing apparatus **110**, cloud **115**, and database **120**. Image processing apparatus **110** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **7**.

[0041] Referring to FIG. **1**, user **100** provides a text prompt describing an element and an attribute to image processing apparatus **110** via user device **105** and cloud **115**. For example, the text prompt states "A photo of a horse." In some cases, the text prompt includes a nonce token that corresponds to the attribute. For example, the text prompt states "A<V*> photo of a horse," where <V*> represents the nonce token. In some cases, one or more attributes are provided to image processing apparatus **110**. For example, the attribute includes a 3-dimensional characteristic of the element. In some cases, for example, the attribute includes 3-dimensional orientation or 3-dimensional illumination of the element, such as the horse, described by the text prompt. In some cases, the attribute is integrated into a user control of a user interface, where a value of the attribute can be easily modified using the user control. Image processing apparatus **110** generates a synthetic image based on the text prompt and the attribute. For example, the synthetic image depicts a horse described by the text prompt and a 3-dimensional orientation and/or a 3-dimensional illumination based on the attribute. In some cases, image processing apparatus **110** displays the synthetic image to user **100** via user device **105** and cloud **115**.

[0042] User device **105** may be a personal computer, laptop computer, mainframe computer, palmtop computer, personal assistant, mobile device, or any other suitable processing apparatus. In some examples, user device **105** includes software that incorporates an image processing application. In some examples, the image processing application on user device **105** may include functions of image processing apparatus **110**.

[0043] A user interface may enable user **100** to interact with user device **105**. In some embodiments, the user interface may include an audio device, such as an external speaker system, an external display device such as a display screen, or an input device (e.g., a remote-controlled device interfaced with the user interface directly or through an I/O controller module). In some cases, a user interface may be a graphical user interface (GUI). In some examples, a user interface may be represented in code in which the code is sent to the user device **105** and rendered locally by a browser. The process of using the image processing apparatus **110** is further described with reference to FIG. **2**.

[0044] Image processing apparatus **110** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **7**. According to some aspects, image processing apparatus **110** includes a computer implemented network comprising a machine learning model, a text embedding model, a continuous control model, a text encoder, and an image generation model. Image processing apparatus **110** further includes a processor unit, a memory unit, an I/O module, a training component, and a data preparation component. In some cases, the data preparation component includes a training image generation model. In some embodiments, image processing apparatus **110** further includes a communication interface, user interface components, and a bus as described with reference to FIG. **14**. Additionally, image processing apparatus **110** communicates with user device **105** and database **120** via cloud **115**. Further detail regarding the operation of image processing apparatus **110** is provided with reference to FIG. **2**.

[0045] In some cases, image processing apparatus **110** is implemented on a server. A server provides one or more functions to users linked by way of one or more of the various networks. In some cases, the server includes a single microprocessor board, which includes a microprocessor responsible for controlling aspects of the server. In some cases, a server uses the microprocessor and protocols to exchange data with other devices/users on one or more of the networks via hypertext transfer protocol (HTTP), and simple mail transfer protocol (SMTP), although other protocols such as file transfer protocol (FTP), and simple network management protocol (SNMP) may also be used. In some cases, a server is configured to send and receive hypertext markup language (HTML) formatted files (e.g., for displaying web pages). In various embodiments, a server comprises a general-purpose computing device, a personal computer, a laptop computer, a mainframe computer, a supercomputer, or any other suitable processing apparatus.

[0046] Cloud **115** is a computer network configured to provide on-demand availability of computer system resources, such as data storage and computing power. In some examples, cloud **115** provides resources without active management by the user (e.g., user **100**). The term cloud is sometimes used to describe data centers available to many users over the Internet. Some large cloud networks have functions distributed over multiple locations from central servers. A server is designated an edge server if the server has a direct or close connection to a user. In some cases, cloud **115** is limited to a single organization. In other examples, cloud **115** is available to many organizations. In one example, cloud **115** includes a multi-layer communications network comprising multiple edge routers and core routers. In another example, cloud **115** is based on a local collection of switches in a single physical location.

[0047] According to some aspects, database **120** stores training data (or training set) including a plurality of training images depicting an object with a plurality of values of a continuous attribute. Database **120** is an organized collection of data. For example, database **120** stores data in a specified format known as a schema. Database **120** may be structured as a single database, a distributed database, multiple distributed databases, or an emergency backup database. In some cases, a database controller may manage data storage and processing in database **120**. In some cases, a user (e.g., user **100**) interacts with the database controller. In other cases, the database controller may operate automatically without user interaction.

[0048] FIG. **2** shows an example of a method **200** for text-to-image generation according to aspects of the present disclosure. In some examples, these operations are performed by a system including a processor executing a set of codes to control functional elements of an apparatus. Additionally or alternatively, certain processes are performed using special-purpose hardware. Generally, these operations are performed according to the methods and processes described in accordance with aspects of the present disclosure. In some cases, the operations described herein are composed of various substeps, or are performed in conjunction with other operations.

[0049] Referring to FIG. **2**, a user (e.g., the user described with reference to FIG. **1**) provides a text prompt and an attribute to the image processing apparatus (e.g., the image processing apparatus described with reference to FIGS. **1** and **7**). For example, the text prompt states "A<V*> photo of a horse." In some cases, the nonce token <V*> is added to the text prompt by the machine learning model. In some cases, the nonce token <V*> is not displayed to the user and is processed by the machine learning model. In some cases, the nonce token <V*> is replaced by the attribute. The attribute describes a 3-dimensional characteristic of the object described by the text prompt. For example, the attribute describes the orientation, illumination, pose, and zoom. The image processing apparatus generates a text embedding based on the text prompt and generates an attribute embedding based on the attribute. In some cases, the text embedding and the attribute embedding are combined to generate an input embedding to a text encoder of the machine learning model. The text encoder generates a guidance embedding based on the input embedding to guide an image generation model to generate a synthetic image. The synthetic image depicts a horse described by the text prompt and a 3-dimensional characteristic based on the attribute.

[0050] At operation **205**, the system provides a text prompt and an attribute. In some cases, the operations of this step refer to, or may be performed by, a user as described with reference to FIG. **1**. For example, the user provides a text prompt "A photo of a horse" and an attribute to the image processing apparatus via a user interface provided by the image processing apparatus on a user device (e.g., the user device described with reference to FIG. **1**). In some cases, for example, the attribute is integrated into a user control, where the attribute can be easily modified by the user. In some cases, the attribute includes 3-dimensional characteristics (such as orientation, pose, and illumination) of the element described by the text prompt.

[0051] At operation **210**, the system embeds the attribute to obtain an attribute embedding. In some cases, the opera-

tions of this step refer to, or may be performed by, an image processing apparatus as described with reference to FIGS. **1** and **7**. In some cases, the operations of this step refer to, or may be performed by, a continuous control model as described with reference to FIGS. **7**, **8**, and **13**. In some cases, for example, the continuous control model includes a multilayer perceptron (MLP) trained to embed the attribute to obtain the attribute embedding. In some cases, the machine learning model embeds the text prompt to obtain a text embedding. In some cases, the attribute embedding is added to a region of a sequence of the text embedding.

[0052] At operation **215**, the system encodes the text prompt and the attribute embedding to obtain guidance information. In some cases, the operations of this step refer to, or may be performed by, an image processing apparatus as described with reference to FIGS. **1** and **7**. In some cases, the operations of this step refer to, or may be performed by, a text encoder as described with reference to FIGS. **7-9**. In some embodiments, the text encoder receives the text embedding (including the attribute embedding) to generate a guidance embedding (e.g., guidance information). The guidance embedding is used to guide the image generation model to generate a synthetic image.

[0053] At operation **220**, the system generates a synthetic image based on the guidance information. In some cases, the operations of this step refer to, or may be performed by, an image processing apparatus as described with reference to FIGS. **1** and **7**. In some cases, the operations of this step refer to, or may be performed by, an image generation model as described with reference to FIGS. **4**, **7**, **8**, **12**, and **13**. In some embodiments, the image generation model receives a noise input (e.g., a noise map) and the guidance embedding to generate the synthetic image. In some cases, the synthetic image includes the element described by the text prompt and the attribute from the user input. In some cases, the synthetic image is displayed on a user device via a user interface of the image processing apparatus and cloud.

[0054] FIG. **3** shows an example of a mixed-text to image generation according to aspects of the present disclosure. The example shown includes text prompt **300**, attribute **305**, machine learning model **310**, and synthetic image **315**. In some embodiments, the example shown is integrated into a user interface.

[0055] Referring to FIG. **3**, machine learning model **310** receives text prompt **300** and attribute **305** to generate synthetic image **315**. For example, text prompt **300** states "photo of a race car on the road." In some cases, text prompt **300** includes a placeholder for attribute **305**. For example, attribute **305** can be placed in the beginning, middle, or end of text prompt **300**. Attribute **305** includes a 3-dimensional characteristic of the element described by text prompt **300**. For example, attribute **305** includes illumination direction. In some embodiments, attribute **305** is integrated into a user control in a user interface, where a user can easily modify an attribute value of attribute **305**. For example, the user control may include scrollbars, buttons, text input controls, drop-down lists, sliders, progress bars, switches, tabs, dropdown menus, etc.

[0056] In some cases, synthetic image **315** includes one or more synthetic images depicting the element described by text prompt **300** and a 3-dimensional characteristic from attribute **305**. For example, synthetic image **315** on the left depicts a car (i.e., the element described by text prompt **300**) and an illumination direction (i.e., the 3-dimensional characteristic from attribute **305**) specified by, for example, the user. In some cases, the illumination direction is depicted by the shadow of the car. For example, the illumination direction shows that the light source is at the upper right-hand corner of the element. As a result, the shadow is reflected on the opposite side of the light source, for example, the bottom left-hand corner of the element. Synthetic image **315** in the middle depicts a car (e.g., a different car) and a second illumination direction. Synthetic image **315** on the right depicts a car (e.g., a different car) and a third illumination direction.

