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(54) **USER PRESENCE/ABSENCE RECOGNITION DURING ROBOTIC SURGERIES USING DEEP LEARNING**

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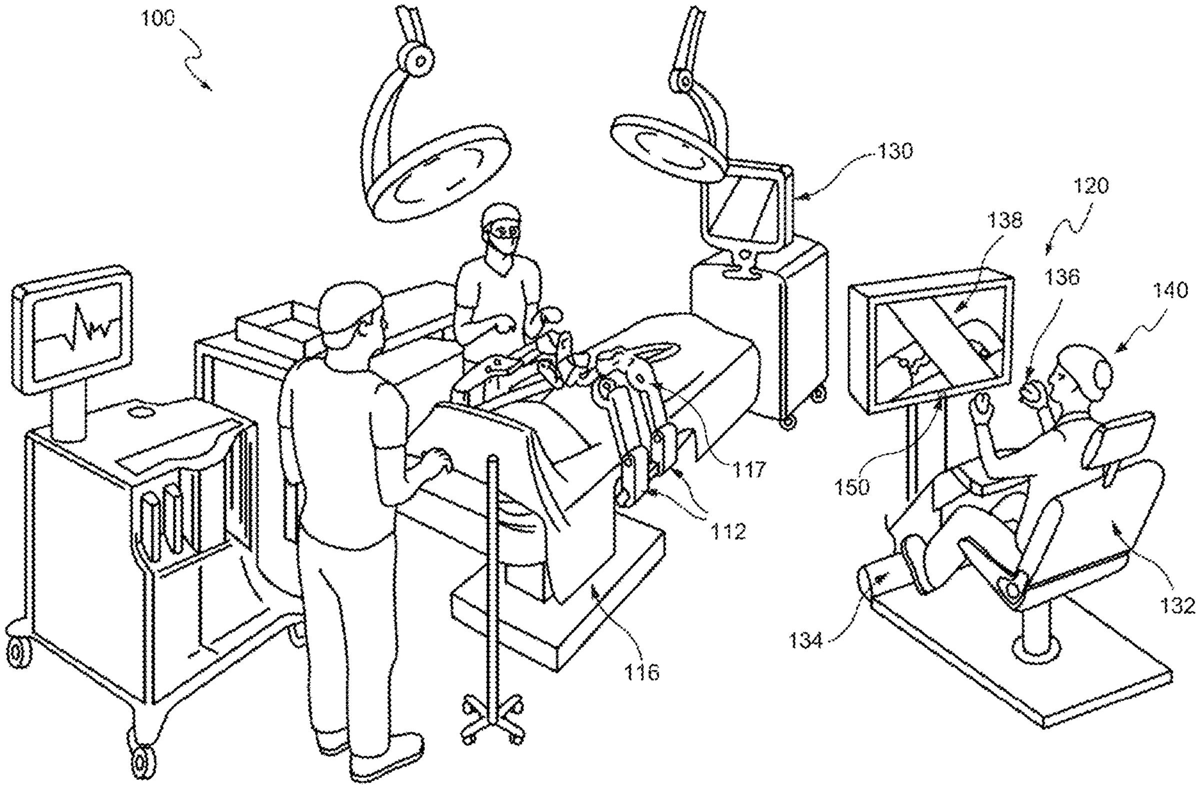
(57) **ABSTRACT**

Disclosed are various user-presence/absence recognition techniques based on deep learning. More specifically, various user-presence/absence recognition techniques include building/training a CNN-based image recognition model including a user-presence/absence classifier based on training images collected from the user-seating area of a surgeon console under various clinically-relevant conditions/cases. The trained user-presence/absence classifier can then be used during teleoperation/surgical procedures to monitor/track users in the user-seating area of the surgeon console, and continuously classify the real-time video images of the user-seating area as either a user-presence state or a user-absence state. In some embodiments, the disclosed techniques can be used to detect a user-switching event at the surgeon console when a second user is detected to have entered the user-seating area after a first user is detected to have exited the user-seating area. If the second user is identified as a new user, the disclosed techniques can trigger a recalibration procedure for the new user.



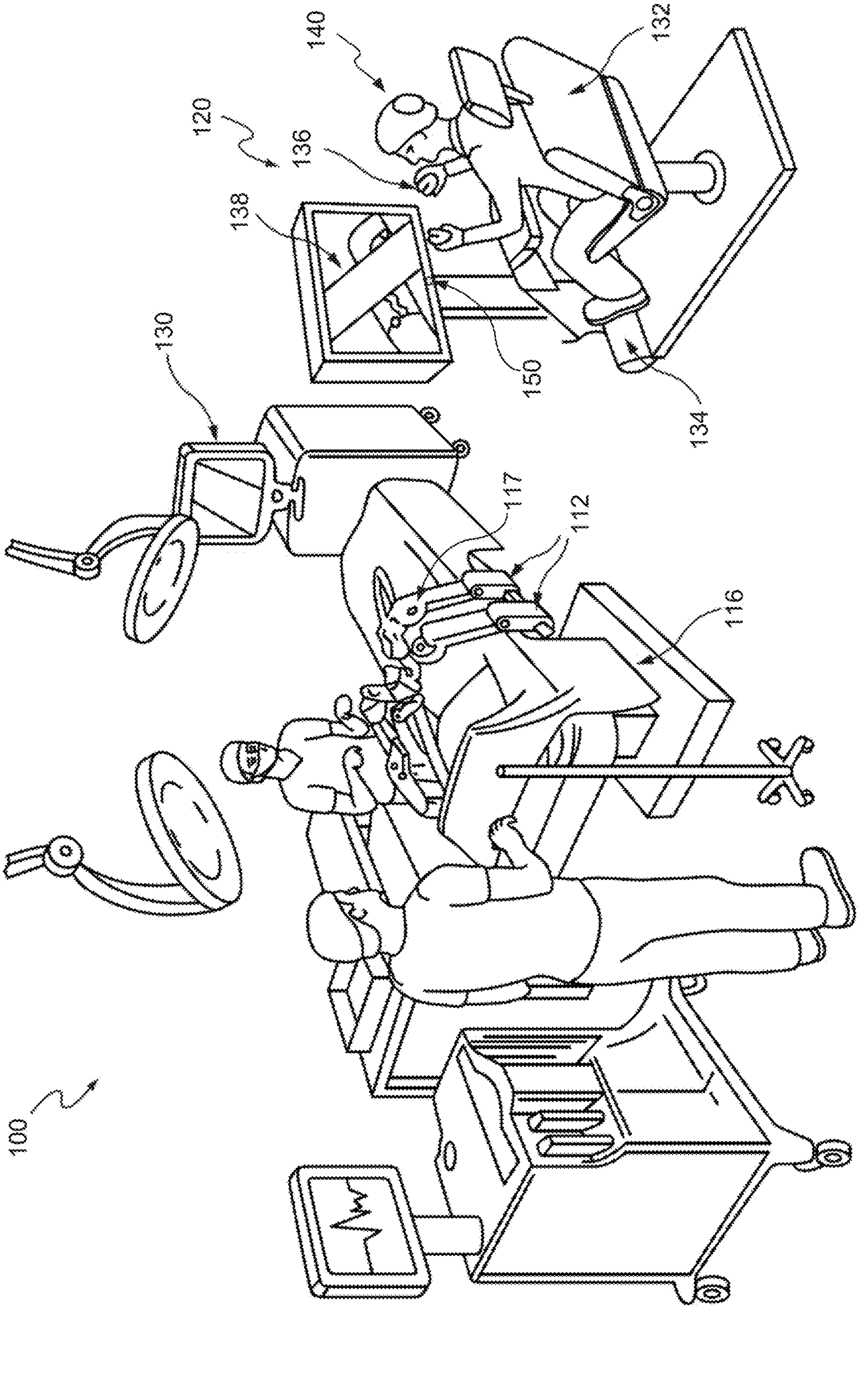
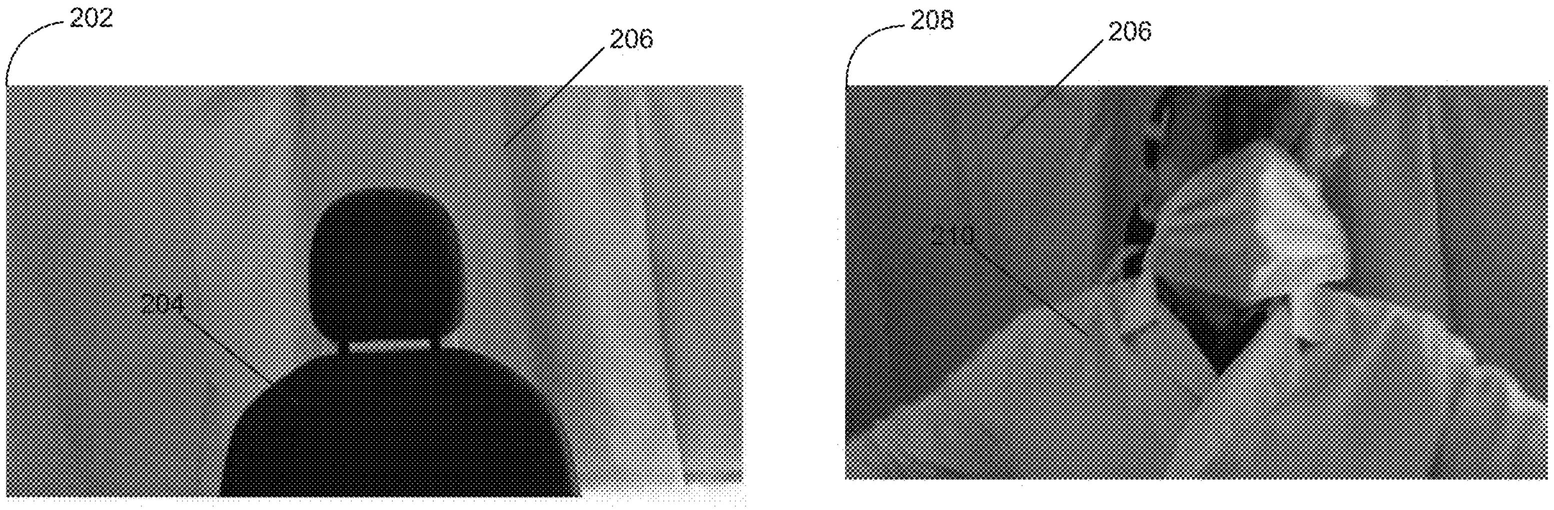


