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Gopal et al.

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(54) **SYSTEM AND METHOD FOR LEARNING LONG-DISTANCE RECOGNITION AND PERSONALIZATION OF GESTURES**

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G06V 10/774	(2022.01)
G06V 10/82	(2022.01)
G06V 40/20	(2022.01)

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CPC ***G06V 10/776*** (2022.01); ***G06V 10/44*** (2022.01); ***G06V 10/764*** (2022.01); ***G06V 10/774*** (2022.01); ***G06V 10/82*** (2022.01); ***G06V 40/20*** (2022.01)

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See application file for complete search history.

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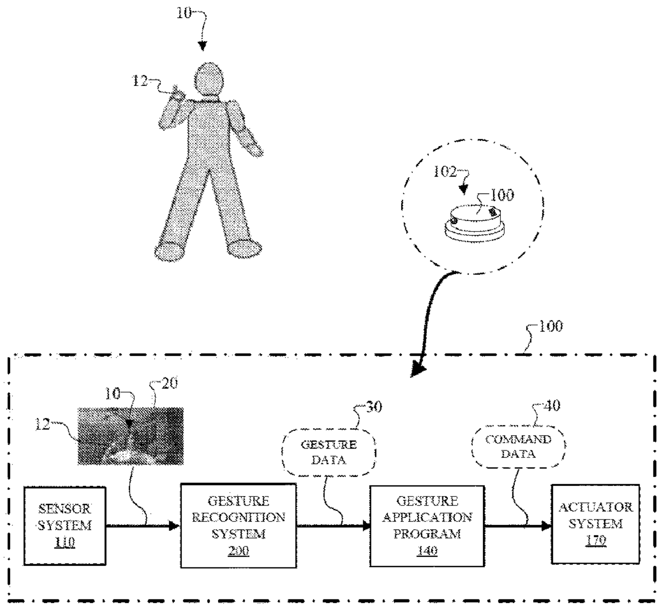
(57) **ABSTRACT**

A computer-implemented system and method relate to gesture recognition. A machine learning system is trained using a training dataset of sensor data that include a set of gestures. The training dataset includes at least a first subset that displays a first gesture. Loss data is generated based on a first loss function that includes a first cross entropy loss and a second cross entropy loss. Parameters of the machine learning system are updated based on the loss data. The machine learning system is outputted and configured for gesture recognition of the set of gestures. The machine learning system includes (i) a first subnetwork to generate feature data based on the sensor data, (ii) a second subnetwork to extract a selected patch of the feature data, and (iii) a third subnetwork to generate gesture data based on a classification of the corresponding feature data of the selected patch. The first cross entropy loss is based on a first performance of the second subnetwork in relation to the training dataset. The second cross entropy loss is based on a second performance of third subnetwork in relation to the training dataset.

20 Claims, 7 Drawing Sheets



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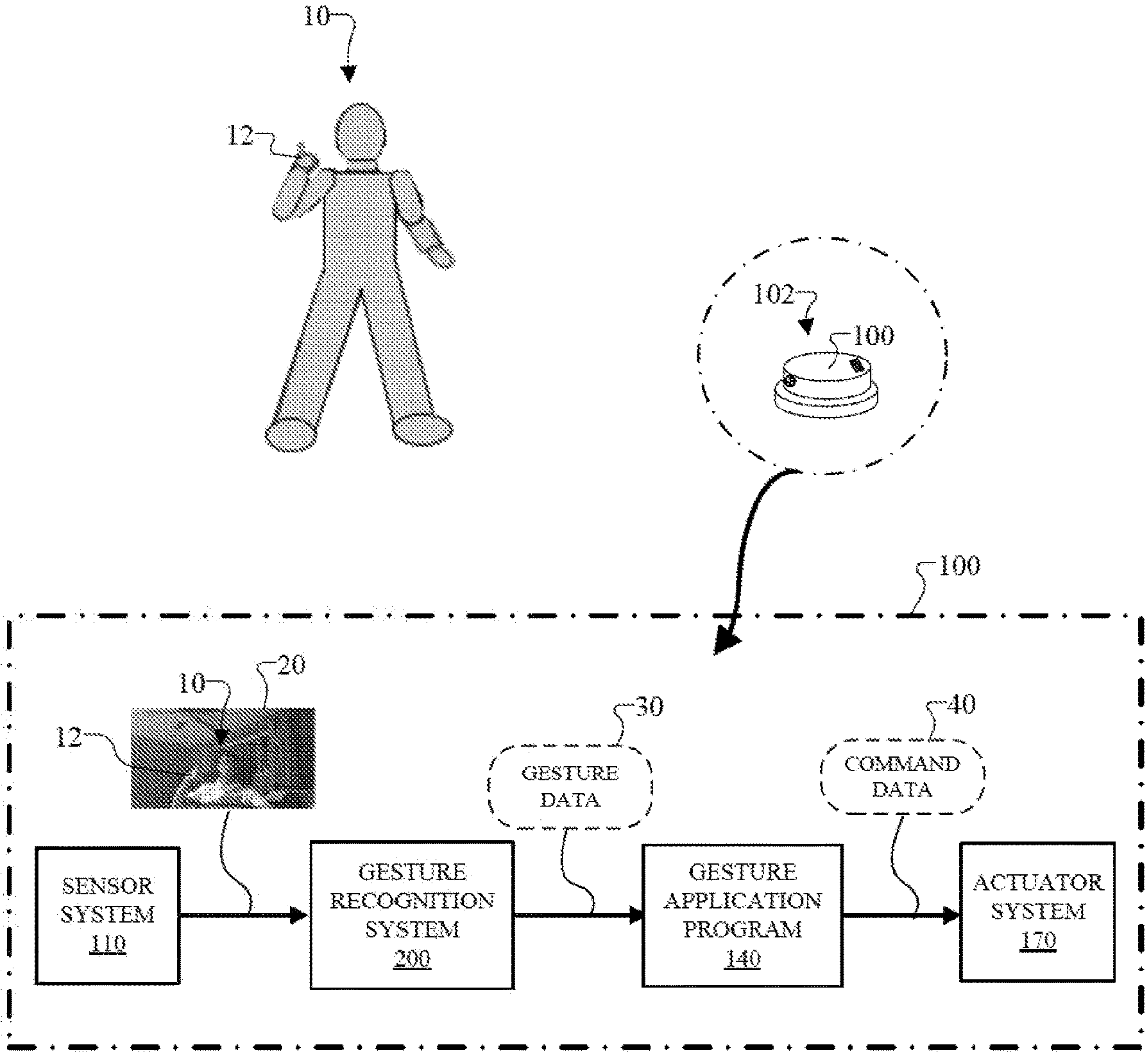

10
12
102
100
100
10
20
12
30
GESTURE DATA
40
COMMAND DATA
SENSOR SYSTEM 110
GESTURE RECOGNITION SYSTEM 200
GESTURE APPLICATION PROGRAM 140
ACTUATOR SYSTEM 170

FIG. 1

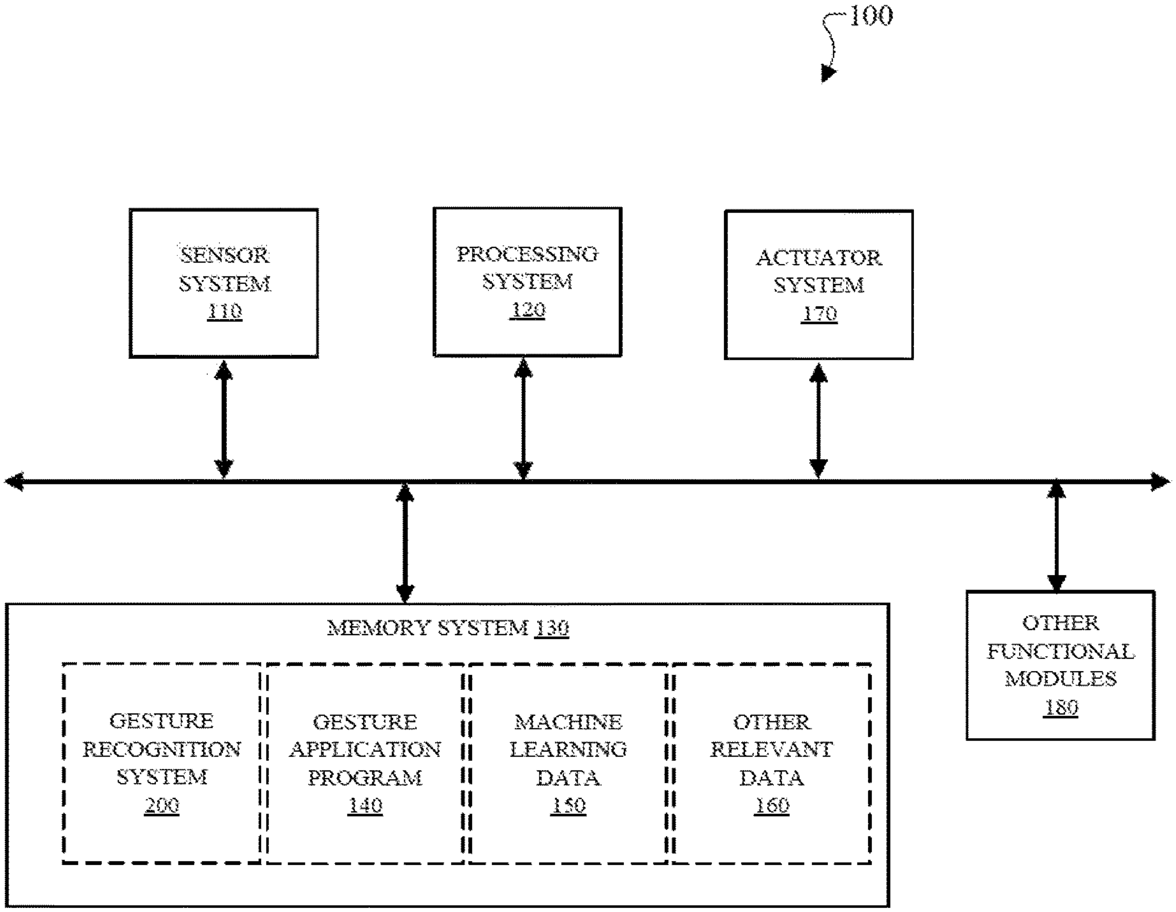

100
SENSOR SYSTEM 110
PROCESSING SYSTEM 120
ACTUATOR SYSTEM 170
MEMORY SYSTEM 130
GESTURE RECOGNITION SYSTEM 200
GESTURE APPLICATION PROGRAM 140
MACHINE LEARNING DATA 150
OTHER RELEVANT DATA 160
OTHER FUNCTIONAL MODULES 180