[0057] Text prompt **300** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **4**, **5**, **8**, **9**, **12**, and **13**. Attribute **305** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **8**, **12**, and **13**. Machine learning model **310** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **4**, **5**, **7**, **8**, **12**, and **13**. Synthetic image **315** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **4**, **8**, **12**, and **13**.

[0058] FIG. **4** shows an example of a mixed-text to image generation according to aspects of the present disclosure. The example shown includes text prompt **400**, first attribute **405**, second attribute **410**, machine learning model **415**, and synthetic image **420**. In some embodiments, the example shown is integrated into a user interface.

[0059] Referring to FIG. **4**, machine learning model **415** receives text prompt **400**, first attribute **405**, and second attribute **410** to generate synthetic image **420**. For example, text prompt **400** states "Photo of an owl." In some cases, text prompt **400** includes placeholders for first attribute **405** and second attribute **410**. For example, first attribute **405** and second attribute **410** can be placed in the beginning, middle, or end of text prompt **400**. In some embodiments, first attribute **405** and second attribute **410** are integrated into a single user control. In some embodiments, first attribute **405** and second attribute **410** are integrated into two different user controls. First attribute **405** includes the wing pose of the element. Second attribute **410** includes the 3-dimensional orientation of the element.

[0060] In some cases, synthetic image **420** includes one or more synthetic images depicting the element described by text prompt **400** and 3-dimensional characteristics from first attribute **405** and second attribute **410**. For example, synthetic image **420** on the left depicts an owl (i.e., the element described by text prompt **400**), a wing pose (i.e., the 3-dimensional characteristic from first attribute **405**), and a 3-dimensional orientation (i.e., the 3-dimensional characteristic from second attribute **410**) specified by, for example, the user. Synthetic image **420** on the left, middle, and right depicts different combinations of first attribute **405** and second attribute **410**. For example, synthetic image **420** on the left depicts a first wing pose and a first 3-dimensional orientation, synthetic image **420** in the middle depicts a second wing pose and a second 3-dimensional orientation, and synthetic image **420** on the right depicts a third wing pose and a third 3-dimensional orientation. In some cases, machine learning model **415** can generate synthetic image **420** having first attribute **405** fixed and second attribute **410** changed, or vice versa. For example, synthetic image **420** on the left may depict a first wing pose and a first 3-dimensional orientation, synthetic image **420** in the middle may depict a first wing pose and a second 3-dimensional orientation, and

synthetic image **420** on the right may depict a first wing pose and a third 3-dimensional orientation.

[0061] Text prompt **400** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **5**, **8**, **9**, **12**, and **13**. Machine learning model **415** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **7**, **8**, **12**, and **13**. Synthetic image **420** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **8**, **12**, and **13**.

[0062] FIG. **5** shows an example of an image interpolation using an attribute value according to aspects of the present disclosure. The example shown includes text prompt **500**, first attribute value **505**, second attribute value **510**, machine learning model **515**, first synthetic image **520**, intermediate synthetic images **525**, and final synthetic image **530**. In some embodiments, the example shown is integrated into a user interface.

[0063] Referring to FIG. **5**, machine learning model **515** receives text prompt **500**, first attribute value **505**, and second attribute value **510** to generate a plurality of synthetic images (e.g., first synthetic image **520**, intermediate synthetic images **525**, and final synthetic image **530**). For example, text prompt **500** states "Photo of a flying eagle in woods." In some embodiments, first attribute value **505** and second attribute value **510** are part of the same attribute integrated into a single user control. For example, first attribute value **505** includes a first information of an attribute (e.g., wing pose). Second attribute value **510** includes a second information of the same attribute. For example, first attribute value **505** and second attribute value **510** represent the shape/location of the wing pose of the owl (e.g., the element described by text prompt **500**). For example, first attribute value **505** represents the wing pose in a downward direction and second attribute value **510** represents the wing pose in an upward direction.

[0064] Machine learning model **515** generates first synthetic image **520** and final synthetic image **530** based on first attribute value **505** and second attribute value **510**, respectively. Additionally, machine learning model **515** generates intermediate synthetic images **525** by interpolating wing pose information based on first attribute value **505** and second attribute value **510**. For example, machine learning model **515** may generate a plurality of intermediate attribute values based on the first attribute value **505** and second attribute value **510**, where intermediate synthetic images **525** are generated based on the plurality of intermediate attribute values, respectively. In one aspect, each of the plurality of synthetic images (e.g., first synthetic image **520**, intermediate synthetic images **525**, and final synthetic image **530**) depicts the same owl (e.g., the element described by text prompt **500**) but with changing wing poses. In one aspect, the visual change of the wing pose is continuous and dynamic.

[0065] Text prompt **500** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **8**, **9**, **12**, and **13**. Machine learning model **515** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **7**, **8**, **12**, and **13**. First synthetic image **520**, intermediate synthetic images **525**, and final synthetic image **530** are examples of, or include aspects of, the synthetic image described with reference to FIGS. **3**, **4**, **8**, **12**, and **13**.

[0066] FIG. **6** shows an example of a method **600** for generating a synthetic image based on a text prompt according to aspects of the present disclosure. In some examples, these operations are performed by a system including a processor executing a set of codes to control functional elements of an apparatus. Additionally or alternatively, certain processes are performed using special-purpose hardware. Generally, these operations are performed according to the methods and processes described in accordance with aspects of the present disclosure. In some cases, the operations described herein are composed of various substeps, or are performed in conjunction with other operations.

[0067] At operation **605**, the system obtains a text prompt describing an element and an attribute value for a continuous attribute of the element. In some cases, the operations of this step refer to, or may be performed by, a machine learning model as described with reference to FIGS. **3**, **5**, **7**, **8**, **12**, and **13**. In some cases, a user provides the text prompt and the attribute value to the machine learning model of the image generation system. For example, the text prompt describes a dog and the attribute value includes attribute information of the dog, such as orientation.

[0068] The continuous attribute, such orientation of an object or an apparent camera view of the scene can be difficult to describe precisely using text. For example, it can include one or more numerical parameters such as distance and angle (e.g., the distance between an object and the viewpoint, or angles describing the relationship between an object and a light source). Accordingly, these parameters can be provided separately from the text. For example, a user can move one or more slider or other UI elements to adjust an object orientation, a view, a pose, or a lighting position. The attribute can be described in terms of one or more continuous variables such as 3D position coordinates, Euler angles, or orientation angles such as yaw, pitch and roll.

[0069] In some aspects, for example, the text prompt can be short, long, or compound. For example, the text prompt may describe one or more elements or objects. In some cases, an element includes an object (e.g., a chair, table, or book), a feature (e.g., shadow, lighting, or color), a category (e.g., photo, image, or sketch), etc. In some cases, an attribute value may include information that can be understood by a computing device. For example, the attribute value may include a value, a natural language, a shape, a coordinate, a data point, etc. In some cases, continuous attribute includes a 3-dimensional characteristic of the element. For example, a continuous attribute may include a 3-dimensional orientation, illumination direction, non-rigid shape transformation, object pose, zoom effect, etc. In some cases, the continuous attribute may include 2-dimensional characteristics of the element, such as edges, contours, color intensity, etc. In one aspect, the continuous attribute includes a variable 3-dimensional characteristic of the element described by the text prompt. For example, the variable 3-dimensional characteristic include a range of values or a value that can be changed.

[0070] At operation **610**, the system embeds the text prompt to obtain a text embedding in a text embedding space. In some cases, the operations of this step refer to, or may be performed by, a text embedding model as described with reference to FIGS. **7** and **8**. In some cases, the text prompt is divided into a plurality of tokens, where the text embedding is based on the plurality of tokens. In some cases, the text prompt includes a nonce token corresponding to the

continuous attribute. In some cases, the text prompt includes a word corresponding to the continuous attribute. In some cases, the text embedding may be represented in the form of a table, where each cell of the text embedding represents a word token of the text prompt.

[0071] According to some aspects, the text embedding model generates the text embedding based on the text prompt. In one aspect, an embedding (such as text embedding, image embedding, or guidance embedding) refers to a numerical representation of words, sentences, documents, or images in a vector space. The embedding is used to encode semantic meaning, relationships, and context of the words, sentences, documents, or images where the encoding can be processed by a machine learning model.

[0072] In one aspect, an embedding space refers to the space formed by vectors (e.g., embeddings) representing data points (e.g., text prompts). Vector space provides a framework for representing and manipulating data (in the form of vectors), computing distances between vectors, and transforming input data for complex relationships. The dimensionality of the vector space is determined by the number of features in the feature vector. For example, if each data point has three features (e.g., length, width, and height), the vector space is three-dimensional. In some cases, a joint vector space includes a high-dimensional vector space and a low-dimensional vector space. In some cases, an image embedding is in a high-dimensional vector space and a text embedding is in a low-dimensional vector space.

[0073] In one aspect, text tokens or tokens refer to a meaningful unit of a natural language. Tokenization is the process of breaking down a sequence of text into individual tokens. In some cases, tokens can be words, sub-words, or characters. For example, a word token represents each individual word in the text. The sub-word token represents a further breakdown of the word. For example, if the word is "individual", the sub-word tokens may be "indi" and "vidual". Character token is the breakdown of a word in the text into individual characters. For example, character tokens for the word "token" are "t", "o", "k", "e", and "n". Tokenization allows the machine learning model to understand, process, analyze, or classify data that includes texts.

[0074] In one aspect, a nonce token refers to a placeholder token that can be added to a text or text prompt. For example, the nonce token may be represented by a symbol, shape, or letter. The nonce token may be placed in a specific location of the text prompt. The value of the nonce token may be a variable rather than a specific value.