FIG. 1

TWO SCENARIOS OF USER SEATING AERA 200



USER ABSENCE (0)

USER PRESENCE (1)

FIG. 2

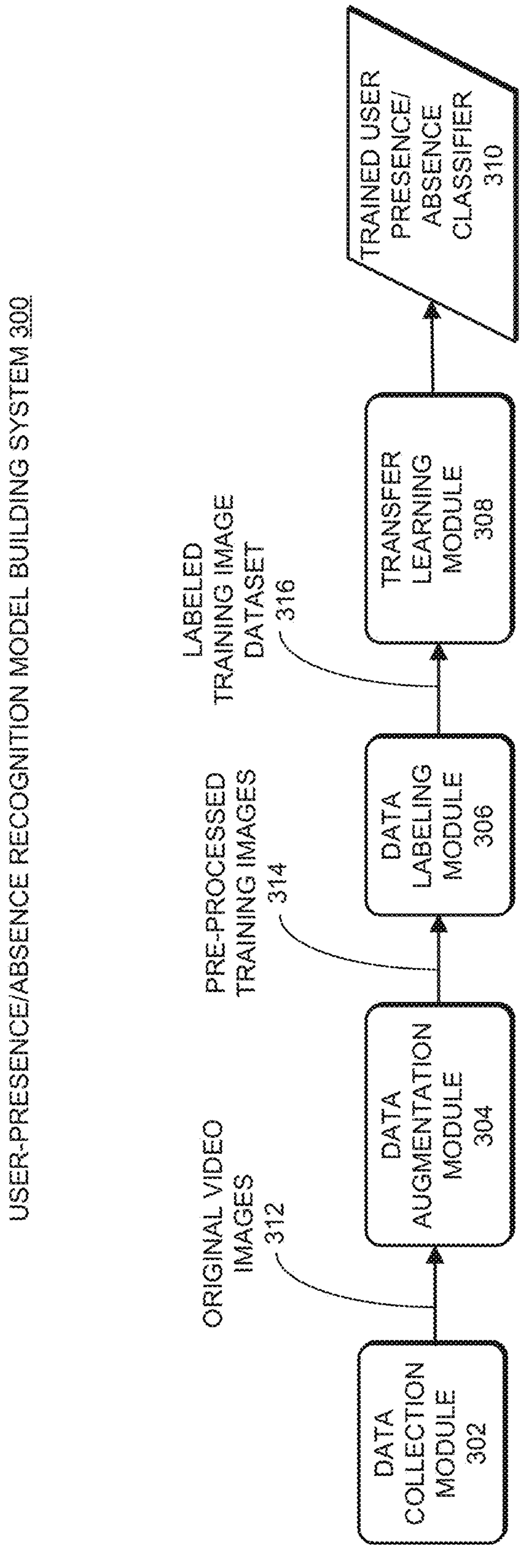

USER-PRESENCE/ABSENCE RECOGNITION MODEL BUILDING SYSTEM 300
DATA COLLECTION MODULE 302
ORIGINAL VIDEO IMAGES 312
DATA AUGMENTATION MODULE 304
PRE-PROCESSED TRAINING IMAGES 314
DATA LABELING MODULE 306
LABELED TRAINING IMAGE DATASET 316
TRANSFER LEARNING MODULE 308
TRAINED USER PRESENCE/ ABSENCE CLASSIFIER 310

FIG. 3

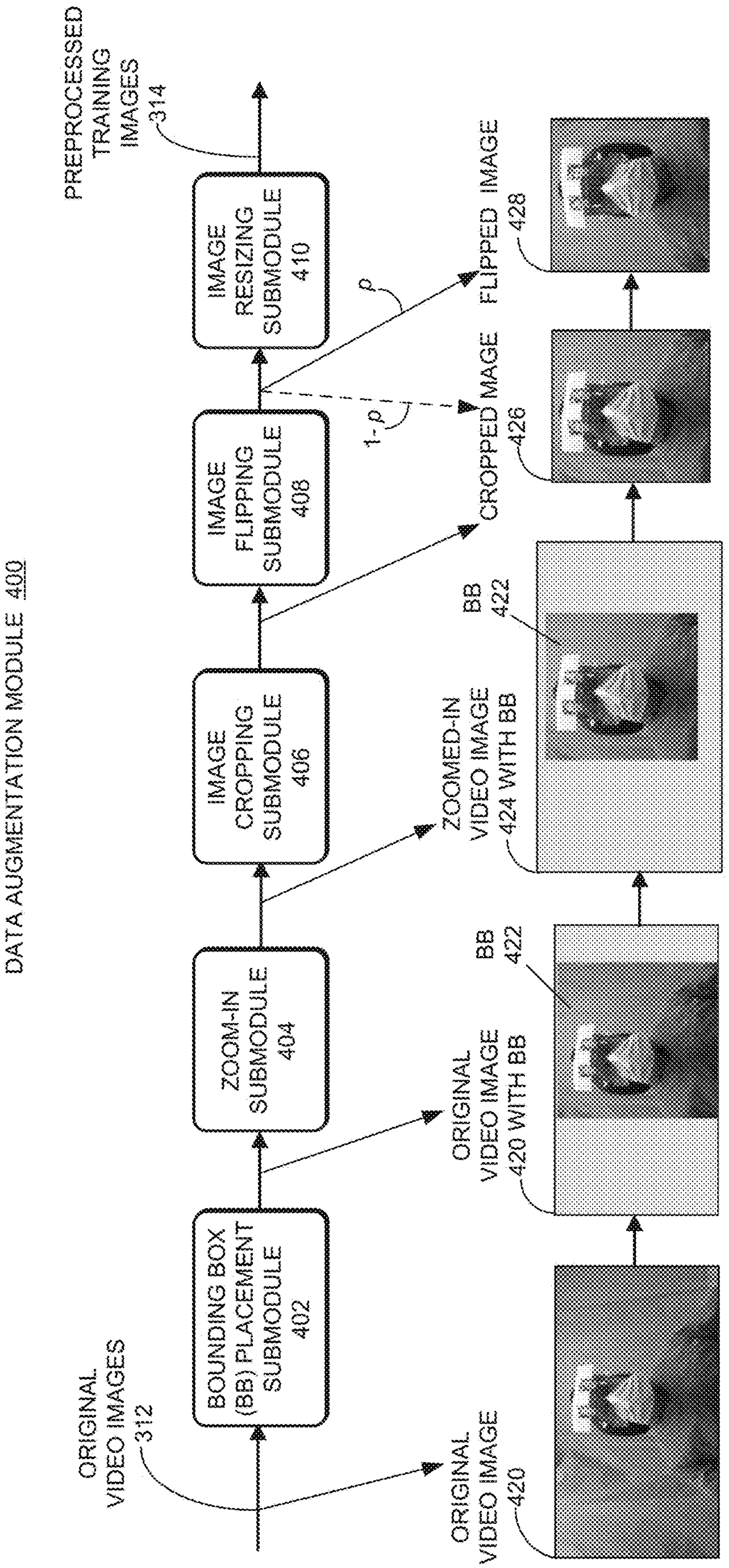

DATA AUGMENTATION MODULE 400
ORIGINAL VIDEO IMAGES 312
BOUNDING BOX (BB) PLACEMENT SUBMODULE 402
ZOOM-IN SUBMODULE 404
IMAGE CROPPING SUBMODULE 406
IMAGE FLIPPING SUBMODULE 408
IMAGE RESIZING SUBMODULE 410
PREPROCESSED TRAINING IMAGES 314
ORIGINAL VIDEO IMAGE 420
ORIGINAL VIDEO IMAGE 420 WITH BB
BB 422
ZOOMED-IN VIDEO IMAGE 424 WITH BB
BB 422
CROPPED IMAGE 426
1-p
p
FLIPPED IMAGE 428