FIG. 2

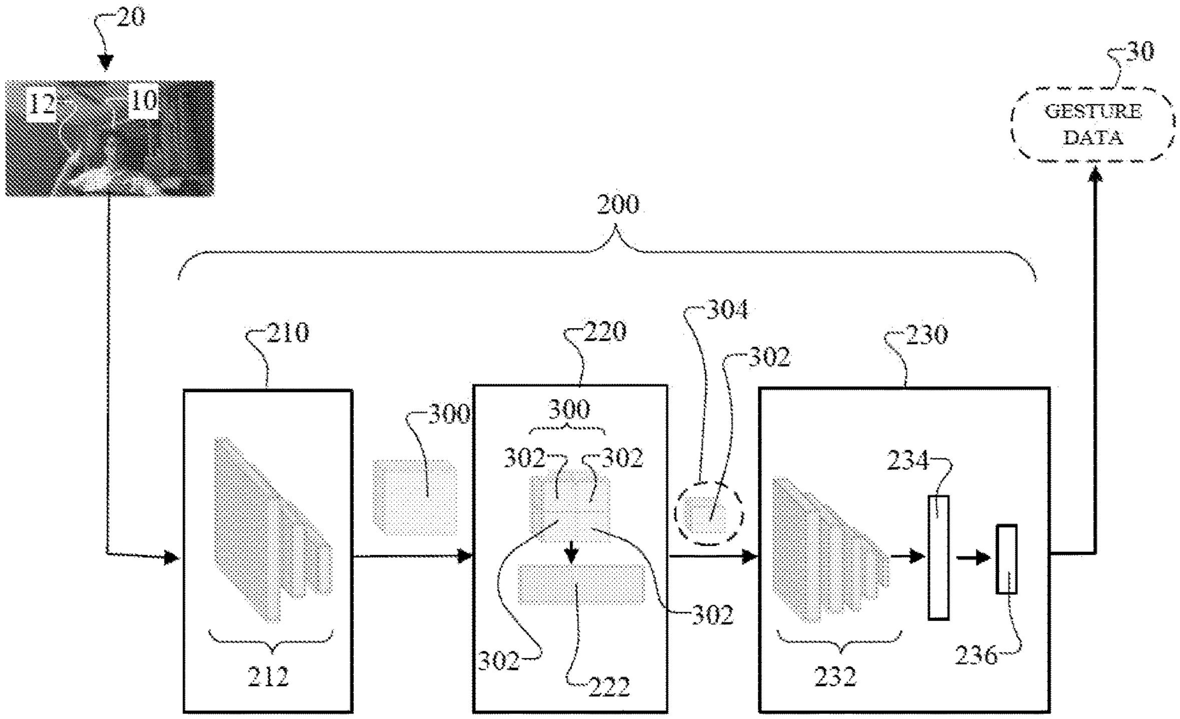
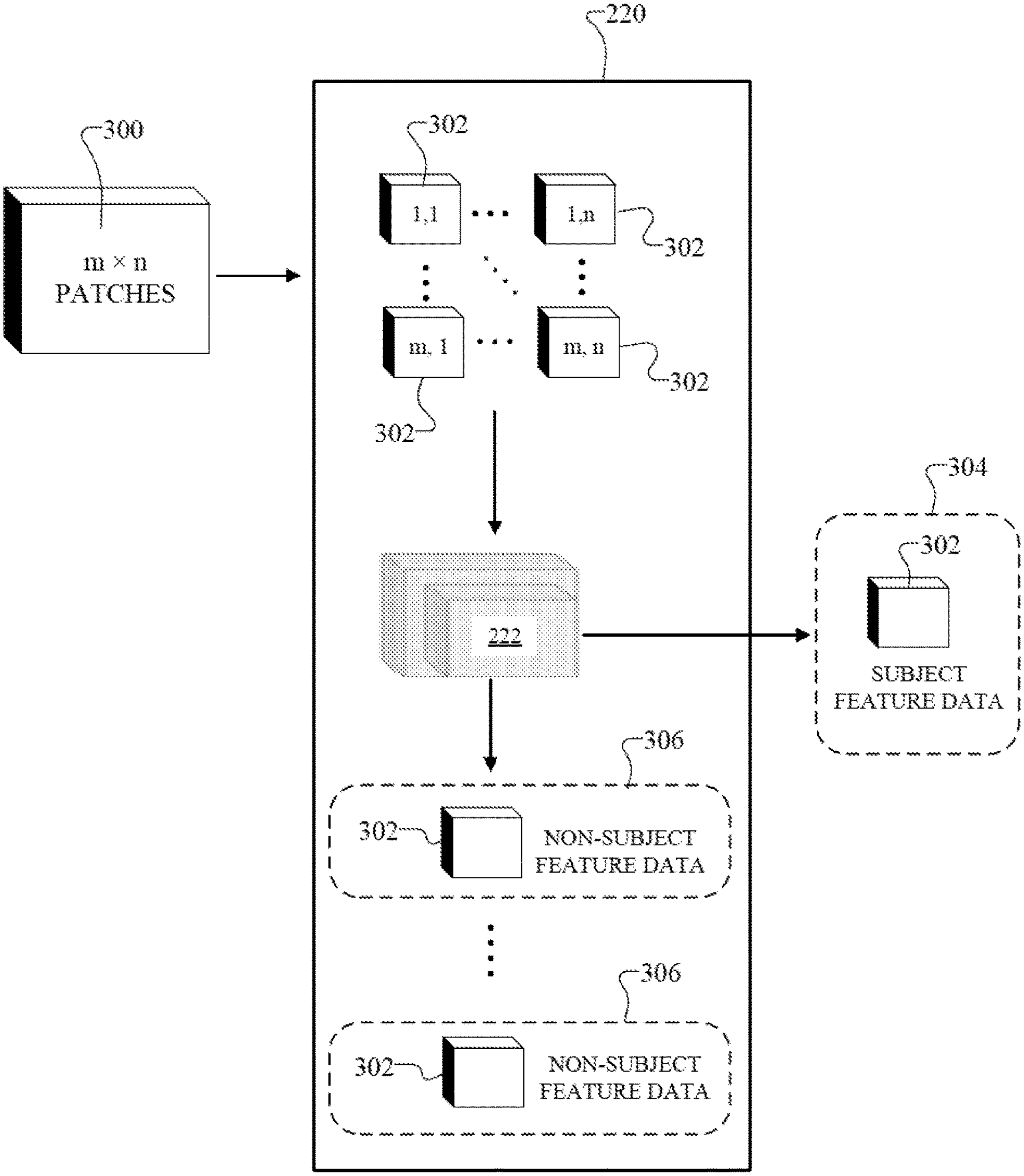

20
12
10
30
GESTURE DATA
200
210
212
300
220
300
302
302
302
302
222
304
302
230
232
234
236

FIG. 3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300
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PATCHES
302
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1,n
302
m, 1
m, n
302
302
304
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222
SUBJECT
FEATURE DATA
306
302
NON-SUBJECT
FEATURE DATA
306
302
NON-SUBJECT
FEATURE DATA