[0075] At operation **615**, the system embeds, using a continuous control model, the attribute value to obtain an attribute embedding in the text embedding space. In some cases, the operations of this step refer to, or may be performed by, a continuous control model as described with reference to FIGS. **7**, **8**, and **13**. For example, the continuous control model includes a multilayer perceptron (MLP), where the MLP is able to receive a continuous input (e.g., the attribute value) and generate a continuous output (e.g., the attribute embedding). In some cases, the attribute embedding of the attribute value is combined with the text embedding of the text prompt as input to the image generation model. For example, the attribute embedding is added to a region of a sequence of the text embedding.

[0076] In some examples, the attribute embedding can be used as a token and combined with tokens from the text in the same embedding space. Although the attributes can be difficult to describe using words, the text embedding space can have sufficient parameters to represent them accurately. In some cases, these tokens are further processed in combination. For example, a transformer may be used to encode contextual information within individual tokens, or to generate an individual embedding that represents the text and the attribute embedding combined. The combined text and attribute embedding can be used as an input to an image generation model.

[0077] At operation **620**, the system generates, using an image generation model, a synthetic image based on the text embedding and the attribute embedding, where the synthetic image depicts the continuous attribute of the element based on the attribute value. In some cases, the operations of this step refer to, or may be performed by, an image generation model as described with reference to FIGS. **4**, **7**, **8**, **12**, and **13**. For example, the image generation model receives the text embedding (including the attribute embedding) and a noise input (e.g., a noise map) to generate the synthetic image. In some cases, the image generation model includes a diffusion model. The diffusion model is an example of, or includes aspects of, the corresponding element described with reference to FIG. **9**.

System Architecture

[0078] In FIGS. **1**, **7-9**, and **14**, an apparatus and system for image processing include at least one processor, at least one memory storing instructions executable by the at least one processor, a continuous control model comprising parameters stored in the at least one memory and trained to embed an attribute value of a continuous attribute to obtain an attribute embedding in a text embedding space, and an image generation model comprising parameters stored in the at least one memory and trained to generate a synthetic image based on a text embedding of a text prompt and the attribute embedding, where the synthetic image depicts the continuous attribute based on the attribute value.

[0079] Some examples of the apparatus and system further include a text encoder comprising parameters stored in the at least one memory and configured to encode the text embedding and the attribute embedding to obtain guidance information for the image generation model. In some aspects, the continuous control model comprises a multilayer perceptron (MLP). In some aspects, the image generation model comprises a diffusion model.

[0080] FIG. **7** shows an example of an image processing apparatus **700** according to aspects of the present disclosure. The example shown includes image processing apparatus **700**, processor unit **705**, I/O module **710**, memory unit **715**, data preparation component **745**, and training component **755**. In one aspect, memory unit **715** includes machine learning model **720**, text embedding model **725**, continuous control model **730**, text encoder **735**, and image generation model **740**. In one aspect, data preparation component **745** includes training image generation model **750**.

[0081] According to some embodiments of the present disclosure, image processing apparatus **700** includes a computer-implemented artificial neural network (ANN). An ANN is a hardware or a software component that includes a number of connected nodes (e.g., artificial neurons), which loosely correspond to the neurons in a human brain. Each connection, or edge, transmits a signal from one node to another (like the physical synapses in a brain). When a node receives a signal, the node processes the signal and then

transmits the processed signal to other connected nodes. In some cases, the signals between nodes comprise real numbers, and the output of each node is computed by a function of the sum of its inputs. In some examples, nodes may determine the output using other mathematical algorithms (e.g., selecting the max from the inputs as the output) or any other suitable algorithm for activating the node. Each node and edge is associated with one or more node weights that determine how the signal is processed and transmitted. Image processing apparatus **700** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **1**.

[0082] Processor unit **705** is an intelligent hardware device, (e.g., a general-purpose processing component, a digital signal processor (DSP), a central processing unit (CPU), a graphics processing unit (GPU), a microcontroller, an application-specific integrated circuit (ASIC), a field programmable gate array (FPGA), a programmable logic device, a discrete gate or transistor logic component, a discrete hardware component, or any combination thereof). In some cases, processor unit **705** is configured to operate a memory array using a memory controller. In other cases, a memory controller is integrated into the processor. In some cases, processor unit **705** is configured to execute computer-readable instructions stored in a memory to perform various functions. In some embodiments, processor unit **705** includes special-purpose components for modem processing, baseband processing, digital signal processing, or transmission processing. Processor unit **705** is an example of, or includes aspects of, the processor described with reference to FIG. **14**.

[0083] I/O module **710** (e.g., an input/output interface) may include an I/O controller. An I/O controller may manage input and output signals for a device. I/O controller may also manage peripherals not integrated into a device. In some cases, an I/O controller may represent a physical connection or port to an external peripheral. In some cases, an I/O controller may utilize an operating system such as iOS®, ANDROID®, MS-DOS®, MS-WINDOWS®, OS/2®, UNIX®, LINUX®, or another known operating system. In other cases, an I/O controller may represent or interact with a modem, a keyboard, a mouse, a touchscreen, or a similar device. In some cases, an I/O controller may be implemented as part of a processor. In some cases, a user may interact with a device via an I/O controller or via hardware components controlled by an I/O controller.

[0084] In some examples, I/O module **710** includes a user interface. A user interface may enable a user to interact with a device. In some embodiments, the user interface may include an audio device, such as an external speaker system, an external display device such as a display screen, or an input device (e.g., a remote control device interfaced with the user interface directly or through an I/O controller module). In some cases, a user interface may be a graphical user interface (GUI). In some examples, a communication interface operates at the boundary between communicating entities and the channel and may also record and process communications. A communication interface is provided herein to enable a processing system coupled to a transceiver (e.g., a transmitter and/or a receiver). In some examples, the transceiver is configured to transmit (or send) and receive signals for a communications device via an antenna. I/O module **710** is an example of, or includes aspects of, the I/O interface described with reference to FIG. **14**. The user interface is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **1**, **3**, **4**, **5**, and **14**.

[0085] Examples of memory unit **715** include random access memory (RAM), read-only memory (ROM), or a hard disk. Examples of memory unit **715** include solid-state memory and a hard disk drive. In some examples, memory unit **715** is used to store computer-readable, computer-executable software including instructions that, when executed, cause a processor to perform various functions described herein.

[0086] In some cases, memory unit **715** includes, among other things, a basic input/output system (BIOS) that controls basic hardware or software operations such as the interaction with peripheral components or devices. In some cases, a memory controller operates memory cells. For example, the memory controller can include a row decoder, column decoder, or both. In some cases, memory cells within memory unit **715** store information in the form of a logical state.

[0087] In one aspect, memory unit **715** includes machine learning model **720**, text embedding model **725**, continuous control model **730**, text encoder **735**, and image generation model **740**. Memory unit **715** is an example, of, or includes aspects of, the memory subsystem described with reference to FIG. **14**.

[0088] According to some aspects, machine learning model **720** includes text embedding model **725**, continuous control model **730**, text encoder **735**, and image generation model **740**. In some cases, machine learning model **720** is a computational algorithm, model, or system designed to recognize patterns, make predictions, or perform a specific task (for example, image processing) without being explicitly programmed. According to some aspects, machine learning model **720** is implemented as software stored in memory unit **715** and executable by processor unit **705**, as firmware, as one or more hardware circuits, or as a combination thereof.

[0089] According to some embodiments of the present disclosure, machine learning model **720** includes an ANN, which is a hardware or a software component that includes a number of connected nodes (e.g., artificial neurons), which loosely correspond to the neurons in a human brain. Each connection, or edge, transmits a signal from one node to another (like the physical synapses in a brain). When a node receives a signal, the node processes the signal and then transmits the processed signal to other connected nodes. In some cases, the signals between nodes comprise real numbers, and the output of each node is computed by a function of the sum of its inputs. In some examples, nodes may determine the output using other mathematical algorithms (e.g., selecting the max from the inputs as the output) or any other suitable algorithm for activating the node. Each node and edge is associated with one or more node weights that determine how the signal is processed and transmitted.

[0090] During the training process, the one or more node weights are adjusted to increase the accuracy of the result (e.g., by minimizing a loss function that corresponds in some way to the difference between the current result and the target result). The weight of an edge increases or decreases the strength of the signal transmitted between nodes. In some cases, nodes have a threshold below which a signal is not transmitted at all. In some examples, the nodes are aggregated into layers. Different layers perform different

transformations on the corresponding inputs. The initial layer is known as the input layer and the last layer is known as the output layer. In some cases, signals traverse certain layers multiple times.

[0091] According to some embodiments, machine learning model **720** includes a computer-implemented convolutional neural network (CNN). CNN is a class of neural networks commonly used in computer vision or image classification systems. In some cases, a CNN may enable processing of digital images with minimal pre-processing. A CNN may be characterized by the use of convolutional (or cross-correlational) hidden layers. These layers apply a convolution operation to the input before signaling the result to the next layer. Each convolutional node may process data for a limited field of input (e.g., the receptive field). During a forward pass of the CNN, filters at each layer may be convolved across the input volume, computing the dot product between the filter and the input. During the training process, the filters may be modified so that the filters activate when the filters detect a particular feature within the input.

[0092] In one aspect, machine learning model **720** includes machine learning parameters. Machine learning parameters, also known as model parameters or weights, are variables that provide behavior and characteristics of machine learning model **720**. Machine learning parameters can be learned or estimated from training data and are used to make predictions or perform tasks based on learned patterns and relationships in the data.

[0093] Machine learning parameters are adjusted during a training process to minimize a loss function or maximize a performance metric. The goal of the training process is to find optimal values for the parameters that allow machine learning model **720** to make accurate predictions or perform well on the given task.

[0094] For example, during the training process, an algorithm adjusts machine learning parameters to minimize an error or loss between predicted outputs and actual targets according to optimization techniques like gradient descent, stochastic gradient descent, or other optimization algorithms. Once the machine learning parameters are learned from the training data, the machine learning parameters are used to make predictions on new, unseen data.