FIG. 4

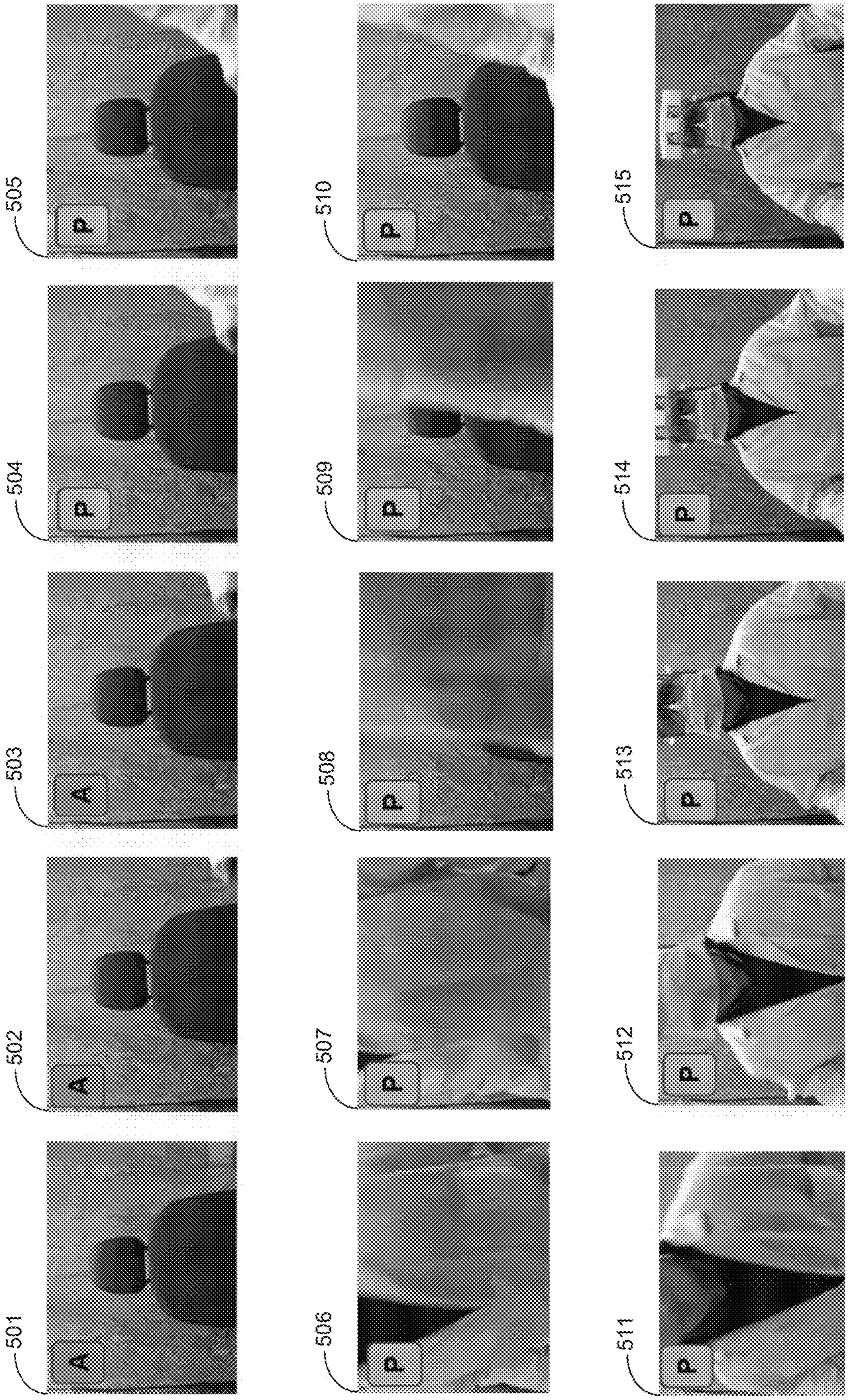

501
A
502
A
503
A
504
P
505
P
506
P
507
P
508
P
509
P
510
P
511
P
512
P
513
P
514
P
515
P

FIG. 5

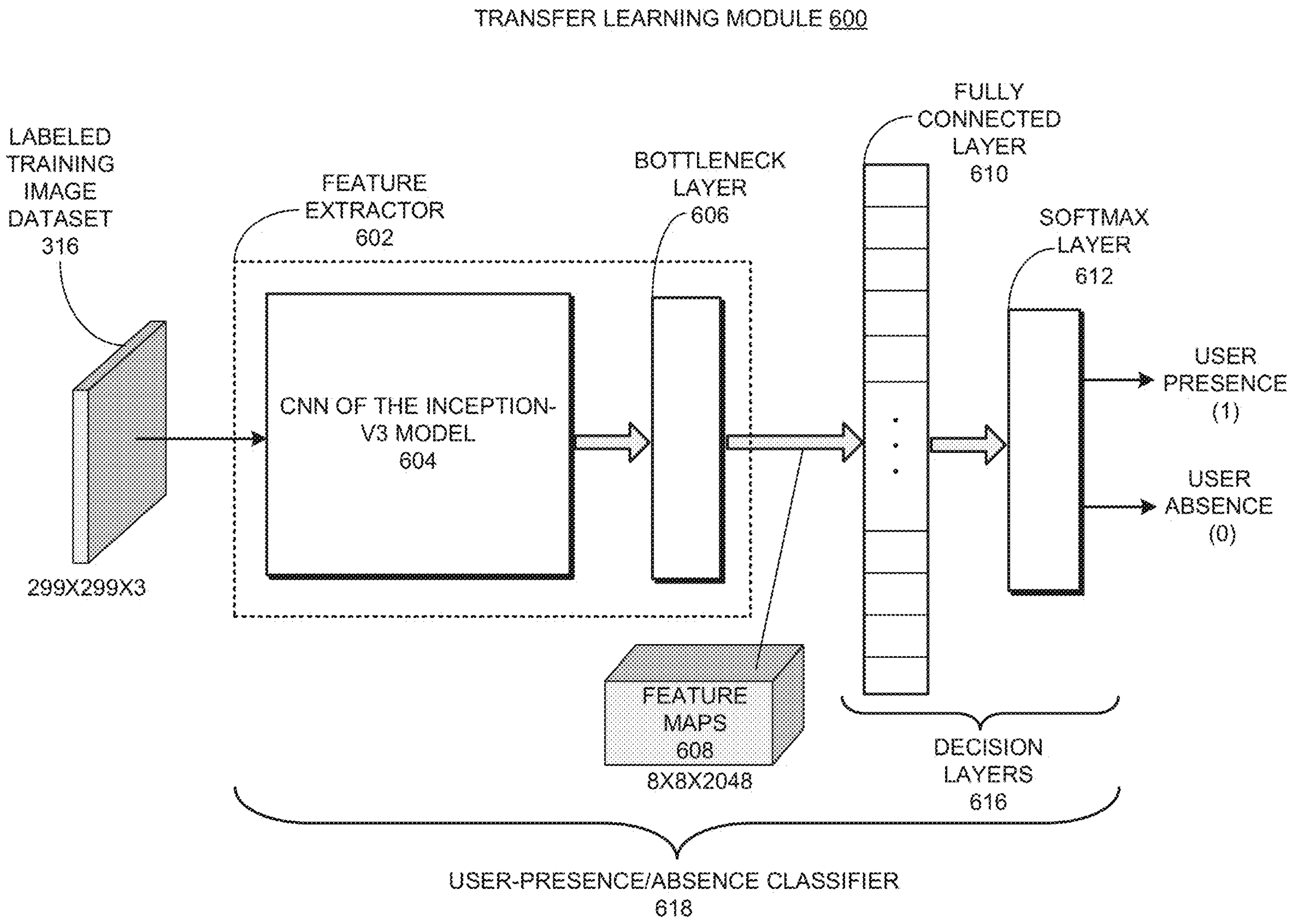

TRANSFER LEARNING MODULE 600
LABELED TRAINING IMAGE DATASET 316
299X299X3
FEATURE EXTRACTOR 602
CNN OF THE INCEPTION-V3 MODEL 604
BOTTLENECK LAYER 606
FEATURE MAPS 608
8X8X2048
FULLY CONNECTED LAYER 610
SOFTMAX LAYER 612
USER PRESENCE (1)
USER ABSENCE (0)
DECISION LAYERS 616
USER-PRESENCE/ABSENCE CLASSIFIER 618