FIG. 4

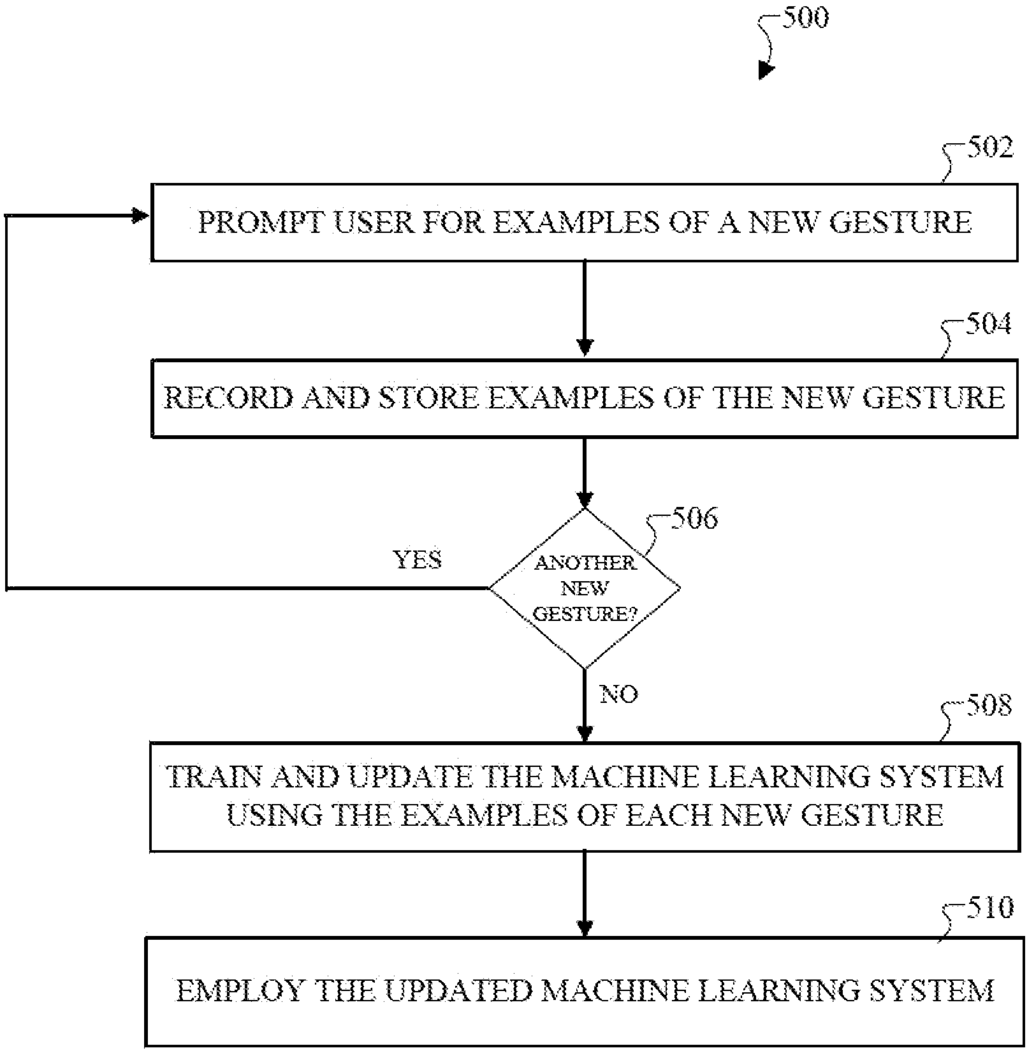
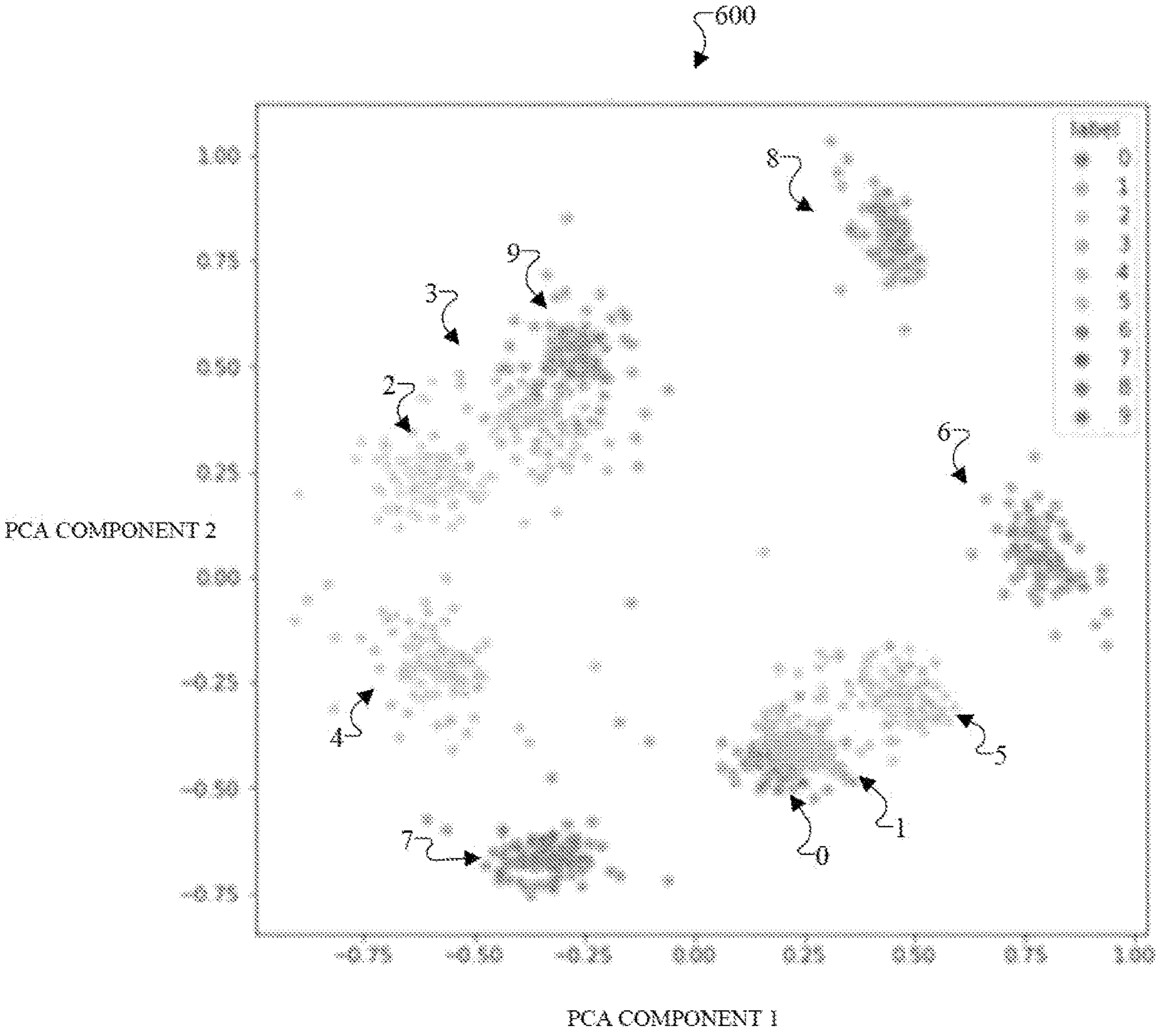

500
502
PROMPT USER FOR EXAMPLES OF A NEW GESTURE
504
RECORD AND STORE EXAMPLES OF THE NEW GESTURE
506
ANOTHER NEW GESTURE?
YES
NO
508
TRAIN AND UPDATE THE MACHINE LEARNING SYSTEM USING THE EXAMPLES OF EACH NEW GESTURE
510
EMPLOY THE UPDATED MACHINE LEARNING SYSTEM

FIG. 5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label
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1
2
3
4
5
6
7
8
9
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0.50
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0.00
−0.25
−0.50
−0.75
−0.75
−0.50
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0.00
0.25
0.50
0.75
1.00
PCA COMPONENT 2
PCA COMPONENT 1

FIG. 6

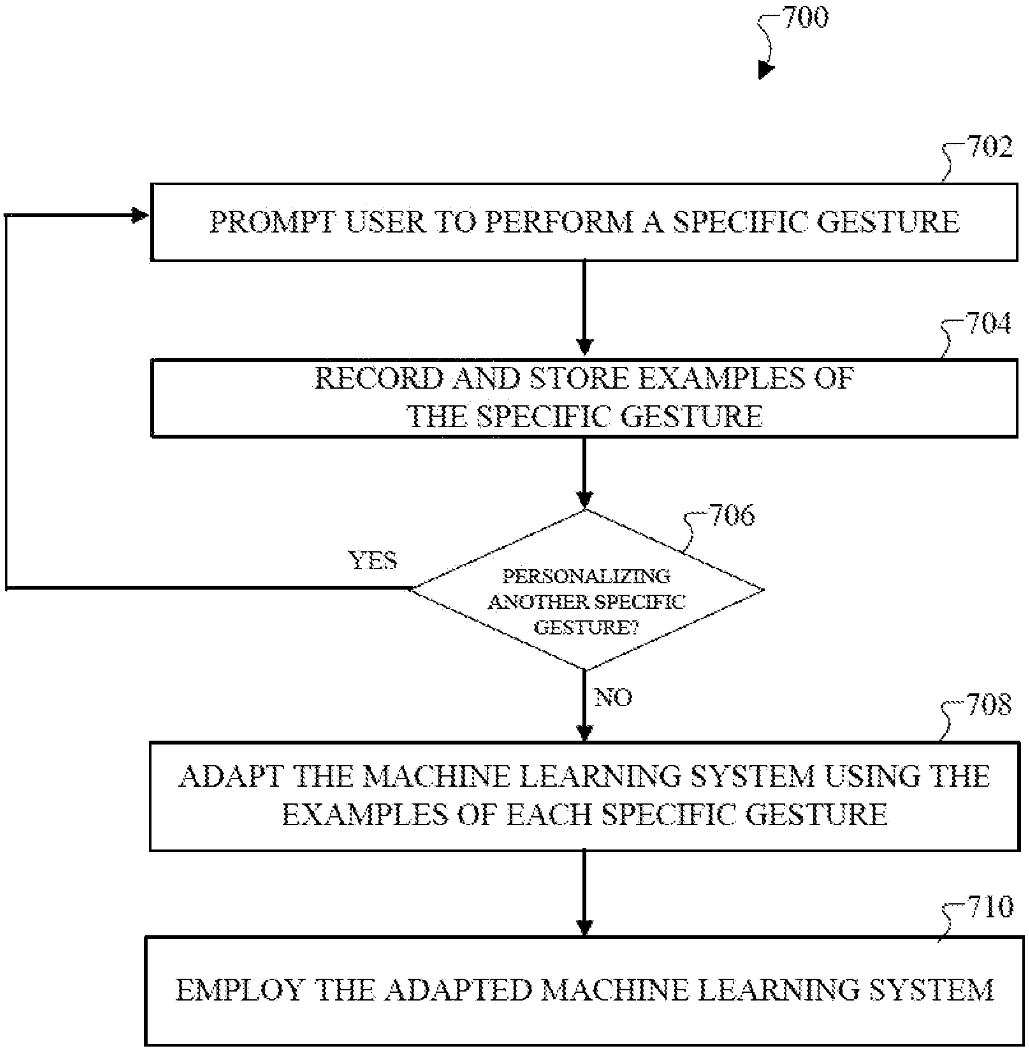
700
702
PROMPT USER TO PERFORM A SPECIFIC GESTURE
704
RECORD AND STORE EXAMPLES OF THE SPECIFIC GESTURE
706
PERSONALIZING ANOTHER SPECIFIC GESTURE?
YES
NO
708
ADAPT THE MACHINE LEARNING SYSTEM USING THE EXAMPLES OF EACH SPECIFIC GESTURE
710
EMPLOY THE ADAPTED MACHINE LEARNING SYSTEM

FIG. 7

SYSTEM AND METHOD FOR LEARNING LONG-DISTANCE RECOGNITION AND PERSONALIZATION OF GESTURES

FIELD

This disclosure relates generally to computer vision, and more particularly to digital image processing with gesture recognition.

BACKGROUND

Gesture recognition systems provide intuitive user interfaces for consumers to communicate with various devices. For instance, Microsoft's Kinect is an example of a device that uses gesture recognition. However, some devices may need to perform gesture recognition from a relatively long distance, such as more than one meter away. For example, vacuuming robots typically have their onboard cameras positioned at relatively low heights such that their subjects come into view only when those subjects are more than one meter away. Unfortunately, there are a number of gesture recognition systems, which fail to recognize gestures accurately when a subject is relatively far away (e.g., greater than one meter away). These gesture recognition systems have difficulty performing gesture recognition since the gestures occupy only small spatial regions of their field-of-view (FOV) of their sensors when the subjects are more than one meter away. In addition, such gesture recognition systems may be limited to recognizing only those gestures that they learned during training and may not be able to adapt to variations of those gestures when performed by different users.