[0095] According to some embodiments, machine learning model **720** includes a computer-implemented recurrent neural network (RNN). An RNN is a class of ANN in which connections between nodes form a directed graph along an ordered (e.g., a temporal) sequence. This enables an RNN to model temporally dynamic behavior such as predicting what element should come next in a sequence. Thus, an RNN is suitable for tasks that involve ordered sequences such as text recognition (where words are ordered in a sentence). In some cases, an RNN includes one or more finite impulse recurrent networks (characterized by nodes forming a directed acyclic graph), one or more infinite impulse recurrent networks (characterized by nodes forming a directed cyclic graph), or a combination thereof.

[0096] According to some embodiments, machine learning model **720** includes a transformer (or a transformer model, or a transformer network), where the transformer is a type of neural network model used for natural language processing tasks. A transformer network transforms one sequence into another sequence using an encoder and a decoder. The encoder and decoder include modules that can be stacked on top of each other multiple times. The modules comprise multi-head attention and feed-forward layers. The inputs and outputs (target sentences) are first embedded into an n-dimensional space. Positional encoding of the different words (e.g., give each word/part in a sequence a relative position since the sequence depends on the order of its elements) is added to the embedded representation (n-dimensional vector) of each word. In some examples, a transformer network includes an attention mechanism, where the attention looks at an input sequence and decides at each step which other parts of the sequence are important. The attention mechanism involves a query, keys, and values denoted by Q, K, and V, respectively. Q is a matrix that contains the query (vector representation of one word in the sequence), K are the keys (vector representations of the words in the sequence) and V are the values, which are again the vector representations of the words in the sequence. For the encoder and decoder, multi-head attention modules, V consists of the same word sequence as Q. However, for the attention module that takes into account the encoder and the decoder sequences, V is different from the sequence represented by Q. In some cases, values in V are multiplied and summed with some attention-weights a.

[0097] In the machine learning field, an attention mechanism (e.g., implemented in one or more ANNs) is a method of placing differing levels of importance on different elements of an input. Calculating attention may involve three basic steps. First, a similarity between the query and key vectors obtained from the input is computed to generate attention weights. Similarity functions used for this process can include the dot product, splice, detector, and the like. Next, a softmax function is used to normalize the attention weights. Finally, the attention weights are weighed together with the corresponding values. In the context of an attention network, the key and value are vectors or matrices that are used to represent the input data. The key is used to determine which parts of the input the attention mechanism should focus on, while the value is used to represent the actual data being processed.

[0098] An attention mechanism is a key component in some ANN architectures, particularly ANNs employed in natural language processing (NLP) and sequence-to-sequence tasks, that allows an ANN to focus on different parts of an input sequence when making predictions or generating output. Some sequence models (such as RNNs) process an input sequence sequentially, maintaining an internal hidden state that captures information from previous steps. However, in some cases, this sequential processing leads to difficulties in capturing long-range dependencies or attending to specific parts of the input sequence.

[0099] The attention mechanism addresses these difficulties by enabling an ANN to selectively focus on different parts of an input sequence, assigning varying degrees of importance or attention to each part. The attention mechanism achieves the selective focus by considering a relevance of each input element with respect to a current state of the ANN.

[0100] The term "self-attention" refers to a machine learning model in which representations of the input interact with each other to determine attention weights for the input. Self-attention can be distinguished from other attention models because the attention weights are determined at least in part by the input itself.

[0101] According to some aspects, machine learning model **720** obtains a text prompt describing an element and

an attribute value for a continuous attribute of the element. In some aspects, the continuous attribute includes a 3-dimensional characteristic of the element. In some aspects, the text prompt includes a nonce token corresponding to the attribute value. In some aspects, the text prompt includes a word corresponding to the continuous attribute.

[0102] In some examples, machine learning model **720** identifies a negative prompt based on the object from the set of training images, where the synthetic image is generated based on the negative prompt. In some examples, machine learning model **720** obtains an additional attribute value corresponding to an additional continuous attribute, where the synthetic image is generated to depict the additional attribute value. In some examples, machine learning model **720** obtains a set of attribute values for the continuous attribute. Machine learning model **720** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **5**, **8**, **12**, and **13**.

[0103] According to some aspects, text embedding model **725** is implemented as software stored in memory unit **715** and executable by processor unit **705**, as firmware, as one or more hardware circuits, or as a combination thereof. According to some aspects, text embedding model **725** embeds the text prompt to obtain a text embedding in a text embedding space. In some examples, text embedding model **725** divides the text prompt into a set of tokens. In some examples, text embedding model **725** embeds each of the set of tokens using a text embedding model **725**. Text embedding model **725** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **8**.

[0104] According to some aspects, continuous control model **730** is implemented as software stored in memory unit **715** and executable by processor unit **705**, as firmware, as one or more hardware circuits, or as a combination thereof. According to some aspects, continuous control model **730** embeds, using a continuous control model **730**, the attribute value to obtain an attribute embedding in the text embedding space.

[0105] According to some aspects, continuous control model **730** comprises parameters stored in the at least one memory and trained to embed an attribute value of a continuous attribute to obtain an attribute embedding in a text embedding space. In some aspects, the continuous control model **730** includes a multilayer perceptron (MLP). Continuous control model **730** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **8** and **13**.

[0106] According to some aspects, text encoder **735** is implemented as software stored in memory unit **715** and executable by processor unit **705**, as firmware, as one or more hardware circuits, or as a combination thereof. According to some aspects, text encoder **735** encodes the text embedding and the attribute embedding to obtain guidance information for the image generation model **740**, where the synthetic image is generated based on the guidance information.

[0107] According to some aspects, text encoder **735** comprises parameters stored in the at least one memory and configured to encode the text embedding and the attribute embedding to obtain guidance information for the image generation model **740**. Text encoder **735** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **8** and **9**.

[0108] According to some aspects, image generation model **740** is implemented as software stored in memory unit **715** and executable by processor unit **705**, as firmware, as one or more hardware circuits, or as a combination thereof. According to some aspects, image generation model **740** generates a synthetic image based on the text embedding and the attribute embedding, where the synthetic image depicts the continuous attribute of the element based on the attribute value. In some examples, image generation model **740** performs a diffusion process on a noise input to obtain the synthetic image.

[0109] In some aspects, the image generation model **740** is trained using a training set including a set of training images depicting an object with a set of values of the continuous attribute, respectively. In some examples, image generation model **740** generates a set of synthetic images based on a same random input and the set of attribute values, respectively. In some aspects, the image generation model **740** is trained individually in a first stage. In some aspects, the image generation model **740** is trained together with the continuous control model **730** in a second stage.

[0110] According to some aspects, image generation model **740** comprises parameters stored in the at least one memory and trained to generate a synthetic image based on a text embedding of a text prompt and the attribute embedding, wherein the synthetic image depicts the continuous attribute based on the attribute value. In some aspects, the image generation model **740** includes a diffusion model. Image generation model **740** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **4**, **8**, **12**, and **13**.

[0111] According to some aspects, data preparation component **745** is implemented as software stored in memory unit **715** and executable by processor unit **705**, as firmware, as one or more hardware circuits, or as a combination thereof. According to some embodiments, data preparation component **745** is implemented as software stored in a memory unit and executable by a processor in a processor unit of a separate computing device, as firmware in a separate computing device, as one or more hardware circuits of the separate computing device, or as a combination thereof. In some examples, data preparation component **745** is part of another apparatus other than image processing apparatus **700** and communicates with the image processing apparatus **700**. In some examples, data preparation component **745** is part of image processing apparatus **700**.

[0112] According to some aspects, data preparation component **745** includes training image generation model **750**. In one aspect, data preparation component **745** obtains a training set including a set of training images depicting an object with a set of values of a continuous attribute, respectively. In some examples, data preparation component **745** renders the set of training images based on a 3D model of the object.

[0113] According to some aspects, training image generation model **750** is implemented as software stored in memory unit **715** and executable by processor unit **705**, as firmware, as one or more hardware circuits, or as a combination thereof. According to some embodiments, training image generation model **750** is implemented as software stored in a memory unit and executable by a processor in a processor unit of a separate computing device, as firmware in a separate computing device, as one or more hardware circuits of the separate computing device, or as a combina-

tion thereof. In some examples, training image generation model **750** is part of another apparatus other than image processing apparatus **700** and communicates with the image processing apparatus **700**. In some examples, training image generation model **750** is part of image processing apparatus **700**.

[0114] According to some aspects, training image generation model **750** generates a training image based on a 3D model of the object. Training image generation model **750** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **12** and **13**. In some embodiments, training image generation model **750** includes a 3D render. In some embodiments, training image generation model **750** includes a ControlNet.

[0115] According to some aspects, training component **755** is implemented as software stored in memory unit **715** and executable by processor unit **705**, as firmware, as one or more hardware circuits, or as a combination thereof. According to some embodiments, training component **755** is implemented as software stored in a memory unit and executable by a processor in a processor unit of a separate computing device, as firmware in a separate computing device, as one or more hardware circuits of the separate computing device, or as a combination thereof. In some examples, training component **755** is part of another apparatus other than image processing apparatus **700** and communicates with the image processing apparatus **700**. In some examples, training component **755** is part of image processing apparatus **700**.

[0116] According to some aspects, training component **755** initializes a machine learning model **720**. In some examples, training component **755** trains, using the training set, an image generation model **740** to generate synthetic images with the set of values of the continuous attribute. In some examples, training component **755** trains, using the training set, a continuous control model **730** to generate an input for the image generation model **740** corresponding to the continuous attribute.

[0117] In some examples, training component **755** computes a reconstruction loss based on the training set. In some examples, training component **755** updates parameters of the image generation model **740** and parameters of the continuous control model **730** based on the reconstruction loss.