FIG. 6

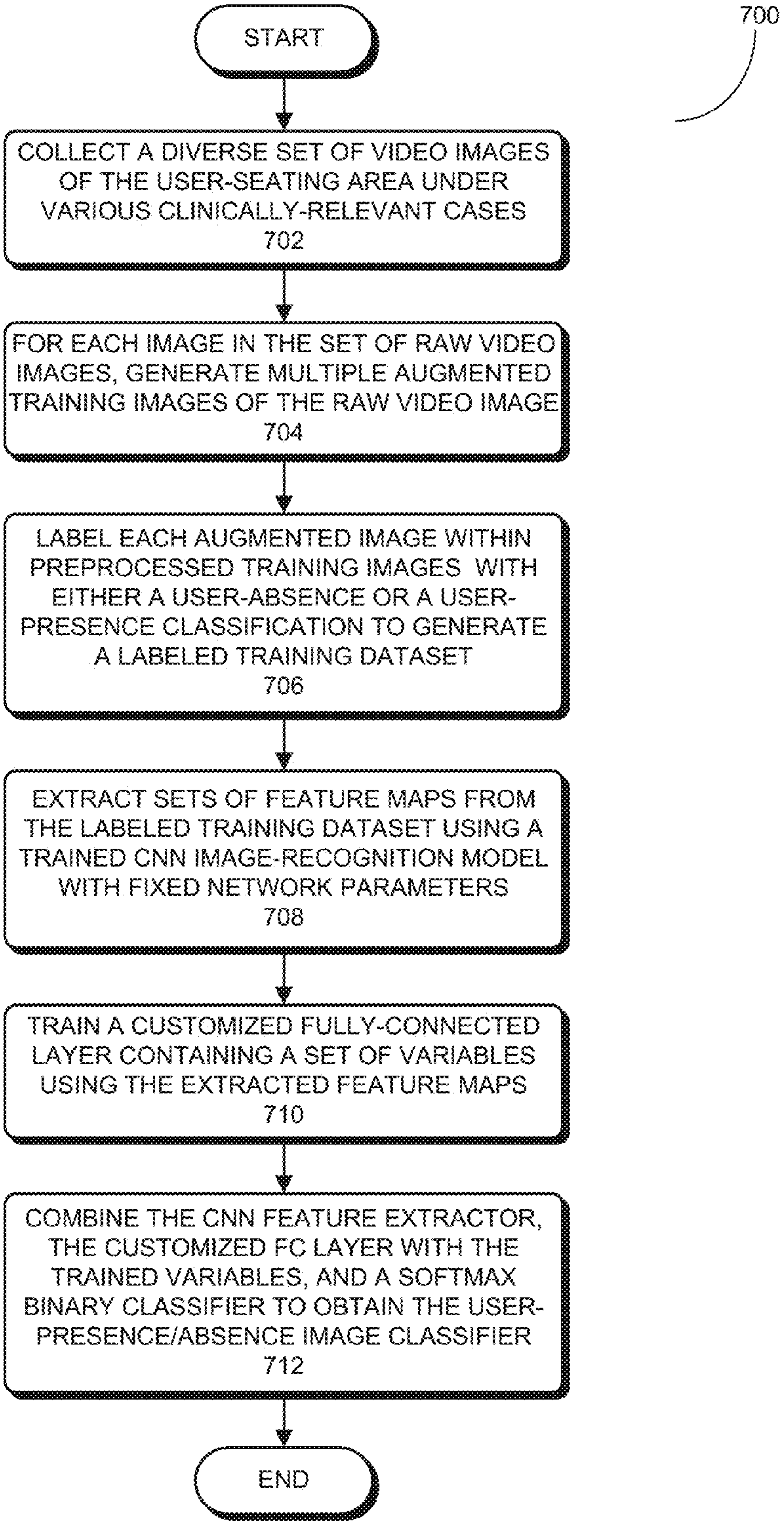

700
START
COLLECT A DIVERSE SET OF VIDEO IMAGES OF THE USER-SEATING AREA UNDER VARIOUS CLINICALLY-RELEVANT CASES
702
FOR EACH IMAGE IN THE SET OF RAW VIDEO IMAGES, GENERATE MULTIPLE AUGMENTED TRAINING IMAGES OF THE RAW VIDEO IMAGE
704
LABEL EACH AUGMENTED IMAGE WITHIN PREPROCESSED TRAINING IMAGES WITH EITHER A USER-ABSENCE OR A USER-PRESENCE CLASSIFICATION TO GENERATE A LABELED TRAINING DATASET
706
EXTRACT SETS OF FEATURE MAPS FROM THE LABELED TRAINING DATASET USING A TRAINED CNN IMAGE-RECOGNITION MODEL WITH FIXED NETWORK PARAMETERS
708
TRAIN A CUSTOMIZED FULLY-CONNECTED LAYER CONTAINING A SET OF VARIABLES USING THE EXTRACTED FEATURE MAPS
710
COMBINE THE CNN FEATURE EXTRACTOR, THE CUSTOMIZED FC LAYER WITH THE TRAINED VARIABLES, AND A SOFTMAX BINARY CLASSIFIER TO OBTAIN THE USER-PRESENCE/ABSENCE IMAGE CLASSIFIER
712
END

FIG. 7

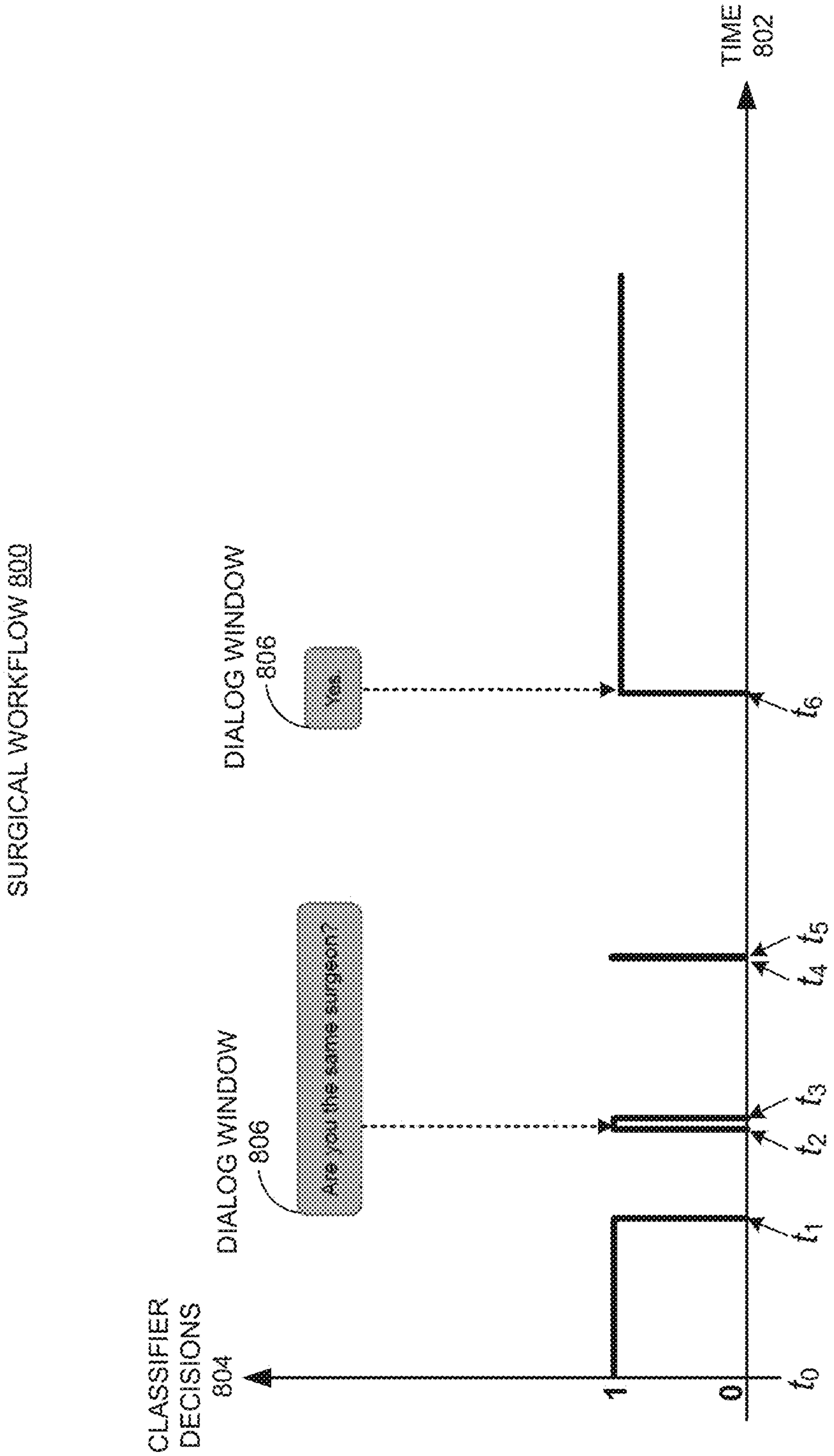

SURGICAL WORKFLOW 800
CLASSIFIER DECISIONS 804
1
0
t_0
t_1
DIALOG WINDOW 806
Are you the same surgeon?
t_2
t_3
t_4
t_5
DIALOG WINDOW 806
Yes
t_6
TIME 802