SUMMARY

The following is a summary of certain embodiments described in detail below. The described aspects are presented merely to provide the reader with a brief summary of these certain embodiments and the description of these aspects is not intended to limit the scope of this disclosure. Indeed, this disclosure may encompass a variety of aspects that may not be explicitly set forth below.

According to at least one aspect, a computer-implemented method relates to gesture recognition. The method includes training a machine learning system using a training dataset of sensor data that include a set of gestures. The training dataset includes at least a first subset that displays a first gesture and a second subset that displays a second gesture. The method includes generating loss data based on a first loss function that includes a first cross entropy loss and a second cross entropy loss. The method includes updating parameters of the machine learning system based on the loss data. The method includes outputting the machine learning system for gesture recognition of the set of gestures. The machine learning system includes (i) a first subnetwork to generate feature data based on the sensor data, (ii) a second subnetwork to extract a selected patch of the feature data, and (iii) a third subnetwork to generate gesture data based on a classification of the corresponding feature data of the selected patch. The first cross entropy loss is based on a first performance of the second subnetwork in relation to the training dataset. The second cross entropy loss is based on a second performance of third subnetwork in relation to the training dataset.

According to at least one aspect, a system for gesture recognition includes at least a processor and a non-transitory computer readable medium. The non-transitory computer readable medium is in data communication with the processor. The non-transitory computer readable medium having computer readable data including instructions stored thereon that when executed by the processor is configured to cause the processor to perform a method. The method includes training a machine learning system using a training dataset of sensor data that include a set of gestures. The training dataset including at least a first subset that displays a first gesture and a second subset that displays a second gesture. The method includes generating loss data based on a first loss function that includes a first cross entropy loss and a second cross entropy loss. The method includes updating parameters of the machine learning system based on the loss data. The method includes outputting the machine learning system for gesture recognition of the set of gestures. The machine learning system includes (i) a first subnetwork to generate feature data based on the sensor data, (ii) a second subnetwork to extract a selected patch of the feature data, and (iii) a third subnetwork to generate gesture data based on a classification of the corresponding feature data of the selected patch. The first cross entropy loss is based on a first performance of the second subnetwork in relation to the training dataset. The second cross entropy loss is based on a second performance of third subnetwork in relation to the training dataset.

According to at least one aspect, a non-transitory computer readable medium has computer readable data including instructions stored thereon that, when executed by a processor, is configured to cause the processor to perform a method. The method includes training a machine learning system using a training dataset of sensor data that include a set of gestures. The training dataset includes at least a first subset that displays a first gesture. The method includes generating loss data based on a first loss function that includes a first cross entropy loss and a second cross entropy loss. The method includes updating parameters of the machine learning system based on the loss data. The method includes outputting the machine learning system for gesture recognition of the set of gestures. The machine learning system includes (i) a first subnetwork to generate feature data based on the sensor data, (ii) a second subnetwork to extract a selected patch of the feature data, and (iii) a third subnetwork to generate gesture data based on a classification of the corresponding feature data of the selected patch. The first cross entropy loss is based on a first performance of the second subnetwork in relation to the training dataset. The second cross entropy loss is based on a second performance of third subnetwork in relation to the training dataset.

These and other features, aspects, and advantages of the present invention are discussed in the following detailed description in accordance with the accompanying drawings throughout which like characters represent similar or like parts.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a diagram of an example of an application of a system with a gesture recognition system according to an example embodiment of this disclosure.

FIG. **2** is a block diagram of an example of a system with a gesture recognition system according to an example embodiment of this disclosure.

FIG. **3** is a block diagram of an example of a gesture recognition system according to an example embodiment of this disclosure.

FIG. **4** is a block diagram of an example of a patch selector according to an example embodiment of this disclosure.

FIG. **5** is a flow diagram of an example of a process for adding new gestures to a gesture recognition system during test time according to an example embodiment of this disclosure.

FIG. **6** is a diagram of an example of an embedding space with embeddings corresponding to gestures of a gesture recognition system according to an example embodiment of this disclosure.

FIG. **7** is a flow diagram of an example of a process of adapting a gesture recognition system to one or more gestures of a new domain during test time according to an example embodiment of this disclosure.

DETAILED DESCRIPTION

The embodiments described herein, which have been shown and described by way of example, and many of their advantages will be understood by the foregoing description, and it will be apparent that various changes can be made in the form, construction, and arrangement of the components without departing from the disclosed subject matter or without sacrificing one or more of its advantages. Indeed, the described forms of these embodiments are merely explanatory. These embodiments are susceptible to various modifications and alternative forms, and the following claims are intended to encompass and include such changes and not be limited to the particular forms disclosed, but rather to cover all modifications, equivalents, and alternatives falling within the spirit and scope of this disclosure.

FIG. **1** is a diagram of an example of an application of a system **100**, which includes a gesture recognition system **200**, according to an example embodiment. In FIG. **1**, the system **100** is applied to a robot **102**, which is controlled via the gesture recognition system **200**. In this example, the robot **102** is configured to perform household tasks, such as vacuuming, floor cleaning tasks, etc. As shown in FIG. **1**, the gesture recognition system **200** is configured to recognize gestures **12** of users **10** and control the robot **102** based on commands **40** corresponding to the recognized gestures **12**. In this regard, the gesture recognition system **200** is advantageous in being able to provide an intuitive and touch-free interface for communicating with the robot **102** compared to other command modalities, such as phone app-based controls, remote controls, etc. The system **100** is advantageous in enabling users **10** to use gestures **12** to control or interact with the robot **102** from a distance without requiring the users **10** to physically touch that robot **102** or another device (e.g., remote control, phone-app based controls, etc.).

In FIG. **1**, the robot **102** is configured to be controlled based on a gesture **12** of a user **10**. More specifically, the robot **102** includes an onboard sensor system **110**, which is configured to capture sensor data **20** that includes a gesture **12**. In this example, the robot **102** includes an onboard camera, which captures a sequence or stream of digital images (e.g., digital video data) of the gesture **12** being performed by the user **10**. The gesture recognition system **200** is configured to generate gesture data **30** in response to receiving the sensor data **20** (e.g., digital video data) as input. In addition, the gesture application program **140** is configured to determine a command data **40** for controlling the robot **102** based on the gesture data **30** and provide the command data **40** to the actuator system **170** for execution. For example, in FIG. **1**, when the user **10** provides the "thumbs up" gesture **12**, the robot **102** is configured to capture sensor data **20** (e.g., video data) of the user **10** performing the gesture **12**. In this non-limiting example, the robot **102** is configured to recognize the "thumbs up" gesture **12** of the sensor data **20**, generate gesture data **30** indicative of the "thumbs-up" gesture **12**, and associate the "thumbs up" gesture data **30** with a command data **40**, which includes instructions for the robot **102** to return to its base. This command data **40** (e.g., instructions indicative of "return to base") is then provided to one or more actuators of the actuator system **170**. Upon receiving this command data **40**, the actuator system **170** is configured to move the robot **102** to its base. As discussed in this example, the system **100** allows users **10** to use one or more gestures **12** to interact with and control the robot **102** in an easy and touch-free manner.

TABLE 1 provides non-limiting examples of gesture data **30** indicative of gestures **12** and corresponding commands **40** for controlling the robot **102** of FIG. **1**. The gesture recognition system **200** may include more gesture data **30**, less gesture data **30**, or different gesture data **30** than the gesture data **30** of TABLE 1. Also, the gesture application program **140** may include more commands **40**, less commands **40**, or different commands **40** than those commands **40** of TABLE 1. The robot **102** may include a mapping of gesture data **30** to commands **40** that is different than the mapping of TABLE 1. In this regard, the robot **102** and/or system **100** is not limited to the control implementation of TABLE 1.

TABLE 1

GESTURE DATA	COMMAND DATA EXECUTED BY ROBOT
THUMBS UP	RETURN TO BASE
CROSS FINGERS	CANCEL CURRENT JOB
PINCH (ZOOM IN, ZOOM OUT)	CONTROL VACUUM SUCTION POWER
WAVE HAND	WAKE ROBOT AND SUMMON IT NEAR PERSON
SWIPE FORWARD/ BACKWARD	MOVE ROBOT FORWARD/ BACKWARD
WAVE 2 FINGERS	ACTIVATE A 'FOLLOW PERSON' MODE

As aforementioned, FIG. **1** provides a non-limiting example of one illustrative application (e.g., robot **102** application) of the system **100**, which includes the gesture recognition system **200**. However, the system **100** and/or the gesture recognition system **200** may be applied to other technologies. As other non-limiting examples, the gesture recognition system **200** may be applied to a warehouse robot, a home appliance, a car media system, any technological device, or any number and combination thereof. Furthermore, other technological applications may become apparent based on this disclosure.

FIG. **2** is a block diagram of an example of the system **100** according to an example embodiment. The system **100** is configured to generate gesture data **30** based on the sensor data **20**. In addition, the system **100** is configured to control one or more actuators based on one or more commands **40** that correspond to the gesture data **30**. More specifically, as shown in FIG. **2**, the system **100** is configured to include at least one sensor system **110**. The sensor system **110** is local, remote, or a combination thereof (e.g., partly local and partly remote). The sensor system **110** includes one or more sensors. For example, the sensor system **110** may include an image sensor, a camera, a depth sensor, a Time of flight (ToF) sensor, a structured light sensor (e.g., a LIDAR sensor), an infrared sensor, any suitable sensor, or any number and combination thereof.

The sensor system **110** is configured to generate, capture, and/or provide sensor data **20**. The sensor data **20** may include a gesture **12**, which is being performed by a gesturer or user **10**. The sensor data **20** may include digital image data, a collection/stream of digital image data, video data, etc. The sensor data **20** may include depth data. The sensor data **20** may include ToF data, structured light sensor data, any suitable depth/surface data, or any number and combination thereof. The processing system **120** may receive infrared data, any applicable sensor data, or any number and combination thereof. The sensor data or a combination of different sensor data (e.g., sensor-fusion data) may be further processed to generate a digital image or a sequence/stream of digital images data (e.g., video data). For instance, as a non-limiting example, the sensor data **20** may include (i) red green blue (RGB) video, (ii) depth data, (iii) RGB video and depth data, (iv) infrared (IR) video, or (v), IR video and depth data. The sensor system **110** is operable to communicate with one or more other components (e.g., processing system **120** and memory system **130**) of the system **100**. For example, the sensor system **110** is configured to transmit and/or provide sensor data **20** to the processing system **120**

The system **100** includes at least one processing system **120**. The processing system **120** includes one or more processing devices. For example, the processing system **120** may include an electronic processor, a central processing unit (CPU), a graphics processing unit (GPU), a microprocessor, a field-programmable gate array (FPGA), an application-specific integrated circuit (ASIC), any suitable processing technology, or any number and combination thereof. The processing system **120** is operable to provide the functionality as described herein. The processing system **120** is configured to receive sensor data **20** (e.g., video data) from the sensor system **110** and process the sensor data **20** (e.g., video data) in connection with the gesture recognition system **200**, the gesture application program **140**, the machine learning data **150**, the other relevant data **160**, or any number and combination thereof.