[0118] FIG. **8** shows an example of a machine learning model **800** according to aspects of the present disclosure. The example shown includes machine learning model **800**, text prompt **805**, text embedding model **810**, text embedding **815**, attribute **820**, continuous control model **825**, attribute embedding **830**, text encoder **835**, guidance feature **840**, noise input **845**, image generation model **850**, synthetic image **855**, and negative prompt **860**.

[0119] Referring to FIG. **8**, machine learning model **800** generates synthetic image **855** based on text prompt **805** and attribute **820**. In some cases, synthetic image **855** includes an element described by text prompt **805** and a 3-dimensional characteristic from attribute **820**. In some cases, for example, text prompt **805** states "A view of a chair in woods." In some cases, text prompt **805** includes a nonce token in a region of a sequence of the text prompt **805**. For example, the nonce token is represented as <V*>. For example, text prompt **805** states "A <V*> view of a chair in woods." Text embedding model **810** receives text prompt **805** to generate text embedding **815**. In some embodiments, text embedding model **810** divides text prompt **805** into a plurality of word tokens. In some aspects, text embedding **815** includes a table, where each cell of the table includes a word token of text prompt **805** in sequence.

[0120] According to some embodiments, continuous control model **825** receives attribute **820** to generate an attribute embedding **830**. In some aspects, continuous control model **825** is trained using a continuous function, where continuous control model **825** is able to interpolate between two training data. For example, continuous control model **825** may receive a first value of attribute **820** and a second value of attribute **820** and continuous control model **825** is trained to generate intermediate values between the first value and the second value. Accordingly, continuous control model **825** can generate a continuous output.

[0121] In some cases, attribute **820** includes a 3-dimensional characteristic of the element described by the text prompt. For example, attribute **820** includes a plurality of values of the 3-dimensional orientation of the chair. In some cases, attribute **820** is integrated into a user control, where a value of attribute **820** can be easily modified using the user control. In some cases, for example, attribute embedding includes encoding of the semantic meaning of the 3-dimensional characteristic of attribute **820**, where the encoding can be processed by machine learning model **800**. In some embodiments, attribute embedding **830** is combined with text embedding **815** as input embedding to text encoder **835** of image generation model **850**. For example, attribute embedding **830** is added to a region of a sequence of text embedding **815**.

[0122] In some embodiments, text encoder **835** receives text embedding **815** (including attribute embedding **830**) to generate guidance feature **840** for image generation model **850**. For example, guidance feature **840** is used to guide the diffusion process in image generation model **850**. In some cases, guidance feature **840** is a text embedding of text prompt **805** and attribute **820**. In some embodiments, noise input **845** and guidance feature **840** are provided to image generation model **850** to generate synthetic image **855**. In some cases, noise input **845** is a noise map. In some cases, noise input **845** includes a noisy image obtained by a noise map and a training image. Image generation model **850** performs a diffusion process on noise input **845** to obtain synthetic image **855**.

[0123] In some embodiments, image generation model **850** further receives negative prompt **860** to generate synthetic image **855**. For example, negative prompt **860** is used to guide image generation model **850** away from generating the element described by negative prompt **860**. For example, negative prompt **860** includes elements depicted in the training images. In one embodiment, negative prompt **860** is provided to text encoder **835** to generate a negative prompt embedding, where guidance feature **840** includes the negative prompt embedding.

[0124] Machine learning model **800** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **5**, **7**, **12**, and **13**. Text prompt **805** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3-5**, **9**, **12**, and **13**. Text embedding model **810** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **7**.

[0125] Text embedding **815** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **13**. Attribute **820** is an example of, or includes aspects of, the corresponding element described with refer-

ence to FIGS. **3**, **12**, and **13**. Continuous control model **825** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **7** and **13**.

[0126] Text encoder **835** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **7** and **9**. Guidance feature **840** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **9**. Image generation model **850** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **4**, **7**, **12**, and **13**. Synthetic image **855** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **12**, and **13**.

[0127] FIG. **9** shows an example of a diffusion model **900** according to aspects of the present disclosure. The example shown includes diffusion model **900**, original image **905**, pixel space **910**, image encoder **915**, original image feature **920**, latent space **925**, forward diffusion process **930**, noisy feature **935**, reverse diffusion process **940**, denoised image feature **945**, image decoder **950**, output image **955**, text prompt **960**, text encoder **965**, guidance feature **970**, and guidance space **975**.

[0128] Diffusion models are a class of generative neural networks that can be trained to generate new data with features similar to features found in training data. In particular, diffusion models can be used to generate novel images. Diffusion models can be used for various image generation tasks including image super-resolution, generation of images with perceptual metrics, conditional generation (e.g., generation based on text guidance, color guidance, style guidance, and image guidance), image inpainting, and image manipulation.

[0129] Types of diffusion models include Denoising Diffusion Probabilistic Models (DDPMs) and Denoising Diffusion Implicit Models (DDIMs). In DDPMs, the generative process includes reversing a stochastic Markov diffusion process. DDIMs, on the other hand, use a deterministic process so that the same input results in the same output. Diffusion models may also be characterized by whether the noise is added to the image itself, or to image features generated by an encoder (e.g., latent diffusion).

[0130] Diffusion models work by iteratively adding noise to the data during a forward process and then learning to recover the data by denoising the data during a reverse process. For example, during training, diffusion model **900** may take an original image **905** in a pixel space **910** as input and apply an image encoder **915** to convert original image **905** into original image feature **920** in a latent space **925**. Then, a forward diffusion process **930** gradually adds noise to the original image feature **920** to obtain noisy feature **935** (also in latent space **925**) at various noise levels.

[0131] Next, a reverse diffusion process **940** (e.g., a U-Net ANN) gradually removes the noise from the noisy feature **935** at the various noise levels to obtain the denoised image feature **945** in latent space **925**. In some examples, denoised image feature **945** is compared to the original image feature **920** at each of the various noise levels, and parameters of the reverse diffusion process **940** of the diffusion model are updated based on the comparison. Finally, an image decoder **950** decodes the denoised image feature **945** to obtain an output image **955** in pixel space **910**. In some cases, an output image **955** is created at each of the various noise levels. The output image **955** can be compared to the original image **905** to train the reverse diffusion process **940**. In some cases, output image **955** refers to the synthetic image (e.g., described with reference to FIGS. **3**, **4**, **5**, **8**, **12**, and **13**).

[0132] In some cases, image encoder **915** and image decoder **950** are pre-trained prior to training the reverse diffusion process **940**. In some examples, image encoder **915** and image decoder **950** are trained jointly, or the image encoder **915** and image decoder **950** are fine-tuned jointly with the reverse diffusion process **940**.

[0133] The reverse diffusion process **940** can also be guided based on a text prompt **960** or another guidance prompt, such as an image, a layout, a style, a color, a segmentation map, etc. The text prompt **960** can be encoded using a text encoder **965** (e.g., a multimodal encoder) to obtain guidance feature **970** in guidance space **975**. The guidance feature **970** can be combined with the noisy feature **935** at one or more layers of the reverse diffusion process **940** to ensure that the output image **955** includes content described by the text prompt **960**. For example, guidance feature **970** can be combined with the noisy feature **935** using a cross-attention block within the reverse diffusion process **940**. In some cases, text prompt **960** refers to the corresponding element described with reference to FIGS. **3**, **4**, **5**, **8**, **12**, and **13**.

[0134] Cross-attention, also known as multi-head attention, is an extension of the attention mechanism used in some ANNs, for example, for NLP tasks. In some cases, cross-attention attends to multiple parts of an input sequence simultaneously, capturing interactions and dependencies between different elements. In cross-attention, there are two input sequences: a query sequence and a key-value sequence. The query sequence represents the elements that require attention, while the key-value sequence contains the elements to attend to. In some cases, to compute cross-attention, the cross-attention block transforms (for example, using linear projection) each element in the query sequence into a "query" representation, while the elements in the key-value sequence are transformed into "key" and "value" representations.

[0135] The cross-attention block calculates attention scores by measuring the similarity between each query representation and the key representations, where a higher similarity indicates that more attention is given to a key element. An attention score indicates an importance or relevance of each key element to a corresponding query element.

[0136] The cross-attention block then normalizes the attention scores to obtain attention weights (for example, using a softmax function), where the attention weights determine how much information from each value element is incorporated into the final attended representation. By attending to different parts of the key-value sequence simultaneously, the cross-attention block captures relationships and dependencies across the input sequences, allowing the machine learning model to understand the context and generate more accurate and contextually relevant outputs.

[0137] In some examples, diffusion models are based on a neural network architecture known as a U-Net. The U-Net takes input features having an initial resolution and an initial number of channels, and processes the input features using an initial neural network layer (e.g., a convolutional network layer) to generate intermediate features. The intermediate features are then down-sampled using a down-sampling layer such that down-sampled features have a resolution less

than the initial resolution and a number of channels greater than the initial number of channels.

[0138] This process is repeated multiple times, and then the process is reversed. For example, the down-sampled features are up-sampled using the up-sampling process to obtain up-sampled features. The up-sampled features can be combined with intermediate features having a same resolution and number of channels via a skip connection. These inputs are processed using a final neural network layer to produce output features. In some cases, the output features have the same resolution as the initial resolution and the same number of channels as the initial number of channels.

[0139] In some cases, a U-Net takes additional input features to produce conditionally generated output. For example, the additional input features may include a vector representation of an input prompt. The additional input features can be combined with the intermediate features within the neural network at one or more layers. For example, a cross-attention module can be used to combine the additional input features and the intermediate features.

[0140] A diffusion process may also be modified based on conditional guidance. In some cases, a user provides a text prompt (e.g., text prompt **960**) describing content to be included in a generated image. For example, a user may provide the prompt "A view of a chair in woods" In some examples, guidance can be provided in a form other than text, such as via an image, a sketch, a color, a style, or a layout. The system converts text prompt **960** (or other guidance) into a conditional guidance vector or other multi-dimensional representation. For example, text may be converted into a vector or a series of vectors using a transformer model, or a multi-modal encoder. In some cases, the encoder for the conditional guidance is trained independently of the diffusion model.