FIG. 8

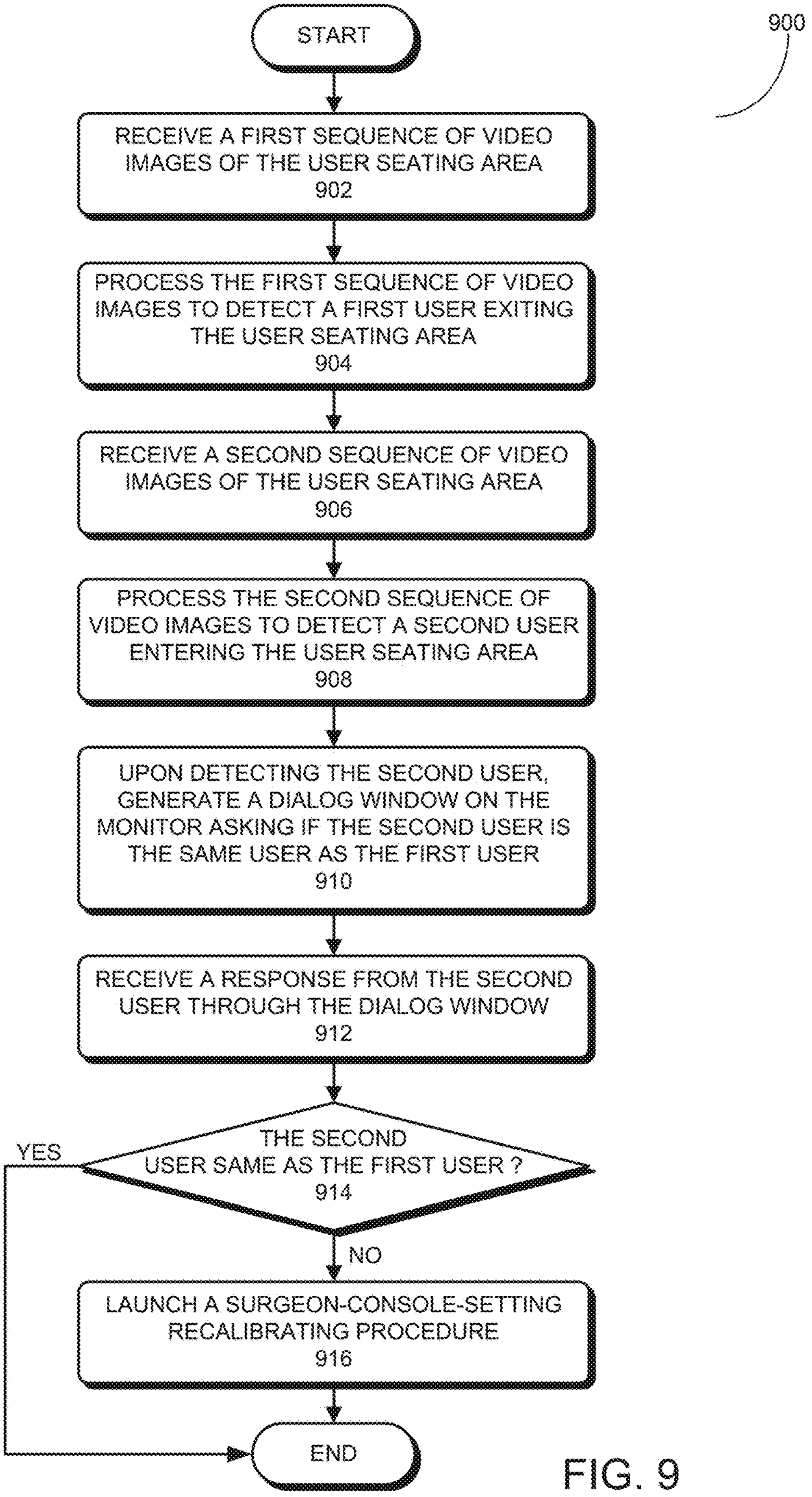

900
START
RECEIVE A FIRST SEQUENCE OF VIDEO IMAGES OF THE USER SEATING AREA
902
PROCESS THE FIRST SEQUENCE OF VIDEO IMAGES TO DETECT A FIRST USER EXITING THE USER SEATING AREA
904
RECEIVE A SECOND SEQUENCE OF VIDEO IMAGES OF THE USER SEATING AREA
906
PROCESS THE SECOND SEQUENCE OF VIDEO IMAGES TO DETECT A SECOND USER ENTERING THE USER SEATING AREA
908
UPON DETECTING THE SECOND USER, GENERATE A DIALOG WINDOW ON THE MONITOR ASKING IF THE SECOND USER IS THE SAME USER AS THE FIRST USER
910
RECEIVE A RESPONSE FROM THE SECOND USER THROUGH THE DIALOG WINDOW
912
THE SECOND USER SAME AS THE FIRST USER ?
914
YES
NO
LAUNCH A SURGEON-CONSOLE-SETTING RECALIBRATING PROCEDURE
916
END

FIG. 9

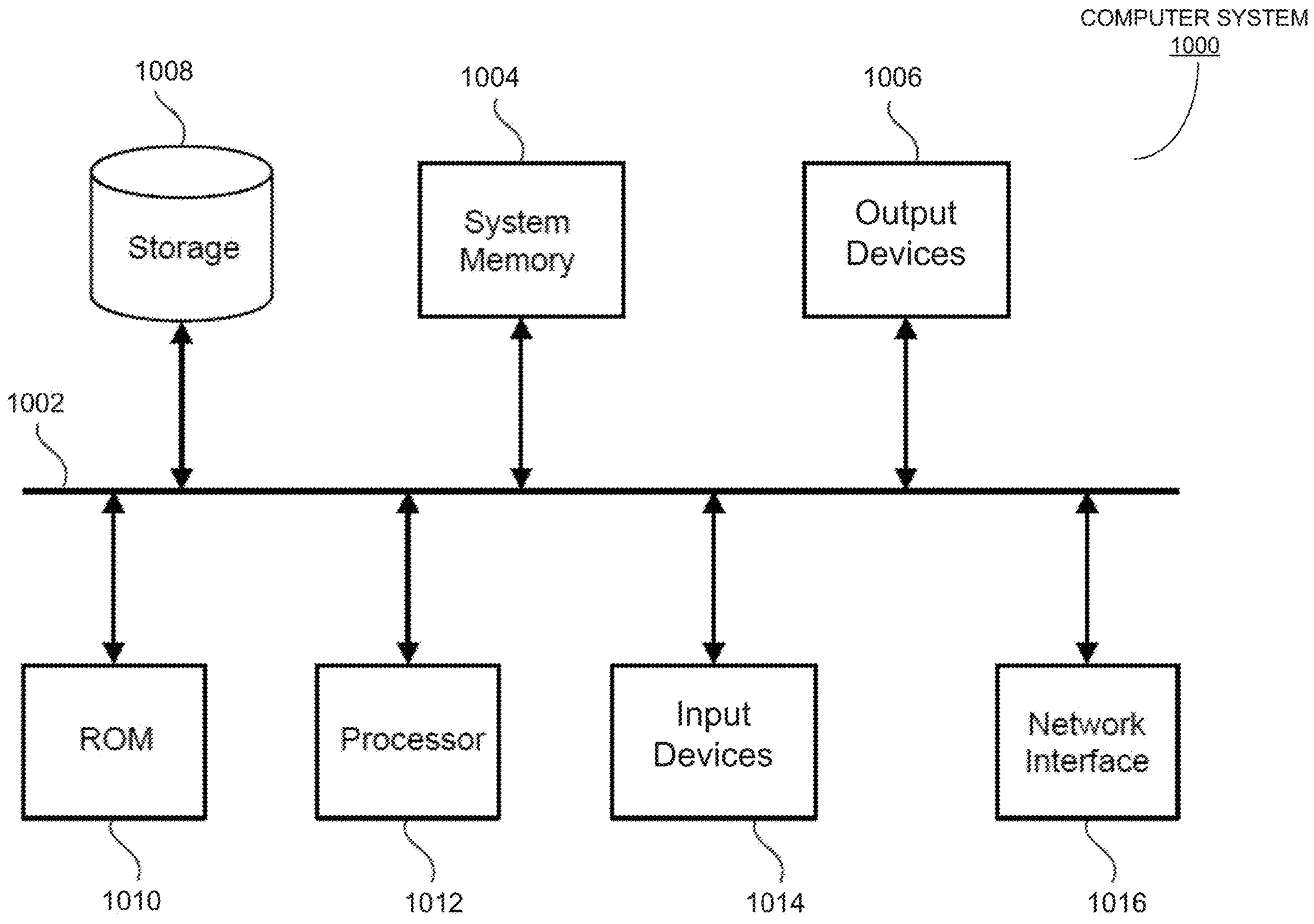

COMPUTER SYSTEM
1000
1008
Storage
1004
System Memory
1006
Output Devices
1002
ROM
Processor
Input Devices
Network Interface
1010
1012
1014
1016

FIG. 10

USER PRESENCE/ABSENCE RECOGNITION DURING ROBOTIC SURGERIES USING DEEP LEARNING

TECHNICAL FIELD

[0001] The present disclosure generally relates to robotic surgical systems, and more specifically to systems, devices and techniques for automatically recognizing users/surgeons' presence at or absence from surgeon consoles during robotic surgeries.

BACKGROUND

[0002] Endoscopic surgery involves looking into a patient's body and performing surgery inside the patient's body using endoscopes and other surgical tools. For example, laparoscopic surgery can use a laparoscope to access and view an abdominal cavity. Endoscopic surgery can be performed using manual tools and/or a robotic surgical system having robotically-assisted tools.

[0003] A robotic surgical system may be remotely operated by a surgeon to command a robotically-assisted surgical tool located at an operating table. Such operation of a robotically-assisted tool remotely controlled by a surgeon may be commonly referred to as teleoperation. For example, the surgeon may use a computer console located in the operating room, or it may be located in a different city, to command a robot to manipulate the surgical tool mounted on the operating table. The robotically-assisted tools can include an endoscope mounted on a robotic arm. Accordingly, the surgical robotic system may be used by the remote surgeon to perform an endoscopic surgery.

[0004] The surgeon console of the robotic surgical system often includes an eye tracking mechanism configured to track the gaze of a user/surgeon during a surgical procedure. For a given surgeon using the surgeon console during a new surgical procedure, the eye tracking mechanism needs to be calibrated or otherwise configured for the surgeon before starting the new surgical procedure. During the subsequent surgical procedure, the surgeon may need to leave the console for a number of reasons, such as to get help with the procedure. After the surgeon has left the console, it is possible that a new surgeon steps in and takes over the surgical procedure. When this user-swap event occurs, the robotic surgical system needs to ensure that the eye tracking settings are recalibrated or reconfigured for the new surgeon, because different users typically have different eye tracking settings. However, existing robotic surgical systems do not include mechanisms to detect such user-swap events during a surgical procedure. As a result, existing robotic surgical systems would continue to use the eye tracking settings of the previous surgeon on the new surgeon, which can lead to inaccurate eye-tracking control signals that would further lead to unsafe/unintended robotic arm or tool motions.

SUMMARY

[0005] Disclosed are various user-presence/absence recognition techniques based on image processing and deep learning. More specifically, various user-presence/absence recognition techniques include building/training a convolutional neural network (CNN)-based image recognition model including a user-presence/absence classifier based on training images collected from the user-seating area of a surgeon console within a robotic surgical system under various clinically-relevant conditions/cases. The trained user-presence/absence classifier can then be used during teleoperation/surgical procedures to monitor/track users in the user-seating area of the surgeon console, and continuously classify the real-time video images of the user-seating area as either a user-presence state or a user-absence state.

[0006] In some embodiments, the disclosed user-presence/absence recognition techniques can be used to detect a user-switching event at the surgeon console when a second user is detected to have entered the user-seating area after a first user is detected to have exited the user-seating area. The detection of the user-switching event allows for prompting the second user in the user-seating area to identify him/herself as either the same user as the first user or a different user. If the second user is identified as a new user, the disclosed user-presence/absence recognition techniques can trigger a recalibration procedure for the new user of user-console settings, including but are not limited to: user gaze-tracking settings; user UID-control settings; and user seat settings (e.g., the armrest settings).

[0007] In one aspect, a process for detecting user presence/absence at a surgeon console in a robotic surgical system is disclosed. This process can begin by receiving a set of raw video images capturing a user seating area of the surgeon console. Next, the process processes the set of raw video images to generate a set of training images. The process next trains a convolutional neural network (CNN) model using the set of training images. More specifically, the CNN model includes an image classifier configured to output a binary classification for each input image, wherein the binary classification is either a user-presence classification or a user-absence classification. The process further receives a set of real-time video images of the user seating area captured during a surgical session. The process subsequently applies the trained CNN model to the set of real-time video images to automatically classify each video image in the set of real-time video images as either a user-presence classification or a user-absence classification.