The system **100** includes a memory system **130**, which is configured to be in data communication with the processing system **120**. The memory system **130** is configured to be in data communication with the sensor system **110** and may store sensor data **20** thereon. In an example embodiment, the memory system **130** includes at least one non-transitory computer readable storage medium, which is configured to store and provide access to various data to enable at least the processing system **120** to perform the operations and functionality, as disclosed herein. In an example embodiment, the memory system **130** comprises a single memory device or a plurality of memory devices. The memory system **130** may include electrical, electronic, magnetic, optical, semiconductor, electromagnetic, or any suitable storage technology that is operable with the system **100**. For instance, in an example embodiment, the memory system **130** may include random access memory (RAM), read only memory (ROM), flash memory, a disk drive, a memory card, an optical storage device, a magnetic storage device, a memory module, any suitable type of memory technology, or any number and combination thereof. With respect to the processing system **120** and/or other components of the system **100**, the memory system **130** is local, remote, or a combination thereof (e.g., partly local and partly remote). For example, the memory system **130** can include at least a cloud-based storage system (e.g. cloud-based database system), which is remote from the processing system **120** and/or other components (e.g., sensor system **110**, actuator system **170**, etc.) of the system **100**.

The memory system **130** includes at least the gesture recognition system **200**, the gesture application program **140**, machine learning data **150**, and other relevant data **160**, which are stored thereon. The gesture recognition system **200** includes computer readable data with instructions that, when executed by the processing system **120**, is configured to recognize various gestures **12** in sensor data **20** and generate gesture data **30** indicative of these recognized gestures **12**. The gesture recognition system **200** is configured to generate gesture data **30** as output upon receiving sensor data **20** (e.g., digital video data, infrared data, etc.) as input. The computer readable data can include instructions, code, routines, various related data, any software technology, or any number and combination thereof. The gesture recognition system **200** includes a machine learning system, as shown and discussed with respect to FIG. **3** and FIG. **4**. Also, the gesture application program **140** includes computer readable data with instructions, which, when executed by the processing system **120**, is configured to apply the output of the gesture recognition system **200** to an application, such as one or more actuators of the actuator system **170**. For example, as shown in FIG. **1**, the gesture application program **140** may associate the gesture data **30** with one or more commands **40** and provide these commands **40** to the actuator system **170**. In this regard, the gesture application program **140** is configured to provide a seamless integration of the gesture recognition system **200** with respect to one or more components of the system **100** in relation to the desired application (e.g., robot **102**). In addition, the machine learning data **150** includes various data relating to the training and operation of the gesture recognition system **200** as described in this disclosure. For example, the machine learning data **150** includes training data, parameter data, loss data, embedding data, mean embedding data, embedding vector data, transformed vector data, distance data, sample data, sensor data (e.g., digital image/video data and depth data), any relevant data for the gesture recognition system **200**, or any number and combination thereof. Meanwhile, the other relevant data **160** provides various data (e.g. operating system, etc.), which enables the system **100** to perform the functions as discussed herein.

The system **100** is configured to include an actuator system **170**. The actuator system **170** includes one or more actuators for controlling an action (e.g., movement) of a device (e.g., robot **102**) based on one or more control commands, which include at least gesture-based commands **40**. The control commands may also include voice commands, app-based commands, remote control commands, any command mechanism, or any number and combination thereof. In addition, the one or more actuators may include a software component, an electrical/electronic component, a hardware component, an electromechanical component, a mechanical component, a computer component, or any number and combination thereof. As an example, for instance, in FIG. **1**, the robot **102** includes at least a motion actuator, a control actuator, a brake actuator, etc. In this regard, the actuator system **170** includes one or more actuators, which are configured to provide one or more actions relating to advancing and/or executing the control commands of the system **100**.

In addition, the system **100** may include at least one other component. For example, as shown in FIG. **2**, the memory system **130** is also configured to store other relevant data

160, which relates to operation of the system **100** in relation to one or more components (e.g., sensor system **110**, actuator system **170**, and other functional modules **180**). Also, the system **100** includes other functional modules **180**, such as any appropriate hardware, software, or combination thereof that assist with or contribute to the functioning of the system **100**. For example, the other functional modules **180** include communication technology (e.g. wired communication technology, wireless communication technology, or a combination thereof) that enables components of the system **100** to communicate with each other as described herein. In addition, the other functional modules **180** include one or more I/O devices (e.g., display device, keyboard device, speaker device, etc.), which relate to the system **100**. In this regard, the system **100** is operable to perform gesture recognition, as described herein, to control one or more devices (e.g., one or more actuators of the actuator system **170**), which may include software components, hardware components, mechanical components, electrical components, or any number and combination thereof.

FIG. **3** and FIG. **4** are block diagrams that illustrate aspects of the gesture recognition system **200** according to an example embodiment. The gesture recognition system **200** includes a machine learning system or a machine learning model. The machine learning system comprises a dynamic and artificial neural network model, which is trained end-to-end. The neural network model includes a first subnetwork, a second subnetwork, and a third subnetwork. The neural network model may include a different number of subnetworks provided that such modifications are similar to the spirit of the gesture recognition system **200** provided in this disclosure. During a training phase with an initial training dataset that include an initial set of gestures **12**, the gesture recognition system **200** updates its parameters such that loss data of a loss function is minimized. For instance, as expressed in equation 1, the loss function is a sum of at least (i) a cross entropy loss defined for patch selection and (i) a cross entropy loss defined for gesture classification. In equation 1, LOSS represents the loss of the gesture recognition system **200** (i.e., the neural network model). Also, in equation 1, CE_1 represents the cross entropy loss function that is evaluated with respect to patch selection, CE_2 represents the cross entropy loss function that is evaluated with respect to gesture classification, and λ represents a weighting factor between the two losses (i.e., CE_1 and CE_2).

$$\mathrm{LOSS} = CE_1 + \lambda CE_2 \qquad [1]$$

The first subnetwork is a feature extractor **210**. The feature extractor **210** is configured to receive the sensor data **20** (e.g., video data or both video data and depth data) as input and generate feature data **300** as output. The feature extractor **210** generates the feature data **300** based on the sensor data **20**. The feature extractor **210** includes a set of artificial neural network layers **212**. As an example, for instance, the feature extractor **210** may include two or more convolutional neural network (CNN) layers to extract features from the sensor data **20** and generate the feature data based on the extracted features. The number of CNN layers may be selected based on a desired level of extracted features. In addition, the first subnetwork is configured to provide the feature data **300** to the second subnetwork.

The second subnetwork includes a patch selector **220**. The patch selector **220** is configured to receive feature data **300** from the feature extractor **210**. Upon receiving the feature data **300**, the patch selector **220** is configured to divide the feature data into a total of m×n patches, where m represents an integer number of patches along a first dimension (e.g., width dimension) of the feature data **300** and n represents an integer number of patches along a second dimension (e.g., length dimension) of the feature data **300**. Each patch **302** comprises a corresponding part of the feature data based on the division of the feature data **300**. Upon dividing the feature data **300** into patches **302**, the patch selector **220** provides each patch **302** of feature data to a patch classifier **222**. For example, in FIG. **3** and FIG. **4**, the patch classifier **222** is a binary classifier, which includes a set of artificial neural network layers. For example, the patch classifier **222** includes CNN layers, recurrent neural network (RNN) layers, a transformer neural network, any suitable machine learning layers, or any number and combination thereof.

The patch classifier **222** is configured to classify feature data of a given patch **302** as having and/or being indicative of (i) subject data or (ii) non-subject data. The patch classifier **222** is configured to generate confidence scores based on the classification of feature data of each patch **302**. The patch selector **220** is configured to select a patch **302** of feature data as output based on the confidence score. For example, in FIG. **3**, the patch selector **220** selects a target patch having feature data, which is classified as subject data based on its confidence score being above a predetermined threshold and/or within a predetermined range. In this regard, the patch selector **220** selects a target patch with a high confidence or high probability that its feature data includes at least some subject data therein. The subject data refers to the feature data, which corresponds to a subject. In this case, the subject is defined to be the gesturing part (e.g., the hand) of a gesturer (e.g., user **10**).

The patch selector **220** is configured to output each selected patch **304**, which is classified by the patch classifier **222** as having the feature data corresponding to subject data. Each selected patch **304** may also be referred to as a target patch for having feature data that corresponds to subject data, which is the target data that the patch selector **220** seeks to provide to the gesture recognizer **230**. In some cases, there may be more than one selected patch **304** of feature data that is classified as having subject data and transmitted to the third subnetwork. The patch selector **220** filters out the non-selected patches **306** of feature data such that the non-selected patches **306** are not provided to and/or handled by the third subnetwork. The patch selector **220** provides only the feature data of interest (e.g., subject data of the gesturing hand) to the third subnetwork via one or more selected patches **304**. The patch selector **220** provides each selected patch **304** (i.e., each patch **302** classified as subject data) of feature data to the third subnetwork, and does not provide non-selected patches **306** (e.g., each patch **302** classified as non-subject data) to the third subnetwork.

The third subnetwork includes a gesture recognizer **230**. The gesture recognizer **230** receives only each selected patch **304** of feature data as input from among the entire feature data **300**, which is generated by the feature extractor **210**. The gesture recognizer **230** does not receive the non-selected patches **306** of feature data. In this regard, the patch selector **220** reduces the amount of feature data from the entirety of feature data **300**, which is output by the feature extractor **210**, to only one or more selected patches **304** of feature data such that the amount of feature data that is handled by the gesture recognizer **230** is significantly reduced to features of interest (i.e., gesturing part such as a hand or the like). In this regard, the patch selector **220** ensures that the gesture recognizer **230** only classifies feature data, which is classified as including subject data (e.g., gesturing part, such as a hand, body, face, leg, foot, etc.) while relieving the gesture recognizer **230** of the burden of handling feature data, which is classified as non-subject data.