[0141] A noise map is initialized that includes random noise. The noise map may be in a pixel space or a latent space. By initializing an image with random noise, different variations of an image including the content described by the conditional guidance can be generated. Then, the diffusion model **900** generates an image based on the noise map and the conditional guidance vector.

[0142] A diffusion process can include both a forward diffusion process **930** for adding noise to an image (e.g., original image **905**) or features (e.g., original image feature **920**) in a latent space **925** and a reverse diffusion process **940** for denoising the images (or features) to obtain a denoised image (e.g., output image **955**). The forward diffusion process **930** can be represented as $q(x_t|x_{t-1})$, and the reverse diffusion process **940** can be represented as $p(x_{t-1}|x_t)$. In some cases, the forward diffusion process **930** is used during training to generate images with successively greater noise, and a neural network is trained to perform the reverse diffusion process **940** (e.g., to successively remove the noise).

[0143] In an example forward diffusion process **930** for a latent diffusion model (e.g., diffusion model **900**), the diffusion model **900** maps an observed variable x_0 (either in a pixel space **910** or a latent space **925**) intermediate variables $x_1, \ldots, x_T$ using a Markov chain. The Markov chain gradually adds Gaussian noise to the data to obtain the approximate posterior $q(x_{1:T}|x_0)$ as the latent variables are passed through a neural network such as a U-Net, where $x_1, \ldots, x_T$ have the same dimensionality as x_0.

[0144] The neural network may be trained to perform the reverse diffusion process **940**. During the reverse diffusion process **940**, the diffusion model **900** begins with noisy data x_T, such as a noisy image and denoises the data to obtain the $p(x_{t-1}|x_t)$. At each step t-1, the reverse diffusion process **940** takes x_t, such as the first intermediate image, and t as input. Here, t represents a step in the sequence of transitions associated with different noise levels, The reverse diffusion process **940** outputs x_{t-1}, such as the second intermediate image iteratively until x_T is reverted back to x_0, the original image **905**. The reverse diffusion process **940** can be represented as:

$$p_\theta(x_{t-1} \mid x_t) := N\left(x_{t-1}; \mu_\theta(x_t, t), \sum_\theta(x_t, t)\right). \tag{1}$$

[0145] The joint probability of a sequence of samples in the Markov chain can be written as a product of conditionals and the marginal probability:

$$x_T: \; p_\theta(x_{0:T}) := p(x_T)\prod_{t=1}^{T} p_\theta(x_{t-1} \mid x_t), \tag{2}$$

where $p(x_T)=N(x_T; 0, I)$ is the pure noise distribution as the reverse diffusion process **940** takes the outcome of the forward diffusion process **930**, a sample of pure noise, as input and $\pi_{t=1}{}^{T} p_\theta(x_{t-1}|x_t)$ represents a sequence of Gaussian transitions corresponding to a sequence of addition of Gaussian noise to the sample.

[0146] At interference time, observed data x_0 in a pixel space can be mapped into a latent space **925** as input and a generated data $\tilde{x}$ is mapped back into the pixel space **910** from the latent space **925** as output. In some examples, x_0 represents an original input image with low image quality, latent variables $x_1, \ldots, x_T$ represent noisy images, and z represents the generated image with high image quality.

[0147] A diffusion model **900** may be trained using both a forward diffusion process **930** and a reverse diffusion process **940**. In one example, the user initializes an untrained model. Initialization can include defining the architecture of the model and establishing initial values for the model parameters. In some cases, the initialization can include defining hyper-parameters such as the number of layers, the resolution and channels of each layer block, the location of skip connections, and the like.

[0148] The system then adds noise to a training image using a forward diffusion process **930** in N stages. In some cases, the forward diffusion process **930** is a fixed process where Gaussian noise is successively added to an image. In latent diffusion models, the Gaussian noise may be successively added to features (e.g., original image feature **920**) in a latent space **925**.

[0149] At each stage n, starting with stage N, a reverse diffusion process **940** is used to predict the image or image features at stage n-1. For example, the reverse diffusion process **940** can predict the noise that was added by the forward diffusion process **930**, and the predicted noise can be removed from the image to obtain the predicted image. In some cases, an original image **905** is predicted at each stage of the training process.

[0150] The training component (e.g., training component described with reference to FIG. **7**) compares predicted

image (or image features) at stage n-1 to an actual image (or image features), such as the image at stage n-1 or the original input image. For example, given observed data x, the diffusion model **900** may be trained to minimize the variational upper bound of the negative log-likelihood $-\log p_\theta(x)$ of the training data. The training component then updates parameters of the diffusion model **900** based on the comparison. For example, parameters of a U-Net may be updated using gradient descent. Time-dependent parameters of the Gaussian transitions can also be learned.

[0151] Text prompt **960** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3-5**, **8**, **12**, and **13**. Text encoder **965** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **7** and **8**. Guidance feature **970** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **8**.

[0152] FIG. **10** shows an example of a method **1000** for generating a synthetic image based on an embedding according to aspects of the present disclosure. In some examples, these operations are performed by a system including a processor executing a set of codes to control functional elements of an apparatus. Additionally or alternatively, certain processes are performed using special-purpose hardware. Generally, these operations are performed according to the methods and processes described in accordance with aspects of the present disclosure. In some cases, the operations described herein are composed of various substeps, or are performed in conjunction with other operations.

[0153] At operation **1005**, the system divides a text prompt into a set of tokens. In some cases, the operations of this step refer to, or may be performed by, a text embedding model as described with reference to FIGS. **7** and **8**. In some cases, the text embedding model divides the text prompt into a plurality of word tokens.

[0154] At operation **1010**, the system embeds each of the set of tokens to obtain a text embedding. In some cases, the operations of this step refer to, or may be performed by, a text embedding model as described with reference to FIGS. **7** and **8**. In some cases, the text embedding includes a lookup table, where each cell of the table includes a word token of the text prompt in sequence.

[0155] At operation **1015**, the system encodes the text embedding and an attribute embedding of a continuous attribute to obtain guidance information for an image generation model, where a synthetic image is generated based on the guidance information. In some cases, the operations of this step refer to, or may be performed by, a text encoder as described with reference to FIGS. **7-9**. For example, the guidance information is used to guide the diffusion process in the image generation model. In some cases, the guidance information is a text embedding of the text prompt and the attribute. In some embodiments, a noise input and the guidance information are provided to the image generation model to generate the synthetic image.

Training and Evaluation

[0156] In FIGS. **11-13**, a method, apparatus, non-transitory computer readable medium, and system for image processing include initializing a machine learning model, obtaining a training set including a plurality of training images depicting an object with a plurality of values of a continuous attribute, respectively, training, using the training set, an image generation model to generate synthetic images with the plurality of values of the continuous attribute, and training, using the training set, a continuous control model to generate an input for the image generation model corresponding to the continuous attribute.

[0157] Some examples of the method, apparatus, non-transitory computer readable medium, and system further include rendering the plurality of training images based on a 3D model of the object. Some examples of the method, apparatus, non-transitory computer readable medium, and system further include generating, using a training image generation model, a training image based on a 3D model of the object.

[0158] In some aspects, the image generation model is trained individually in a first stage. In some aspects, the image generation model is trained together with the continuous control model in a second stage. Some examples of the method, apparatus, non-transitory computer readable medium, and system further include computing a reconstruction loss based on the training set. Some examples further include updating parameters of the image generation model and parameters of the continuous control model based on the reconstruction loss.

[0159] FIG. **11** shows an example of a method **1100** for training a machine learning model according to aspects of the present disclosure. In some examples, these operations are performed by a system including a processor executing a set of codes to control functional elements of an apparatus. Additionally or alternatively, certain processes are performed using special-purpose hardware. Generally, these operations are performed according to the methods and processes described in accordance with aspects of the present disclosure. In some cases, the operations described herein are composed of various substeps, or are performed in conjunction with other operations.

[0160] At operation **1105**, the system initializes a machine learning model. In some cases, the operations of this step refer to, or may be performed by, a training component as described with reference to FIG. **7**. In some cases, initialization can include defining the architecture of the machine learning model and establishing initial values for the model parameters. In some cases, the initialization can include defining hyper-parameters such as the number of layers, the resolution and channels of each layer block, the location of skip connections, and the like.

[0161] At operation **1110**, the system obtains a training set including a set of training images depicting an object with a set of values of a continuous attribute, respectively. In some cases, the operations of this step refer to, or may be performed by, a data preparation component as described with reference to FIG. **7**. In some cases, obtaining a training set includes creating the training set using a data preparation component. For example, the data preparation component obtains an image/that includes objects O from category C as a function of several attributes $l=f(a_1, a_2, a_3, \ldots, a_n)$, where a_i belongs to a set of image attributes A: shape, material reflectivity, rotation/translation, camera intrinsic/extrinsic, shape deformations, etc. In some embodiments, an attribute a is controlled by using a rendering engine to generate training images having an attribute value a=x. In addition, a token T_x is assigned to an identified image with the same attribute value. In some aspects, the attribute a is continuous and has multiple values, where the image generation model is trained using the tokens and corresponding attribute values to have fine-grained control over the attributes. In

some cases, the training image generation model includes a 3D renderer that generates training images based on 3D data of an object and a plurality of continuous attributes.

[0162] In some embodiments, the training set is augmented to prevent the fine-tuning process from overfitting to simple white backgrounds and pre-defined object textures. For example, a training image generation model is used to augment the backgrounds and textures of the training images in the rendering process (e.g., generation of training images). In some embodiments, a ControlNet is used to generate augmented training images. In some cases, when an attribute reflects on shape changes (e.g., wing pose), the training image generation model uses the ground-truth depth maps as conditioning for ControlNet to generate the augmented training images. In some cases, when an attribute cannot reflect from depth maps (e.g., illumination), the training image generation model generates a preliminary training image without texture and uses a line-art extractor to obtain a sketch of the preliminary training image. The sketch of the preliminary training image captures features such as shades and shadows in pixel space, which can be used as conditioning for ControlNet to generate the augmented training images.