[0008] In some embodiments, the process processes the set of raw video images to generate the set of training images by, for each raw video image in the set raw of video images: generating a plurality of augmented images of the raw video image using a set of image augmentation techniques; and including one or more of the plurality of augmented images in the set of training images.

[0009] In some embodiments, the process generates the plurality of augmented images using the set of image augmentation techniques by first placing a bounding box of first predetermined dimensions within the frame of the raw video image. The process subsequently crops the raw image with the bounding box to generate a first augmented image of the raw image having the first predetermined dimensions.

[0010] In some embodiments, the process further includes zooming in on the first augmented image with a random zoom-in factor to generate a second augmented image of the raw image having the first predetermined dimensions.

[0011] In some embodiments, the process further includes flipping the second augmented image horizontally to generate a third augmented image of the raw image having the first predetermined dimensions.

[0012] In some embodiments, the first predetermined dimensions include a vertical dimension and a horizontal dimension which are both equal to the smaller dimension of the raw image.

[0013] In some embodiments, after generating the set of training images, the process further includes automatically annotating each training image in the set of training images with either a user-presence label indicating the presence of a user in the training image or a user-absence label indicating the absence of any user in the training image.

[0014] In some embodiments, the process automatically annotates the training image in the set of training images by first detecting a seat object within the training image using an image recognition technique. The process next determines if a part of the detected seat object is blocked by another object in the training image. If so, the process labels the training image with the user-presence label. Otherwise, the process labels the training image with the user-absence label.

[0015] In some embodiments, the process annotates the training image in the set of training images by labeling the training image with the user-presence label if the image recognition technique fails to detect a seat object.

[0016] In some embodiments, the CNN model is composed of a stack of feature-extraction layers including a sequence of convolutional layers and a sequence of pooling layers having a first set of parameters. The stack of feature-extraction layers is followed a fully-connected layer having a second set of parameters, which is further followed by a final output layer.

[0017] In some embodiments, to train the CNN model using the set of training images, the process uses the stack of feature-extraction layers to extract a set of two-dimensional (2D) feature maps for each training image in the set of training images while fixing the first set of parameters. The process then trains the second set of parameters of the fully-connected layer based at least on the sets of extracted 2D feature maps extracted from the set of training images to obtain a trained fully-connected layer. The process subsequently fixes both the first set of parameters and the trained second set of parameters in the CNN model to obtain the trained CNN model.

[0018] In some embodiments, the stack of feature-extraction layers includes a portion of a Inception-v3 image-recognition model from the input layer up to the bottleneck layer. Moreover, the Inception-v3 image-recognition model was previously trained to detect and recognize objects unrelated to detecting user presence/absence at the surgeon console.

[0019] In another aspect, an apparatus for detecting user presence/absence at a surgeon console in a robotic surgical system is disclosed. This apparatus includes one or more processors; and a memory coupled to the one or more processors. The memory of the apparatus stores instructions that, when executed by the one or more processors, cause the apparatus to: receive a set of raw video images capturing a user seating area of the surgeon console; process the set of raw video images to generate a set of training images; train a deep-learning image classifier using the set of training images, wherein the deep-learning image classifier is configured to receive an input image, process the input image, and output a binary classification for the input image, and wherein the binary classification is either a user-presence classification or a user-absence classification; receive a set of real-time video images of the user seating area captured during a surgical session; and apply the trained deep-learning image classifier to the set of real-time video images to automatically classify each video image in the set of real-time video images as either the user-presence classification or the user-absence classification.

[0020] In yet another aspect, a robotic surgical system is disclosed. This robotic surgical system can include: a surgeon console including a user seating area; and a computer at the surgeon console configured to detect user presence/absence/absence at the surgeon console by: receiving a set of raw video images capturing a user seating area of the surgeon console; processing the set of raw video images to generate a set of training images; training a CNN model using the set of training images, the CNN model includes an image classifier configured to output a binary classification for each input image, and wherein the binary classification is either a user-presence classification or a user-absence classification; further receiving a set of real-time video images of the user seating area captured during a surgical session; and applying the trained CNN model to the set of real-time video images to automatically classify each video image in the set of real-time video images as either the user-presence classification or the user-absence classification.

BRIEF DESCRIPTION OF THE DRAWINGS

[0021] The structure and operation of the present disclosure will be understood from a review of the following detailed description and the accompanying drawings in which like reference numerals refer to like parts and in which:

[0022] FIG. **1** shows a diagram illustrating an exemplary operating room environment with a robotic surgical system for implementing the disclosed user presence/absence recognition techniques in accordance with some embodiments described herein.

[0023] FIG. **2** presents two exemplary video images of a user-seating area illustrating a user-absence state and a user-presence state of the user-seating area during a surgical procedure in accordance with some embodiments described herein.

[0024] FIG. **3** illustrates a block diagram of the disclosed user-presence/absence recognition model building system for building a CNN-based user-presence/absence classifier based on video images of the user-seating area in accordance with some embodiments described herein.

[0025] FIG. **4** illustrates a block diagram of an exemplary implementation of the disclosed data augmentation module in the disclosed user-presence/absence recognition model building system in accordance with some embodiments described herein.

[0026] FIG. **5** illustrates an exemplary process of labeling a time-sequence of video images as either the user-presence classification or the user-absence classification in accordance with some embodiments described herein.

[0027] FIG. **6** illustrates an exemplary implementation of the disclosed transfer learning module based on using the Inception-v3 image-recognition model in accordance with some embodiments described herein.

[0028] FIG. **7** presents a flowchart illustrating an exemplary process for building a CNN-based user-presence/absence classifier based on captured video images of the user-seating area in accordance with some embodiments described herein.

[0029] FIG. **8** illustrates an exemplary surgical workflow which tracks users at a surgeon console during a surgical session using the trained user-presence/absence image classifier in accordance with some embodiments described herein.

[0030] FIG. **9** presents a flowchart illustrating an exemplary process for tracking users at a surgeon console during a surgical session using a trained user-presence/absence classifier in accordance with some embodiments described herein.

[0031] FIG. **10** conceptually illustrates a computer system with which some embodiments of the subject technology can be implemented.

DETAILED DESCRIPTION

[0032] The detailed description set forth below is intended as a description of various configurations of the subject technology and is not intended to represent the only configurations in which the subject technology may be practiced. The appended drawings are incorporated herein and constitute a part of the detailed description. The detailed description includes specific details for the purpose of providing a thorough understanding of the subject technology. However, the subject technology is not limited to the specific details set forth herein and may be practiced without these specific details. In some instances, structures and components are shown in block diagram form in order to avoid obscuring the concepts of the subject technology.

[0033] Disclosed are various user-presence/absence recognition techniques based on image processing and deep learning. More specifically, various user-presence/absence recognition techniques include building/training a convolutional neural network (CNN)-based image recognition model including a user-presence/absence classifier based on training images collected from the user-seating area of a surgeon console within a robotic surgical system under various clinically-relevant conditions/cases. The trained user-presence/absence classifier can then be used during teleoperation/surgical procedures to monitor/track users in the user-seating area of the surgeon console, and continuously classify the real-time video images of the user-seating area as either a user-presence state or a user-absence state.

[0034] In some embodiments, the disclosed user-presence/absence recognition techniques can be used to detect a user-switching event at the surgeon console when a second user is detected to have entered the user-seating area after a first user is detected to have left the user-seating area. The detection of the user-switching event allows for prompting the second user in the user-seating area to identify him/herself as either the same user as the first user or a different user. If the second user is identified as a new user, the disclosed user-presence/absence recognition techniques can trigger a recalibration procedure for the new user of surgeon-console settings, including but are not limited to: user gaze-tracking settings; user UID-control settings; and user seat settings (e.g., the armrest settings).

[0035] FIG. **1** shows a diagram illustrating an exemplary operating room environment with a robotic surgical system **100** for implementing the disclosed user-presence/absence recognition techniques in accordance with some embodiments described herein. As shown in FIG. **1**, robotic surgical system **100** comprises a user/surgeon console **120**, a control tower **130**, and one or more surgical robotic arms **112** located at a robotic surgical platform **116** (e.g., a table or a bed etc.), where surgical tools with end effectors are attached to the distal ends of the robotic arms **112** for executing a surgical procedure. The robotic arms **112** are shown as a table-mounted system, but in other configurations, the robotic arms may be mounted in a cart, ceiling or sidewall, or other suitable support surface. Robotic surgical system **100** can include any currently existing or future-developed robot-assisted surgical systems for performing robot-assisted surgeries.

[0036] Generally, a user/operator **140**, such as a surgeon or other operator, may use the surgeon console **120** to remotely manipulate the robotic arms **112** and/or surgical instruments (e.g., teleoperation). Surgeon console **120** may be located in the same operating room as robotic surgical system **100**, as shown in FIG. **1**. In other environments, surgeon console **120** may be located in an adjacent or nearby room, or teleoperated from a remote location in a different building, city, or country. Surgeon console **120** may comprise a seat **132**, foot-operated controls **134**, one or more handheld user interface devices (UIDs) **136**, and at least one user display/monitor **138** configured to display, for example, a view of the surgical site inside a patient. As shown in the exemplary surgeon console **120**, a surgeon located in the seat **132** and viewing the user display/monitor **138** may manipulate the foot-operated controls **134** and/or UIDs **136** to remotely control the robotic arms **112** and/or surgical instruments mounted to the distal ends of the arms.

[0037] In some variations, a user may also operate robotic surgical system **100** in an "over the bed" (OTB) mode, in which the user is at the patient's side and simultaneously manipulating a robotically driven tool/end effector attached thereto (e.g., with a handheld user interface device (UID) **136** held in one hand) and a manual laparoscopic tool. For example, the user's left hand may be manipulating a handheld UID **136** to control a robotic surgical component, while the user's right hand may be manipulating a manual laparoscopic tool. Thus, in these variations, the user may perform both robotic-assisted (minimally invasive surgery) MIS and manual laparoscopic surgery on a patient.