The gesture recognizer **230** includes a gesture classifier **232**. The gesture classifier **232** includes a set of artificial neural network layers. For example, the gesture classifier **232** includes a set of CNN layers, RNN layers, a transformer neural network, any suitable machine learning layers, or any number and combination thereof. The gesture classifier **232** only classifies the feature data of each selected patch **304**. The gesture classifier **232** does not handle the non-selected patches **306** from the set of patches. More specifically, the gesture classifier **232** is configured to classify the feature data of each selected patch **304** as belonging to a particular gesture class. Upon receiving a selected patch **304** of feature data as input, the gesture classifier **232** generates an embedding vector **234** to represent a classification of the gesture **12** identified in the selected patch **304** of feature data. The embedding vector **234** is indicative of the gesture class in which the gesture classifier **232** classified the feature data of the selected patch **304** (e.g., the target patch having feature data classified as subject data). In addition, the gesture recognizer **230** is configured to generate a gesture prediction vector **236** based on the embedding vector **234**. In this example, the gesture prediction vector **236** represents a discrete probability distribution. For instance, if the gesture recognition system **200** is trained to recognize "N" gestures (where N represents an integer value greater than 0), then the gesture prediction vector **236** would be an N-dimensional vector. As a non-limiting example, if the gesture recognition system **200** recognizes five gestures, then N=5 and the gesture prediction vector **236** is a 5-dimensional vector, such as the non-limiting example of P=[0.8, 0.05, 0.05, 0.09, 0.02]. In addition, the gesture recognizer **230** is configured to generate gesture data **30** based on the gesture prediction vector **236**. The gesture data **30** identifies the gesture **12** and/or is indicative of the gesture **12**. For example, in FIG. **3**, the gesture recognition system **200** is configured to output "thumbs up" as the gesture data **30** in response to receiving the sensor data **20** (e.g., video data) of the user **10** performing the gesture **12** as input. In this regard, the gesture recognizer **230** is configured to classify the feature data (containing the subject data, such as a gesture **12** of gesturing hand) of the selected patch **304** as belonging to a particular gesture class (e.g., thumbs-up gesture class) and provide corresponding gesture data **30** (e.g., thumbs-up data) for that particular gesture class.

FIG. **5** is a flow diagram of an example of a process **500** relating to continual learning of the gesture recognition system **200** according to an example embodiment. More specifically, the process **500** relates to adding one or more new gestures to the gesture recognition system **200** during test time and/or inference. With this process **500**, the gesture recognition system **200** is not limited to the existing gestures that the gesture recognition system **200** learned during its training with the initial training dataset. The process **200** is advantageous in providing the gesture recognition system **200** with the capability to learn to recognize more gestures and/or new gestures, which are different from the existing gestures **12** that have already been learned by the gesture recognition system **200**. The process **500** is performed by one or more processors of the processing system **120** together with the gesture recognition system **200** and the machine learning data **150**. The gesture application program **140** may also be involved in the process **500**. As a non-limiting example, the process **500** may be performed on the device itself (e.g., the robot **102**), a cloud network, another device (e.g., mobile phone of user **10**) that communicates with the device (e.g., robot **102**), etc. The process **500** may include more steps or less steps than that shown in FIG. **5** provided that such modification provides similar functionalities and objectives as described in this disclosure.

At step **502**, according to an example, the system **100** prompts a user **10** for examples of a new gesture. The system **100** is configured to prompt a user **10** via a graphical user interface, an audio prompt, a visual prompt, any prompting mechanism, or any number and combination thereof. After prompting the user **10** for examples of a new gesture, the system **100** performs step **504**.

At step **504**, according to an example, the system **100** records and stores the examples (or the samples) of the new gesture in the memory system **130**. For example, the system **100** is configured to capture and record sensor data **20** (e.g., video data) of a user **10** performing the new gesture. The system **100** proceeds to capture a predetermined number of new samples of this new gesture. Once the predetermined number of new samples has been reached for this new gesture, then the system **100** performs step **506**.

At step **506**, according to an example, the system **100** determines whether or not there is another new gesture for the gesture recognition system **200** to learn at this time. The system **100** may make this determination by information that is provided by the user **10** with respect to the number of new gestures, which will be added during this iteration of the process **500**. If there is another new gesture for the gesture recognition system **200**, then the process **500** proceeds to step **502**. If there are no other new gestures for the gesture recognition system **200**, then the process proceeds to step **508**.

At step **508**, according to an example, the system **100** trains the gesture recognition system **200** using the examples of each new gesture, which were recorded and stored at step **504**. In addition, the system **100** is configured to minimize loss data to increase a distance (or a separation) between a mean embedding of a new gesture relative to each mean embedding of each existing gesture without significantly perturbing each mean embedding of each existing gesture. In this regard, the system **100** considers an existing gesture to be a gesture **12** that the gesture recognition system **200** already recognizes via any prior training that occurred before that instance, such as the initial training with the training dataset, a prior iteration of process **500**, a prior iteration of process **700**, or any number and combination thereof. The system **100** is also configured to minimize a distance (or a separation) between embeddings of examples belonging to a same, new gesture.

For example, the system **100** is configured to compute loss data via a novel loss function such that the Loss=−(Sum of distances between mean embeddings of new gestures and mean embeddings of existing gestures, respectively)+(average distance between embeddings of stored examples of a gesture and the mean embedding of that same gesture, wherein the average distances are summed for all gestures). In this regard, this novel loss function (i) takes a negative of the first distance term and (ii) adds the second distance term to the first distance term, where the first distance term refers to "(Sum of distances between mean embeddings of new gestures and mean embeddings of existing gestures, respectively)" and the second distance term refers to "(average distance between embeddings of stored examples of a gesture and the mean embedding of that same gesture, wherein the average distances are summed for all gestures)," respectively.

The first distance term is computed by calculating a first total. As an example, the first total includes, for instance, summing a first distance sum for a first new gesture, a second distance sum for a second new gesture, . . . and so forth until an i^{th} distance sum for the i^{th} new gesture, where "r" represents the total number of new gestures. A j^{th} distance sum is computed, for instance, by calculating a sum of a distance between a mean embedding of a j^{th} new gesture and a mean embedding of a first existing gesture, a distance between a mean embedding of that same j^{th} new gesture and a mean embedding of a second existing gesture, . . . and so forth until a distance between a mean embedding of that same j^{th} new gesture and a mean embedding of an s^{th} existing gesture, where "j" represents an integer value such that 1≤j≤r for the new gestures, and where "s" represents the total number of existing gestures. In this regard, the first distance term considers distances between mean embeddings of new gestures and mean embeddings of existing gestures, respectively.

The second distance term is computed by calculating a second total. The second total considers both the new gestures and the existing gestures. As an example, the second total is computed, for instance, by calculating a sum of an average distance of a first gesture, an average distance of a second gesture, . . . and so forth until an average distance of the last gesture of the complete set of gestures (i.e., new gestures and existing gestures). The average distance of a kth gesture is computed, for instance, by calculating an average based on a distance between an embedding of a first stored example of a kth gesture and a mean embedding of that same kth gesture, a distance between an embedding of a second stored example of that same kth gesture and the same mean embedding of that same kth gesture, . . . and so forth until a distance between an embedding of the last stored example of that same kth gesture and the same mean embedding of that same kth gesture, where k represents an integer value such that 1≤k≤(r+s) for all gestures (e.g., new gestures and existing gestures).

For example, equation 2 expresses this novel loss function as LOSS using ℓ_2 distances, as indicated below. More specifically, when considering equation 2 with respect to the novel loss function discussed above, "$\Sigma_{i=1}^{s}\ \Sigma_{j=1}^{r}|\overline{y}_j-\overline{x}_i|_2$" may be considered to represent the first distance term while "$\lambda_1\ \Sigma_{i=1}^{s}\ \Sigma_{q=1}^{p}|\overline{x}_i-x_{i,q}|_2+\lambda_1\ \Sigma_{j=1}^{r}\ \Sigma_{q=1}^{p}|\overline{y}_j-y_{j,q}|_2$" may be considered to be the second distance term. In equation 2, $\overline{x}_i$ represents a mean embedding of the i-th existing gesture while $\overline{y}_j$ represents a mean embedding of the j-th new gesture. In this regard, "i" represents an integer value such that 1≤i≤s for the existing gestures, and r represents an integer value such that 1≤j≤r for the new gestures. Also, $x_{i,q}$ is the q-th stored example of the i-th existing gesture and $y_{j,q}$ is the q-th stored example of the j-th new gesture. In addition, "p" represents the number of examples stored for each of the s existing gestures and r new gestures. As an example, $|x|_2$ denotes the ℓ_2 distance, which is an example of a distance that may be used by the system **100**. Additionally or alternatively to the ℓ_2 distances of equation 2, the system **100** is configured to compute the novel loss function using other distance computations to calculate distances between the corresponding variables (e.g., $\overline{x}_1$, $\overline{y}_j$, $x_{i,q}$, and $y_{j,q}$). λ_1 is a hyperparameter used to decide the relative importance and/or weightage given to the first loss term and the second loss term.

$$\text{LOSS} = -\sum_{i=1}^{s}\sum_{j=1}^{r}|\overline{y_j}-\overline{x_1}|_2 + \lambda_1\sum_{i=1}^{s}\sum_{q=1}^{p}|\overline{x_1}-x_{i,q}|_2 + \lambda_1\sum_{j=1}^{r}\sum_{q=1}^{p}|\overline{y_j}-y_{j,q}|_2 \qquad [2]$$

The system **100** uses this novel loss function (e.g., equation 2) to ensure that the embeddings for existing classes remain roughly intact while also ensuring that the embeddings associated with the new samples of a new gesture class form its own cluster in the embedding space. The system **100** is configured to ensure that each example of a gesture is predicted based on its closeness to the cluster of embeddings associated with its gesture class and its corresponding mean embedding of that same gesture class in the embedding space. The system **100** ensures that the new embeddings of a new gesture are spaced away (or distinguishable) from each cluster of embeddings of each existing gesture class. Also, after training and/or updating the gesture recognition system **200**, the system **100** stores (i) the mean embedding associated with each new gesture and (ii) the few examples of each new gesture. This information relating to the new gestures is stored in the memory system **130** similarly to the information relating to the existing gestures. In addition, the system **100** updates parameters of the gesture recognition system **200** based on loss data associated this additional training of the gesture recognition system **200** based on the new examples of each new gesture.