[0163] In some embodiments, additional prompts describing object appearance and background are provided to ControlNet to generate the augmented training images. In some cases, the additional prompts are simple and short. In some embodiments, the training set includes the training images and the augmented training images. For example, the training set includes a subset of the augmented training images. In some cases, the additional prompts are used to guide the image generation model in the second stage training.

[0164] At operation **1115**, the system trains, using the training set, an image generation model to generate synthetic images with the set of values of the continuous attribute. In some cases, the operations of this step refer to, or may be performed by, a training component as described with reference to FIG. **7**. For example, the image generation model is trained to generate synthetic images depicting the element described by the text prompt and a 3-dimensional characteristic from the attribute input (e.g., the continuous attribute). Further detail on training the image generation model is described with reference to FIGS. **12** and **13**.

[0165] At operation **1120**, the system trains, using the training set, a continuous control model to generate an input for the image generation model corresponding to the continuous attribute. In some cases, the operations of this step refer to, or may be performed by, a training component as described with reference to FIG. **7**. For example, the continuous control model is trained to generate an attribute embedding based on the attribute input, where the attribute embedding is added to the text embedding of the text prompt as input to the image generation model. Further detail on training the continuous control model is described with reference to FIGS. **12** and **13**.

[0166] FIG. **12** shows an example of a first stage training according to aspects of the present disclosure. The example shown includes machine learning model **1200**, training data **1205**, attribute **1210**, training image generation model **1215**, training image **1220**, noisy image **1225**, text prompt **1230**, image generation model **1235**, synthetic image **1240**, and loss **1245**.

[0167] Referring to FIG. **12**, machine learning model **1200** is fine-tuned using loss **1245** during the first stage training. For example, machine learning model **1200** obtains a training set including training data **1205** and attribute **1210**. In one aspect, training data **1205** includes 3D data points (or mesh) of an object, for example, the dog. In one aspect, attribute **1210** includes a 3-dimensional characteristic of the object such as, for example, 3-dimensional orientation, illumination direction, wing pose, etc. Using training data **1205** and attribute **1210**, training image generation model **1215** is used to generate training image **1220** depicting the dog from training data **1205** and a 3-dimensional characteristic from attribute **1210**. In one aspect, training image generation model **1215** includes a 3D renderer that generates images (e.g., training image **1220**) based on the mesh (e.g., training data **1205**).

[0168] According to some embodiments, image generation model **1235** is fine-tuned using loss **1245**. For example, machine learning model **1200** applies a noise map to training image **1220** to obtain noisy image **1225**. Image generation model **1235** receives noisy image **1225** and text prompt **1230** to generate synthetic image **1240**. For example, text prompt **1230** states "A photo of a [obj] dog." In one aspect, [obj] represents the identity of the dog from training data **1205**. By training image generation model **1235** using the identifier [obj], image generation model **1235** is trained to preserve and learn the identity of the dog to be generated in synthetic image **1240**. In some embodiments, loss **1245** is computed based on synthetic image **1240** and training image **1220**. For example, loss **1245** includes a reconstruction loss. In some aspects, the training loss (e.g., loss **1245**) is represented as:

$$\underset{\theta,\Phi}{\operatorname{argmin}} \mathbb{E}_{\hat{I}_{\epsilon,a},a}\left[\left\| S_\theta\left(\hat{I}_{\epsilon,a}, P(g_\Phi(a))\right) - I_a \right\|_2^2\right], \tag{3}$$

where I_O represents training image **1220** depicting attribute a, $\hat{I}_{\epsilon,a}$ represents noisy image **1225** with noise ϵ, and $P(g_\Phi(a))$ represents prompt of attribute a.

[0169] Machine learning model **1200** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **5**, **7**, **8**, and **13**. Training data **1205** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **13**. Attribute **1210** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **8**, and **13**.

[0170] Training image generation model **1215** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **7** and **13**. Training image **1220** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **13**. Noisy image **1225** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **13**.

[0171] Text prompt **1230** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3-5**, **8**, **9**, and **13**. Image generation model **1235** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **4**, **7**, **8**, and **13**. Synthetic image **1240** is an example of, or includes aspects of, the corresponding element described with refer-

ence to FIGS. **3**, **4**, **8**, and **13**. Loss **1245** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **13**.

[0172] FIG. **13** shows an example of a second stage training according to aspects of the present disclosure. The example shown includes machine learning model **1300**, training data **1305**, attribute **1310**, training image generation model **1315**, training image **1320**, noisy image **1325**, continuous control model **1330**, text prompt **1335**, text embedding **1340**, image generation model **1345**, synthetic image **1350**, and loss **1355**.

[0173] Referring to FIG. **13**, machine learning model **1300** is fine-tuned using loss **1355** during the second stage training. For example, machine learning model **1300** obtains a training set including training data **1305** and attribute **1310**. In one aspect, training data **1205** includes 3D data points (or mesh) of an object, for example, a dog. In one aspect, attribute **1310** includes a 3-dimensional characteristic of the object such as, for example, 3-dimensional orientation, illumination direction, wing pose, etc. Using training data **1305** and attribute **1310**, training image generation model **1315** is used to generate training image **1320** depicting the dog from training data **1305** and a 3-dimensional characteristic from attribute **1310**. In one aspect, training image generation model **1315** includes a 3D renderer that generates images (e.g., training image **1320**) based on the mesh (e.g., training data **1305**). In one aspect, training image generation model **1315** includes a ControlNet that generates training image **1320** based on training data **1305** and attribute **1310**.

[0174] According to some embodiments, continuous control model **1330** generates an attribute embedding based on attribute **1310**. In one aspect, machine learning model **1300** encodes text prompt **1335** to obtain text embedding **1340**. In some embodiments, the attribute embedding is combined with text embedding **1340** as input to image generation model **1345**. For example, image generation model **1345** receives noisy image **1325** (for example, obtained from training image **1320**) and text embedding **1340** (for example, obtained from attribute **1310** and text prompt **1335**) to generate synthetic image **1350**. In some cases, image generation model **1345** performs a diffusion process (e.g., the reverse diffusion process described with reference to FIG. **9**) on noisy image **1325** to generate synthetic image **1350**.

[0175] In some embodiments, machine learning model **1300** (including image generation model **1345** and continuous control model **1330**) is trained based on a continuous function $g_\Phi(a)$: D→T, which maps a set of attributes from the continuous domain D to the token embedding domain T. In some embodiments, machine learning model **1300** uses positional encoding to cast each attribute $a \in a$ to a high-frequency space before providing the attribute to the continuous function. For example, the attributes (e.g., attribute **1310**) are provided to continuous control model **1330**, which includes a 2-layer multilayer perceptron (MLP), to generate the attribute embedding. By transforming the attributes to a high-frequency space, machine learning model **1300** enables a user to easily control continuous attributes from text prompt **1335** augmented by the token embedding (e.g., the attribute embedding).

[0176] In some embodiments, image generation model **1345** is fine-tuned using loss **1355** computed based on synthetic image **1350** and training image **1320**. For example, loss **1355** includes a reconstruction loss. In some aspects, the training loss (e.g., loss **1355**) is represented as:

$$\underset{\theta,\Phi}{\operatorname{argmin}} \mathbb{E}_{\hat{I}_{\in,a},a}\left[\left\|S_\theta\left(\hat{I}_{\in,a}, P(T_O, g_\Phi(a))\right) - I_a\right\|_2^2\right], \tag{4}$$

where T_O represents the conditioning of text prompt **1335** depicting object O. According to some aspects, for every image in I_O with varying attribute a, machine learning model **1300** associates the same prompt conditioning $P(T_O)$ to the same object O and train model parameter θ of image generation model **1345** and continuous control model g_Φ using the prompt condition $P(T_O, g_\Phi(a))$ (e.g., text embedding **1340** including the text embedding of text prompt **1335** and attribute embedding of attribute **1310**). Accordingly, machine learning model **1300** can be trained to generate synthetic image **1350** depicting the element described by text prompt **1335** and attribute **1310**.

[0177] Machine learning model **1300** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **5**, **7**, **8**, and **12**. Training data **1305** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **12**. Attribute **1310** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **8**, and **12**.

[0178] Training image generation model **1315** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **7** and **12**. Training image **1320** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **12**. Noisy image **1325** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **12**.

[0179] Continuous control model **1330** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **7** and **8**. Text prompt **1335** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3-5**, **8**, **9**, and **12**. Text embedding **1340** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **8**.

[0180] Image generation model **1345** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **4**, **7**, **8**, and **12**. Synthetic image **1350** is an example of, or includes aspects of, the corresponding element described with reference to FIGS. **3**, **4**, **8**, and **12**. Loss **1355** is an example of, or includes aspects of, the corresponding element described with reference to FIG. **12**.

Commuting Device

[0181] FIG. **14** shows an example of a computing device **1400** according to aspects of the present disclosure. The example shown includes computing device **1400**, processor **1405**, memory subsystem **1410**, communication interface **1415**, I/O interface **1420**, user interface component **1425**, and channel **1430**.

[0182] In some embodiments, computing device **1400** is an example of, or includes aspects of, the image processing apparatus described with reference to FIGS. **1** and **7**. In some embodiments, computing device **1400** includes processor **1405** that can execute instructions stored in memory sub-

system **1410** to obtain a text prompt describing an element and an attribute value for a continuous attribute of the element, embed the text prompt to obtain a text embedding in a text embedding space, embed the attribute value to obtain an attribute embedding in the text embedding space, and generate a synthetic image based on the text embedding and the attribute embedding, where the synthetic image depicts the continuous attribute of the element based on the attribute value.