[0038] During an exemplary procedure or surgery, the patient is prepped and draped in a sterile fashion to achieve anesthesia. Initial access to the surgical site may be performed manually with robotic surgical system **100** in a stowed or withdrawn configuration to facilitate access to the surgical site. Once the access is achieved, initial positioning and/or preparation of the robotic system may be performed. During the procedure, a surgeon in the surgeon console **120** may use the foot-operated controls **134** (e.g., one or more foot pedals) and/or UIDs **136** to manipulate various surgical tools/end effectors and/or imaging systems to perform the surgery. Manual assistance may, also be provided at the procedure table by sterile-gowned personnel, who may perform tasks including, but not limited to, retracting tissues or performing manual repositioning or tool exchange involving one or more robotic arms **112**. Non-sterile personnel may also be present to assist the surgeon at the surgeon console **120**. When the procedure or surgery is completed, robotic surgical system **100** and/or surgeon console **120** may be configured or set in a state to facilitate one or more post-operative procedures including, but not limited to, robotic surgical system **100** cleaning and/or sterilization, and/or healthcare record entry or printout, whether electronic or hard copy, such as via the surgeon console **120**.

[0039] In some aspects, the communication between robotic surgical platform **116** and surgeon console **120** may be through control tower **130**, which may translate user commands from the surgeon console **120** to robotic control commands and transmit them to robotic surgical platform **116**. Control tower **130** may also transmit status and feedback from robotic surgical platform **116** back to surgeon console **120**. The connections between robotic surgical platform **116**, surgeon console **120** and control tower **130** can be via wired and/or wireless connections, and can be proprietary and/or performed using any of a variety of data communication protocols. Any wired connections may be optionally built into the floor and/or walls or ceiling of the operating room. Robotic surgical system **100** can provide video output to one or more displays, including displays within the operating room as well as remote displays accessible via the Internet or other networks. The video output or feed may also be encrypted to ensure privacy and all or portions of the video output may be saved to a server or electronic healthcare record system.

[0040] In some implementations, user/operator **140** may hold and move a UID **136** in one hand to provide input commands to move a robotic arm actuator **117** in robotic surgical system **100**. This UID **136** may be communicatively coupled to the rest of the robotic surgical system **100**, e.g., via a console computer system (not shown) of surgeon console **120**. UID **136** may be ungrounded with respect to another component of robotic surgical system **100** while either tethered or untethered from surgeon console **120**. The term "ungrounded" is intended to refer to implementations where, for example, both UIDs are neither mechanically nor kinematically constrained with respect to surgeon console **120**. For example, user/operator **140** may hold a UID **136** in a hand and move freely to any possible position and orientation within space only limited by, for example, a tracking mechanism of the surgeon console. Hence, the UID **136** can generate spatial state signals corresponding to movement of the UID, e.g. position and orientation of the handheld housing of the UID, and the spatial state signals may be input signals to control a motion of robotic arm actuator **117**. Robotic surgical system **100** may use control signals derived from the spatial state signals, to control proportional motion of the actuator **117**. In some embodiments, the console computer system of surgeon console **120** receives the spatial state signals from the UID **136** and generates the corresponding control signals. Based on these control signals, which control how arm actuator **117** is energized to move a segment or link of a corresponding robotic arm **112**, the movement of a corresponding surgical tool that is attached to the distal end of the robotic arm **112** may mimic the movement of the UID **136**. Similarly, interaction between user/operator **140** and the UID **136** can generate for example, a grip control signal that causes a jaw of a grasper of the corresponding surgical tool to close and grip a tissue of a patient on top of robotic surgical platform **116**.

[0041] Robotic surgical system **100** may include multiple UIDs **136**, where respective control signals are generated for each UID **136** that control the actuators and the surgical tool (end effector) attached to a respective arm **112**. For example, user/operator **140** may move a first UID **136** (e.g., the left UID) in one hand (e.g., the left hand) to control the motion of an arm actuator **117** that is in a left robotic arm **112**, where the actuator responds by moving linkages, gears, etc., in the left robotic arm **112**. Similarly, user/operator **140** may move a second UID **136** (e.g., the right UID) in the other hand (e.g., the right hand) to control the motion of another arm actuator **117** that is in a right robotic arm **112**, which in turn moves other linkages, gears, etc., in the right robotic arm **112**. Motions of a respective actuator **117** in a respective robotic arm **112** can be controlled by the spatial state signals generated from a respective UID **136**. When user/operator **140** has finished manipulating the surgical tools with the UIDs **136**, the user/operator may dock (i.e., store/rest) the UIDs **136** at designated docking areas/docking stations located at console **120**. For example, surgeon console **120** may include docking stations located at each of the left and right armrests (not shown) of seat **132**. To dock the left and right UIDs **136**, the user may move the left UID **136** to the left docking station and the right UID **136** to the right docking station, and place each of the UIDs in their respective docking station holder.

[0042] To detect user presence at or user absence from surgeon console **120** (or "console **120**" hereinafter), video images of a user-seating area of console **120** can be captured and analyzed. In the scope of console **120**, the user-seating area in this patent disclosure generally refers to surgeon seat **132**, which can be with or without user/operator **140**. In some embodiments, images of the user-seating area can be captured by a camera installed on or integrated with user display/monitor **138** (also referred to as "monitor **138**" or "the monitor" hereinafter) and aimed at/pointed to the user-seating area and seat **132**. For example, a camera **150** may be located in the middle of the bottom bezel portion of monitor **138**. A person of ordinary skill in the art will appreciate that images taken of the user-seating area by camera **150** can be classified into two types: the first type of images mostly comprise mostly seat **132** and a background behind seat **132**, but without any user/operator seating in seat **132**. We classify the first type of images as a "user-absence state," or "user-absence classification." Alternatively, the second type of images taken of the user-seating area by camera **150** will comprise mostly a user/operator **140** seating in seat **132** (wherein the seat itself is often blocked), and a background behind seat **132**. We classify the second type of images as a "user-presence state" or "user-presence classification." As will be discussed in more detail below, the disclosed user-presence/absence classifier is configured to recognize/distinguish the two types of seating area images and classify any given user-seating area image into either the user-absence classification or the user-presence classification.

[0043] FIG. **2** presents two exemplary video images of a user-seating area **200** illustrating a user-absence state and a user-presence state of the user-seating area during a surgical procedure in accordance with some embodiments described herein. For example, the left image **202** in FIG. **2** is a user-seating area image associated with the user-absence state because there is no user or any person in image **202**. More specifically, left image **202** shows a console seat **204** including a seat back (the upper portion of the seat) and a headrest/head-holder in front of a background **206**. Note that for training purposes, image **202** will be labeled with the user-absence classification, e.g., using a label "A" or a binary number "0." For user recognition purposes, the disclosed user-presence/absence classifier is configured to automatically classify image **202** with the user-absence classification. In contrast, the right image **208** in FIG. **2** is a user-seating area image associated with the user-presence state. More specifically, right image **208** shows a user **210** seating in console seat **204** in front of background **206**, whereas console seat **204** in image **208** is mostly blocked by user **210**. Note that for training purposes, image **208** will be labeled with a user-presence classification, e.g., using a label "P" or a binary number "1." For user recognition purposes, the disclosed user-presence/absence classifier is configured to automatically classify image **208** with the user-presence classification.

[0044] Note that video image **202** is just one example out of many possible variations for the user-absence state and video image **208** is just one example out of many possible variations for the user-presence state. As will be discussed in more detail below, there are also some less obvious, in-between situations compared to video images **202** and **208**, e.g., during the time periods when a user is leaving/exiting or returning/entering the user-seating area. The disclosed user-presence/absence recognition techniques are also configured to detect such cases and provide proper classifications for these cases.

[0045] The disclosed user-presence/absence recognition techniques include both a user-presence/absence recognition model building system for constructing a CNN-based user-presence/absence classifier based on training images collected from a user-seating area of a surgeon console under various clinically-relevant conditions/cases. The disclosed user-presence/absence recognition techniques also include a user-presence/absence tracking procedure based on the trained user-presence/absence classifier to automatically recognize video images of the user-seating area as either the user-presence state or the user-absence state during a surgical procedure and trigger proper interactions with a current user if a transitional event from the user-absence state to the user-presence state (i.e., a potential user switching event) is detected.

[0046] FIG. **3** illustrates a block diagram of a user-presence/absence recognition model building system **300** for building a CNN-based user-presence/absence classifier based on video images of the user-seating area in accordance with some embodiments described herein. As shown in FIG. **3**, user-presence/absence recognition model building system **300** (also referred to as "model building system **300**" hereinafter) can include a data collection module **302**, a data augmentation module **304**, a data labeling module **306**, a transfer learning module **308**, which are coupled in the manner shown. Note that model building system **300** generates a trained user-presence/absence classifier **310** as its output.

[0047] In some embodiments, data collection module **302** in model building system **300** obtains a diverse set of raw/original video images **312** of a user-seating area of a surgeon console under various clinically-relevant conditions/cases. These various clinically-relevant cases can include various backgrounds of the user-seating area, for example: different background colors (e.g., white, light blue, etc.) and backgrounds with/without people. The various clinically-relevant cases can also include different lighting conditions of the user-seating area. The various clinically-relevant cases can further include various screen angles of monitor **138**, including but are not limited to a straight-on angle and various tilted angels. The various clinically-relevant cases of the user-seating area can also include various heights of monitor **138**.