At step **510**, according to an example, the system **100** provides or outputs the updated gesture recognition system **200** for deployment and/or employment. The gesture recognition system **200** is configured to generate gesture data **30** indicative of a new gesture class, which was learned during the process **500**, as output in response to receiving sensor data **20** (e.g., video data) with the new gesture as input. In this regard, the gesture recognition system **200** is now configured to recognize each new gesture (and generate gesture data **30** indicative of each new gesture **12**) in addition to being able to recognize the existing gestures (and generate gesture data **30** indicative of each existing gesture **12**).

As discussed above, the gesture recognition system **200** is configured to learn one or more new gestures after having been trained with an initial training dataset that includes an initial set of gestures. That is, the gesture recognition system **200** is configured to learn one or more new gestures during test time and/or during inference. The gesture recognition system **200** learns to recognize a new gesture by being trained on just a number of examples (e.g., a few samples) of that new gesture. The gesture recognition system **200** does not require retraining of the network on a full training dataset to learn new gestures. Instead, the gesture recognition system **200** generates a mean embedding vector for a particular gesture based on the set of embedding vectors, which are generated by the gesture recognition system **200** (e.g., gesture recognizer **230**) based on selected patches of feature data of that particular gesture. The gesture recognition system **200** is configured to store (or save in the memory system **130**) only the mean embedding vector for each gesture that has been learned by the gesture recognition system **200**. Additionally, the gesture recognition system **200** is configured to store a number of videos as samples of each gesture from the training dataset.

FIG. **6** is a diagram of an example of a graphical visualization **600** of a principal component analysis (PCA). More specifically, FIG. **6** shows a non-limiting example of a representation of an embedding space between the x-axis and y-axis. Also, FIG. **6** also shows a legend in the upper, right corner of the graphical visualization. The legend shows a mapping of different colored dots, which refer to different embedding vectors, with respect to different numbered labels, which refer to different gesture classes (e.g., different gesture data **30**). However, since the PCA may be shown in black and white according to drawing requirements, the graphical visualization **600** further includes numbered labels adjacent to the clusters to indicate their corresponding colors, as indicated in the legend.

As previously discussed, the gesture recognition system **200** is configured to generate embedding vectors **234** in an embedding space such that embedding vectors **234** corresponding to examples that belong to the same gesture are generally clustered together. In addition, the gesture recognition system **200** is configured such that embedding vectors **234** of examples of one gesture are generally spaced away from other embedding vectors **234** of other examples of other gestures. For example, FIG. **6** shows embedding vectors of a first gesture (label 0, red) forming a first cluster, embedding vectors of a second gesture (label 1, orange) forming a second cluster, embedding vectors of a third gesture (label 2, yellow) forming a third cluster, embedding vectors of a fourth gesture (label 3, light green) forming a fourth cluster, embedding vectors of a fifth gesture (label 4, green) forming a fifth cluster, embedding vectors of a sixth gesture (label 5, light blue) forming a sixth cluster, embedding vectors of a seventh gesture (label 6, blue) forming a seventh cluster, embedding vectors of an eighth gesture (label 7, purple) forming an eighth cluster, embedding vectors of a ninth gesture (label 8, light magenta) forming a ninth cluster, embedding vectors of a tenth gesture (label 9, dark magenta) forming a tenth cluster.

FIG. **7** is a diagram of an example of a process **700** relating to continual learning of the gesture recognition system **200** according to an example embodiment. More specifically, the process **700** relates to adapting the gesture recognition system **200** to a new domain during test time and/or during inference. The process **700** ensures that the gesture recognition system **200** adapts the existing gestures, which was already learned, for example, to the shape of a user's gesturing part (e.g., shape of a user's hand), the appearance of the gesturing part (e.g., appearance of a user's hand), or the performance of a user's style of carrying out the gesture **12**. The user **10** may be a new user of the gesture recognition system **200**. The user **10** may be an existing user of the gesture recognition system **200** in which there has been some change, for example, to the shape of the user's gesturing part (e.g., shape of a user's hand), the appearance of the user's gesturing part (e.g., appearance of a user's hand), or the performance of the user's style of carrying out the gesture **12**. Adapting the gesture recognition system **200** to such inter-user variations helps improve gesture recognition for specific users. The process **700** is performed by one or more processors of the processing system **120** together with the gesture recognition system **200** and the machine learning data **150**. The process **700** may also involve the gesture application program **140**. As a non-limiting example, the process **500** may be performed on the device itself (e.g., the robot **102**), a cloud network, another device (e.g., mobile phone of user **10**) that communicates with the device (e.g., robot **102**), etc. The process **700** may include more steps or less steps than that shown in FIG. **7** provided that such modifications provide similar functionalities and objectives as described in this disclosure.

At step **702**, according to an example, the system **100** prompts a user **10** for examples of a specific gesture. The specific gesture refers to any one of the existing gestures, which the gesture recognition system **200** has already been trained to recognize prior to the current iteration of this process **700**. The system **100** is configured to prompt a user **10** via a graphical user interface, an audio prompt, a visual prompt, any prompting mechanism, or any number and combination thereof.

At step **704**, according to an example, the system **100** records and stores the examples of that specific gesture in the memory system **130**. The system **100** proceeds to capture a predetermined number of new examples (or new samples) of the specific gesture. Once the predetermined number of samples of that specific gesture has been captured, then the process **700** proceeds to step **706**.

At step **706**, according to an example, the system **100** determines whether or not there is another specific gesture to personalize. If there is another specific gesture to personalize, then the process **700** proceeds to step **702**. If there isn't another specific gesture to personalize, then the process **700** proceeds to step **708**.

At step **708**, according to an example, the system **100** trains the gesture recognition system **200** using the examples of each specific gesture, which were recorded and stored at step **704**. During this training, the system **100** uses test time entropy minimization to adapt the gesture recognition system **200** to the new domain. More specifically, for example, the system **100** is configured to generate a transformed embedding vector ("y") by performing an affine transformation on the embedding vector **234** (i.e., "x" that is extracted from the last neural network layer, e.g. CNN layer, of the gesture recognizer **230**) with parameters (e.g., parameter α and parameter β) such that the transformed embedding vector "y" can be defined as y=αx+β. In this example, the parameters are set such that α=1 and β=0. Also, when training with the new examples of each specific gesture, the gesture recognition system **200** is configured to use the transformed embedding vector ("y") in place of the embedding vector **234**. In addition, the system **100** generates loss data by minimizing a loss function with respect to all of the examples of each specific gesture obtained from the user **10** at step **704**. In this example, the loss function is a Shannon entropy loss function associated with the gesture recognizer **230**. For instance, the loss function may be represented as LOSS, as expressed in equation 3.

$$\mathrm{LOSS} = -\sum_{i=1}^{M}\sum_{j=1}^{N} f(y_i)_j \log\left(f(y_i)_j\right) \qquad [3]$$

In equation 3, y_i represents the transformed embedding vector such that $y_i=\alpha x_i+\beta$, where x_i represents the embedding vector ("x") of the i-th example of an existing gesture (or the specific gesture), which is performed by the user **10**. Here, f (y_i) represents the gesture prediction vector **236** (i.e., the probability distribution) associated with the transformed embedding vector y_i. Also, $f(y_i)_j$ is the probability that y_i is classified as the j-th gesture (which the gesture recognition system **200** had already been trained to recognize via previous training). In equation 3, M represents the total number of examples of the existing gesture (or the specific gesture), which is performed by the user **10** while N represents the total number of gestures that the gesture recognition system **200** is configured to recognize.

In addition, the system **100** updates parameter α and parameter β of the gesture recognizer **230** using this loss data, which is based on the additional training of the gesture recognition system **200** with the new examples of each specific gesture. In this regard, parameter α and parameter β are learned by the gesture recognition system **200** while the rest of the weights of the gesture recognition system **200** are frozen. After obtaining and updating the values for parameter α and parameter β while also updating y in place of x, the gesture recognition system **200** is updated and adapted to that user **10**.

At step **710**, according to an example, the processing system **120** provides or outputs the updated gesture recognition system **200** for deployment and/or employment. The gesture recognition system **200** is now adapted to this new domain and configured to generate gesture data **30** as output upon receiving sensor data **20**, which includes an existing gesture from this new domain (e.g. the new user) as input.

As described in this disclosure, the gesture recognition system **200** provides a number of advantages and benefits. For example, the gesture recognition system **200** comprises a novel and dynamic neural network, which is configured to recognize gestures with greater accuracy at longer distances than other systems with similar compute complexity by narrowing down the feature data **300** to a selected patch **304** (or a target patch), which contains the features of interest, for gesture classification. The gesture recognition system **200** is advantageous with respect to its dynamic neural network architecture, continual learning techniques, and domain adaptation techniques.

The gesture recognition system **200** is advantageously structured as a single neural network model, which is trained end-to-end. The gesture recognition system **200** is more efficient than two-stage systems, which comprise two different networks in two different stages. For example, two-stage systems need to train the first network separately from the second network. Also, two-stage systems typically require sensor data as input at both the first stage involving the first network and the second stage involving the second network, thereby increasing processing time. In contrast, the gesture recognition system **200** performs inference faster than similarly sized two-stage systems due to the shared features used by the patch selector **220** and the gesture recognizer **230**. The gesture recognition system **200** also performs faster than two-stage systems as the gesture recognizer **230** only handles and classifies each selected patch **304** of feature data, thereby significantly reducing the workload of the gesture recognizer **230** and enabling the gesture recognizer **230** to focus on features of interest (i.e., feature data corresponding to the subject data, such as a gesturing hand).