[0183] According to some embodiments, processor **1405** includes one or more processors. In some cases, processor **1405** is an intelligent hardware device, (e.g., a general-purpose processing component, a digital signal processor (DSP), a central processing unit (CPU), a graphics processing unit (GPU), a microcontroller, an application-specific integrated circuit (ASIC), a field programmable gate array (FPGA), a programmable logic device, a discrete gate or transistor logic component, a discrete hardware component, or a combination thereof. In some cases, processor **1405** is configured to operate a memory array using a memory controller. In other cases, a memory controller is integrated into processor **1405**. In some cases, processor **1405** is configured to execute computer-readable instructions stored in a memory to perform various functions. In some embodiments, processor **1405** includes special-purpose components for modem processing, baseband processing, digital signal processing, or transmission processing. Processor **1405** is an example of, or includes aspects of, the processor unit described with reference to FIG. **7**.

[0184] According to some embodiments, memory subsystem **1410** includes one or more memory devices. Examples of a memory device include random access memory (RAM), read-only memory (ROM), or a hard disk. Examples of memory devices include solid-state memory and a hard disk drive. In some examples, memory is used to store computer-readable, computer-executable software including instructions that, when executed, cause a processor to perform various functions described herein. In some cases, the memory contains, among other things, a basic input/output system (BIOS) that controls basic hardware or software operations such as the interaction with peripheral components or devices. In some cases, a memory controller operates memory cells. For example, the memory controller can include a row decoder, column decoder, or both. In some cases, memory cells within a memory store information in the form of a logical state. Memory subsystem **1410** is an example of, or includes aspects of, the memory unit described with reference to FIG. **7**.

[0185] According to some embodiments, communication interface **1415** operates at a boundary between communicating entities (such as computing device **1400**, one or more user devices, a cloud, and one or more databases) and channel **1430** and can record and process communications. In some cases, communication interface **1415** is provided to enable a processing system coupled to a transceiver (e.g., a transmitter and/or a receiver). In some examples, the transceiver is configured to transmit (or send) and receive signals for a communications device via an antenna. In some cases, a bus is used in communication interface **1415**.

[0186] According to some embodiments, I/O interface **1420** is controlled by an I/O controller to manage input and output signals for computing device **1400**. In some cases, I/O interface **1420** manages peripherals not integrated into computing device **1400**. In some cases, I/O interface **1420** represents a physical connection or port to an external peripheral. In some cases, the I/O controller uses an operating system such as iOS®, ANDROID®, MS-DOS®, MS-WINDOWS®, OS/2®, UNIX®, LINUX®, or other known operating system. In some cases, the I/O controller represents or interacts with a modem, a keyboard, a mouse, a touchscreen, or a similar device. In some cases, the I/O controller is implemented as a component of a processor. In some cases, a user interacts with a device via I/O interface **1420** or hardware components controlled by the I/O controller. I/O interface **1420** is an example of, or includes aspects of, the I/O module described with reference to FIG. **7**.

[0187] According to some embodiments, user interface component **1425** enables a user to interact with computing device **1400**. In some cases, user interface component **1425** includes an audio device, such as an external speaker system, an external display device such as a display screen, an input device (e.g., a remote-control device interfaced with a user interface directly or through the I/O controller), or a combination thereof.

[0188] The performance of apparatus, systems, and methods of the present disclosure have been evaluated, and results indicate embodiments of the present disclosure have obtained increased performance over existing technology (e.g., conventional image generation models). Example experiments demonstrate that the image processing apparatus based on the present disclosure outperforms conventional image generation models. Details on the example use cases based on embodiments of the present disclosure are described with reference to FIGS. **3**, **4**, and **5**.

[0189] The description and drawings described herein represent example configurations and do not represent all the implementations within the scope of the claims. For example, the operations and steps may be rearranged, combined or otherwise modified. Also, structures and devices may be represented in the form of block diagrams to represent the relationship between components and avoid obscuring the described concepts. Similar components or features may have the same name but may have different reference numbers corresponding to different figures.

[0190] Some modifications to the disclosure may be readily apparent to those skilled in the art, and the principles defined herein may be applied to other variations without departing from the scope of the disclosure. Thus, the disclosure is not limited to the examples and designs described herein, but is to be accorded the broadest scope consistent with the principles and novel features disclosed herein.

[0191] The described methods may be implemented or performed by devices that include a general-purpose processor, a digital signal processor (DSP), an application specific integrated circuit (ASIC), a field programmable gate array (FPGA) or other programmable logic device, discrete gate or transistor logic, discrete hardware components, or any combination thereof. A general-purpose processor may be a microprocessor, a conventional processor, controller, microcontroller, or state machine. A processor may also be implemented as a combination of computing devices (e.g., a combination of a DSP and a microprocessor, multiple microprocessors, one or more microprocessors in conjunction with a DSP core, or any other such configuration). Thus, the functions described herein may be implemented in hardware or software and may be executed by a processor, firmware, or any combination thereof. If implemented in software

executed by a processor, the functions may be stored in the form of instructions or code on a computer-readable medium.

[0192] Computer-readable media includes both non-transitory computer storage media and communication media including any medium that facilitates transfer of code or data. A non-transitory storage medium may be any available medium that can be accessed by a computer. For example, non-transitory computer-readable media can comprise random access memory (RAM), read-only memory (ROM), electrically erasable programmable read-only memory (EEPROM), compact disk (CD) or other optical disk storage, magnetic disk storage, or any other non-transitory medium for carrying or storing data or code.

[0193] Also, connecting components may be properly termed computer-readable media. For example, if code or data is transmitted from a website, server, or other remote source using a coaxial cable, fiber optic cable, twisted pair, digital subscriber line (DSL), or wireless technology such as infrared, radio, or microwave signals, then the coaxial cable, fiber optic cable, twisted pair, DSL, or wireless technology are included in the definition of medium. Combinations of media are also included within the scope of computer-readable media.

[0194] In this disclosure and the following claims, the word "or" indicates an inclusive list such that, for example, the list of X, Y, or Z means X or Y or Z or XY or XZ or YZ or XYZ. Also the phrase "based on" is not used to represent a closed set of conditions. For example, a step that is described as "based on condition A" may be based on both condition A and condition B. In other words, the phrase "based on" shall be construed to mean "based at least in part on." Also, the words "a" or "an" indicate "at least one."

What is claimed is:

1. A method comprising:

obtaining a text prompt describing an element and an attribute value for a continuous attribute of the element;

embedding the text prompt to obtain a text embedding in a text embedding space;

embedding, using a continuous control model, the attribute value to obtain an attribute embedding in the text embedding space; and

generating, using an image generation model, a synthetic image based on the text embedding and the attribute embedding, wherein the synthetic image depicts the continuous attribute of the element based on the attribute value.

2. The method of claim **1**, wherein:

the continuous attribute comprises a 3-dimensional characteristic of the element.

3. The method of claim **1**, wherein embedding the text prompt comprises:

dividing the text prompt into a plurality of tokens; and

embedding each of the plurality of tokens using a text embedding model.

4. The method of claim **1**, wherein:

the text prompt includes a nonce token corresponding to the attribute value.

5. The method of claim **1**, wherein:

the text prompt includes a word corresponding to the continuous attribute.

6. The method of claim **1**, further comprising:

encoding the text embedding and the attribute embedding to obtain guidance information for the image generation model, wherein the synthetic image is generated based on the guidance information.

7. The method of claim **1**, wherein generating the synthetic image comprises:

performing a diffusion process on a noise input to obtain the synthetic image.

8. The method of claim **1**, wherein:

the image generation model is trained using a training set including a plurality of training images depicting an object with a plurality of values of the continuous attribute, respectively.

9. The method of claim **8**, further comprising:

identifying a negative prompt based on the object from the plurality of training images, wherein the synthetic image is generated based on the negative prompt.

10. The method of claim **1**, further comprising:

obtaining an additional attribute value corresponding to an additional continuous attribute, wherein the synthetic image is generated to depict the additional attribute value.

11. The method of claim **1**, further comprising:

obtaining a plurality of attribute values for the continuous attribute; and

generating, using the image generation model, a plurality of synthetic images based on a same random input and the plurality of attribute values, respectively.

12. A method comprising:

initializing a machine learning model;

obtaining a training set including a plurality of training images depicting an object with a plurality of values of a continuous attribute, respectively;

training, using the training set, an image generation model to generate synthetic images with the plurality of values of the continuous attribute; and

training, using the training set, a continuous control model to generate an input for the image generation model corresponding to the continuous attribute.

13. The method of claim **12**, wherein obtaining the training set comprises:

rendering the plurality of training images based on a 3D model of the object.

14. The method of claim **12**, wherein obtaining the training set comprises:

generating, using a training image generation model, a training image based on a 3D model of the object.

15. The method of claim **12**, wherein:

the image generation model is trained individually in a first stage, and the image generation model is trained together with the continuous control model in a second stage.

16. The method of claim **12**, wherein training the image generation model comprises:

computing a reconstruction loss based on the training set; and

updating parameters of the image generation model and parameters of the continuous control model based on the reconstruction loss.

17. An apparatus comprising:

at least one processor;

at least one memory storing instructions executable by the at least one processor;

a continuous control model comprising parameters stored in the at least one memory and trained to embed an

attribute value of a continuous attribute to obtain an attribute embedding in a text embedding space; and

an image generation model comprising parameters stored in the at least one memory and trained to generate a synthetic image based on a text embedding of a text prompt and the attribute embedding, wherein the synthetic image depicts the continuous attribute based on the attribute value.

18. The apparatus of claim **17**, further comprising:

a text encoder comprising parameters stored in the at least one memory and configured to encode the text embedding and the attribute embedding to obtain guidance information for the image generation model.

19. The apparatus of claim **17**, wherein:

the continuous control model comprises a multilayer perceptron (MLP).

20. The apparatus of claim **17**, wherein:

the image generation model comprises a diffusion model.

* * * * *