The gesture recognition system **200** is advantageously configured with a first subnetwork comprising a feature extractor **210**, a second subnetwork comprising a patch selector **220**, and a third subnetwork comprising a gesture recognizer **230**. The feature extractor **210** provides the patch selector **220** with feature data **300**. The feature data **300** is divided into a set of patches **302**. Each patch **302** is provided as input into a patch classifier **222** of the patch selector **220**. The patch selector **220** is dynamically configured to select a target patch as the feature data of interest (e.g., feature data corresponding to subject data such as a hand) for the gesture recognizer **230** to receive as input while filtering out other patches **302** (i.e., patches of feature data corresponding to non-subject data) so that the gesture recognizer **230** does not handle the feature data of these other patches **302**. The gesture recognizer **230** is therefore configured to classify the feature data of interest (e.g. the selected patch **304** of feature data corresponding to subject data such as a hand) while not

being burdened with the task of classifying the other non-selected patches **306** (e.g. feature data classified as non-subject data).

The gesture recognition system **200** is configured to use higher resolution input video compared to other similarly sized networks. By providing the feature extractor **210** at the onset, the gesture recognition system **200** benefits from a reduction in the size of features passing through the rest of the neural network layers (e.g., neural network layers of the patch selector **220** and the neural network layers of the gesture recognizer **230**) with no compromise on resolution unlike pooling. With its neural network architecture, the gesture recognition system **200** is configured to perform the task of gesture recognition accurately with a relatively low compute complexity.

In addition, the gesture recognition system **200** performs continual learning using novel techniques. For example, the gesture recognition system **200** is configured to learn new gestures using only a few examples without requiring the gesture recognition system **200** to be retrained with its entire dataset of training data. In addition, the gesture recognition system **200** is configured to be personalized to the gestures of one or more users **10**. The gesture recognition system **200** is configured to adapt to a new domain (e.g., a new user performing the gesture **12** or a different style of performing the specific gesture **12**) at test time. In addition, unlike other distance-based classifiers that do not retain knowledge of its initial trained classes when learning new classes, the gesture recognition system **200** is configured to retain knowledge of its initial trained gesture classes when learning new gesture classes.

Furthermore, the gesture recognition system **200** may be applied to various technologies to allow users **10** to use gestures to control these various technologies. For example, the gesture recognition system **200** may be applied to a warehouse robot, a home appliance, a car media system, any technological device, or any number and combination thereof. In this regard, the gesture recognition system **200** may be used to communicate with and convey instructions to various types of robots, various types of IoT devices, various televisions/screens, various appliances, various technologies benefiting from touch-free operations, or any number and combination thereof.

That is, the above description is intended to be illustrative, and not restrictive, and provided in the context of a particular application and its requirements. The present invention may be implemented in a variety of forms. In addition, various embodiments may be implemented alone or in combination. Therefore, while the embodiments of the present invention have been described in connection with particular examples thereof, the general principles defined herein may be applied to other embodiments and applications without departing from the spirit and scope of the described embodiments, and the true scope of the embodiments and/or methods of the present invention are not limited to the embodiments shown and described, since various modifications will become apparent upon a study of the drawings, specification, and following claims. Additionally or alternatively, components and functionality may be separated or combined differently than in the manner of the various described embodiments, and may be described using different terminology. These and other variations, modifications, additions, and improvements may fall within the scope of the disclosure as defined in the claims that follow.

What is claimed is:

1. A computer-implemented method for a machine learning system to learn to recognize gestures, the computer-implemented method comprising:

training the machine learning system using a training dataset of sensor data that include a set of gestures, the training dataset including at least a first subset that displays a first gesture and a second subset that displays a second gesture;

generating loss data based on a first loss function that includes a first cross entropy loss and a second cross entropy loss;

updating parameters of the machine learning system based on the loss data; and

outputting the machine learning system for gesture recognition of the set of gestures,

wherein,

the machine learning system includes (i) a first subnetwork to generate feature data based on the sensor data, (ii) a second subnetwork to extract a selected patch of the feature data, and (iii) a third subnetwork to generate gesture data based on a classification of the corresponding feature data of the selected patch,

the first cross entropy loss is based on a first performance of the second subnetwork in relation to the training dataset, and

the second cross entropy loss is based on a second performance of third subnetwork in relation to the training dataset.

2. The computer-implemented method of claim 1, wherein the first subnetwork, the second subnetwork, and the third subnetwork form an artificial neural network model that is trained end-to-end.

3. The computer-implemented method of claim 1, further comprising:

receiving additional sensor data that include samples of a new gesture, the additional sensor data being received after the machine learning system has been trained on the training dataset;

training the machine learning system with the samples of the new gesture;

generating additional loss data via a second loss function based on the training of the machine learning system with respect to at least the samples of the new gesture, the second loss function being different from the first loss function; and

updating the parameters of the machine learning system based on the additional loss data.

4. The computer-implemented method of claim 3, wherein the second loss function is optimized such that the new gesture is associated with new embeddings that form a new cluster in an embedding space.

5. The computer-implemented method of claim 4, wherein the second loss function is optimized such that the new cluster of the new gesture is spaced away from at least (i) a first cluster of embeddings of the first gesture and (ii) a second cluster of embeddings of the second gesture.

6. The computer-implemented method of claim 1, further comprising:

receiving additional sensor data that include samples of the first gesture being performed by a new gesturer;

training the machine learning system using the samples to adapt the machine learning system to the new gesturer;

generating additional loss data via another loss function; and

updating affine parameters of the machine learning system based on the additional loss data.

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

generating, via the machine learning system, embeddings based on the samples;

generating output by performing affine transformations on the embeddings using the affine parameters when the machine learning system is being trained with the samples; and

generating the additional loss data based on the output,

wherein the another loss function is a Shannon entropy loss function.

8. A system for gesture recognition comprising:

a processor; and

a non-transitory computer readable medium in data communication with the processor, the non-transitory computer readable medium having computer readable data including instructions stored thereon that when executed by the processor is configured to cause the processor to perform a method that comprises:

training a machine learning system using a training dataset of sensor data that include a set of gestures, the training dataset including at least a first subset that displays a first gesture and a second subset that displays a second gesture;

generating loss data based on a first loss function that includes a first cross entropy loss and a second cross entropy loss;

updating parameters of the machine learning system based on the loss data; and

outputting the machine learning system for gesture recognition of the set of gestures,

wherein,

the machine learning system includes (i) a first subnetwork to generate feature data based on the sensor data, (ii) a second subnetwork to extract a selected patch of the feature data, and (iii) a third subnetwork to generate gesture data based on a classification of the corresponding feature data of the selected patch,

the first cross entropy loss is based on a first performance of the second subnetwork in relation to the training dataset, and

the second cross entropy loss is based on a second performance of third subnetwork in relation to the training dataset.

9. The system of claim 8, wherein the first subnetwork, the second subnetwork, and the third subnetwork form an artificial neural network model that is trained end-to-end.

10. The system of claim 8, wherein the method further comprises:

receiving additional sensor data that include samples of a new gesture, the additional sensor data being received after the machine learning system has been trained on the training dataset;

training the machine learning system with the samples of the new gesture;

generating additional loss data via a second loss function based on the training of the machine learning system with respect to at least the samples of the new gesture, the second loss function being different from the first loss function; and

updating the parameters of the machine learning system based on the additional loss data.

11. The system of claim 10, wherein the second loss function is optimized such that the new gesture is associated with new embeddings that form a new cluster in an embedding space.

12. The system of claim **11**, wherein the second loss function is optimized such that the new cluster of the new embeddings of the new gesture is spaced away from at least (i) a first cluster of embeddings of the first gesture and (ii) a second cluster of embeddings of the second gesture.

13. The system of claim **10**, further comprising:

receiving additional sensor data that include samples of the first gesture being performed by a new gesturer;

training the machine learning system using the samples to adapt the machine learning system to the new gesturer;

generating additional loss data via another loss function; and

updating affine parameters of the machine learning system based on the additional loss data.

14. The system of claim **13**, further comprising:

generating, via the machine learning system, embeddings based on the samples;

generating output by performing affine transformations on the embeddings using the affine parameters when the machine learning system is being trained with the samples; and

generating the additional loss data based on the output,

wherein the another loss function is a Shannon entropy loss function.

15. A non-transitory computer readable medium having computer readable data including instructions stored thereon that, when executed by a processor, is configured to cause the processor to perform a method that comprises:

training a machine learning system using a training dataset of sensor data that include a set of gestures, the training dataset including at least a first subset that displays a first gesture;

generating loss data based on a first loss function that includes a first cross entropy loss and a second cross entropy loss;

updating parameters of the machine learning system based on the loss data; and

outputting the machine learning system for gesture recognition of the set of gestures,

wherein,

the machine learning system includes (i) a first subnetwork to generate feature data based on the sensor data, (ii) a second subnetwork to extract a selected patch of the feature data, and (iii) a third subnetwork to generate gesture data based on a classification of the corresponding feature data of the selected patch,

the first cross entropy loss is based on a first performance of the second subnetwork in relation to the training dataset, and

the second cross entropy loss is based on a second performance of third subnetwork in relation to the training dataset.

16. The non-transitory computer readable medium of claim **15**, wherein the first subnetwork, the second subnetwork, and the third subnetwork form an artificial neural network model that is trained end-to-end.

17. The non-transitory computer readable medium of claim **15**, further comprising:

receiving additional sensor data that include samples of a new gesture, the additional sensor data being received after the machine learning system has been trained on the training dataset;

training the machine learning system with the samples of the new gesture;

generating additional loss data via a second loss function based on the training of the machine learning system with respect to at least the samples of the new gesture, the second loss function being different from the first loss function; and

updating the parameters of the machine learning system based on the additional loss data.

18. The non-transitory computer readable medium of claim **17**, wherein the second loss function is optimized such that the new gesture is associated with new embeddings that form a new cluster in an embedding space that is spaced away from at least a first cluster of embeddings of the first gesture.

19. The non-transitory computer readable medium of claim **15**, further comprising:

receiving additional sensor data that include samples of the first gesture being performed by a new gesturer;

training the machine learning system using the samples to adapt the machine learning system to the new gesturer;

generating additional loss data via another loss function; and

updating affine parameters of the machine learning system based on the additional loss data.

20. The non-transitory computer readable medium of claim **19**, further comprising:

generating, via the machine learning system, embeddings based on the samples;

generating output by performing affine transformations on the embeddings using the affine parameters when the machine learning system is being trained with the samples; and

generating the additional loss data based on the output,

wherein the another loss function is Shannon entropy loss function.

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