[0048] The various clinically-relevant cases of the user-seating area can further include different distances between user **140** and monitor **138**, e.g., a number of distances within a range from 20-cm to 100-cm. The various clinically-relevant cases of the user-seating area can also include status of UIDs **136**, wherein the status can include stationary UIDs **136** (i.e., when UIDs **136** are docked/laid down) and moving UIDs **136** (i.e., when UIDs **136** are in teleoperation use in the user's hands). The various clinically-relevant cases of the user-seating area can further include user swap events (i.e., events wherein a first user exits the user-seating area followed by a second user enters the user-seating area). The various clinically-relevant cases of the user-seating area can also include various durations of captured video clips of the user-seating area for acquiring training images **312**, e.g., between 30-60 seconds.

[0049] The various clinically-relevant cases of the user-seating area can include different scenarios related to whether user **140** wears or does not wear one or more of the following items on her/his head: QR tags, a face mask, and a three-dimensional (3D) headset. The various clinically-relevant cases of the user-seating area can also include different scenarios related to whether user **140** wears or does not wear a scrub. The various clinically-relevant cases of the user-seating area can also include different scrub color user **140** is wearing, e.g., a white color or a light blue. The various clinically-relevant cases of the user-seating area can further include various headrest angles of seat **132**. The various clinically-relevant cases of the user-seating area can also include various types of head movements of user **140**, e.g., moving to the left, to the right, as well as up and down movements. The various clinically-relevant cases of the user-seating area can also include multiple different types of surgeon console seats. Last but not least, the various clinically-relevant cases of the user-seating area can include collecting user-seating area images from different surgeon consoles of different robotic surgical systems. Note that data collection module **302** can collect video images **312** of the user-seating area including some or all of the above-described types of clinically-relevant scenarios/cases, as well as other types of clinically-relevant scenarios/cases not listed above. Moreover, because all captured images of the user-seating area are to be classified as either the user-presence state or the user-absence state, original video images **312** generated by data collection module **302** should include sufficient number of training images of each of the two image classifications.

[0050] In some embodiments, data augmentation module **304** in model building system **300** is configured to receive original video images **312** (also referred to as the "raw images **312**" hereinafter), preprocess the received raw images and generate preprocessed training images **314**. FIG. **4** illustrates a block diagram of an exemplary implementation **400** of data augmentation module **304** in accordance with some embodiments described herein. As can be seen in FIG. **4**, the input to data augmentation module **400** is an original video image **312** captured by camera **150** of the user-seating area. FIG. **4** shows an exemplary original video image **420** of a user-seating area as an example of original video image **312**, wherein video image **420** captures a user seating in front of a background. In this particular example, video image **420** is a high definition image with a 16:9 aspect ratio. However, other examples of original video image **312** can have other image format different from the example image **420**.

[0051] In FIG. **4**, an original video image **312** is received by a bounding box placement submodule **402**, which is configured to randomly place a bounding box of predetermined dimensions within the frame of original video image **312**. In some embodiments, the predetermined dimensions of the bounding box used by submodule **402** are determined based on the largest bounding box that can fit inside original video image **312**. Because many CNN image recognition models require square input images, preparing CNN input images for either model training or image detection/recognition requires cropping out square images from the original non-square video images. Hence, in some embodiments, the largest bounding box that can fit inside a non-square original video image **312** is also a square image which has both the vertical dimension and the horizontal dimension equal to the smaller dimension (of the two dimensions) of original video image **312**. For example, FIG. **4** also shows randomly placing a largest square bounding box **422** inside the exemplary video image **420**. In this example, because bounding box **422** already fills the full vertical extent of video image **420**, bounding box placement submodule **402** implements the degree of randomness of placing the bounding box **422** only in the horizontal direction, which is shown to be off-centered toward the right border of video image **420**. However, the proposed randomness in placing bounding box **422** means that bounding box **422** can be located inside video image **420** anywhere between the left border and the right border of video image **420**.

[0052] Bounding box placement submodule **402** in data augmentation module **400** is followed by a zoom-in submodule **404** which is configured to randomly zoom in on original video image **312** by a random factor. For example, FIG. **4** also illustrates the effect of zooming in on original video image **420** by a random factor on both video image **420** and bounding box **422**. As can be seen in FIG. **4**, the zoom-in operation increases the size of original video image **420** by the random factor to create a larger zoomed-in video image **424**, whereas the size of bounding box **422** within zoomed-in video image **424** remains unchanged. However, as can be clearly observed from zoomed-in video image **424**, the portion of the image inside bounding box **422** now corresponds to a smaller portion of original video image **420** than the portion of image inside the same bounding box **422** placed inside original video image **312** prior to applying the zoom-in effect by zoom-in submodule **404**.

[0053] Zoom-in submodule **404** in data augmentation module **400** is further followed by an image cropping submodule **406**, which is configured to crop out the portion of the zoomed-in video image outputted by zoom-in submodule **404** inside the placed bounding box, and as a result to generate a cropped image. For example, FIG. **4** illustrates the effect of image cropping submodule **406**, which includes cropping out the portion of zoomed-in video image **424** inside bounding box **422** to obtain a cropped image **426**. Image cropping submodule **406** in data augmentation module **400** is further followed by an image flipping submodule **408** which is configured to flip the cropped image from the previous stage horizontally with a predetermined probability p (e.g., p=50%) to generate either a flipped version of the cropped image or the original cropped image. For example, FIG. **4** shows the effect of flipping cropped image **426** horizontally to generate a flipped image **428**. Note that because image flipping submodule **408** only performs the image clipping operation based on the predetermined probability p ($p \in (0, 1)$), the output of image flipping submodule **408** does not have to include the flipping effect, i.e., it can also output cropped image **426** instead of flipped image **428**.

[0054] Finally in data augmentation module **400**, image flipping submodule **408** is followed by image resizing submodule **410** configured to resize the output image of image flipping submodule **408** to the predetermined dimensions of a downstream CNN image recognition model. For example, the predetermined dimensions in image resizing submodule **410** can be 299×299 if the downstream CNN model is an Inception-v3 model. Eventually, data augmentation module **400** outputs a preprocessed training image **314** for the original input video image **312** with the predetermined dimensions, such as 299×299.

[0055] As described above, each of bounding box placement submodule **402** and zoom-in submodule **404** within the disclosed data augmentation module **400** can be configured with a degree of randomness. Moreover, image flipping submodule **408** operates based on the predetermined probability p and therefore can have two different outcomes. Consequently, the combined randomness and probability of data augmentation module **400** ensures that each time the same input video image **312** is passed through data augmentation module **400**, data augmentation module **400** will almost always generate a different preprocessed training image **314**. In some embodiments, for each original video image **312** in the set of original video images **312** generated by data collection module **302**, image **312** is passed through data augmentation module **400** multiple times to generate multiple preprocessed training images **314** based on the same original image **312**. As such, a single original image **312** can be used to generate a diverse set of augmented training images **314**. Note that because the amount of original/raw training images **312** collected by data collection module **302** are often limited due to time and resource constraints, the disclosed data augmentation module **400** allows for generating a sufficiently large and diverse training dataset based on a smaller set of original video images **312**, thereby saving both time and resources required to collect raw training images **312**.

[0056] Referring back to FIG. **3**, note that data augmentation module **304** in model building system **300** is coupled to data labeling module **306**, which is configured to receive preprocessed training images **314** and subsequently label each training image in preprocessed training images **314** with either the user-absence classification, e.g., using a label "A" or a binary number "0," or the user-presence classification, e.g., using a label "P" or a binary number "1." Note that data labeling module **306** generates a labeled training image dataset **316** as output.

[0057] Referring back to FIG. **2**, note that while exemplary video images **202** and **208** represent more common and obvious cases of the user-absence state images and the user-presence state images, respectively, there are many different scenarios/variations of the user-presence state which are not as obvious as image **208** for receiving a user-presence classification. For example, a user in a given image may be off-centered and/or only partially visible. Similarly, there are also many different scenarios/variations of the user-absence state which are not as obvious as image **202** for receiving a user-absence classification. For example, a part of a user's body may be visible in a given image but the user is clearly not in the seat shown within the image. In some embodiments, data labeling module **306** in FIG. **3** is configured to label each preprocessed training image **314** based on the following rules: an image showing a fully-visible seat (i.e., no part of the seat is blocked by a portion of a user's body) is labeled with a user-absence classification; whereas an image showing a partially-visible or non-visible seat (i.e., any part of the seat is blocked by a user's body) is labeled with a user-presence classification.

[0058] FIG. **5** illustrates an exemplary process of labeling a time-sequence of video images as either the user-presence classification or the user-absence classification in accordance with some embodiments described herein. As can be seen in FIG. **5**, a sequence of 15 video images **501-515** represents **15** consecutive video frames of a video clip illustrating an event where a user entering a user seating area and taking a seat. Note that video images **501-503** have been labeled with "A," i.e., the user-absence classification. This is because these three video images showed a fully-visible seat, even if a part of the user's body is visible in some of the above images. Also note that images **504-515** have been labeled with "P," i.e., the user-presence classification. This is because these twelve video images showed either a partially-visible/partially-blocked seat or non-visible fully-blocked seat.

[0059] In some embodiments, the above-described labeling process can be fully automatic by constructing a machine-learning-based object recognition model trained to detect and recognize a fully-visible/unblocked seat in the user-seating area. For example, this proposed object recognition model can be separately trained on training images of various configurations of fully-visible/unblocked seats under various user-seating area conditions (e.g., under different backgrounds, lighting conditions, and possible seat angles relative to the monitor/camera). When implementing this object recognition model into data labeling module **306** in model building system **300**, data labeling module **306** can then apply the trained object recognition model to each preprocessed training image **314** and automatically generate a binary decision and a corresponding label/classification for the training image **314**, i.e.: (1) fully-visible-seat is-recognized decision and the corresponding user-absence label/classification; or (2) fully-visible-seat not-recognized decision and the corresponding user-presence label/classification.

[0060] Referring back to FIG. **3**, note that data labeling module **306** in model building system **300** is coupled to transfer learning module **308**, which is configured to receive the labeled training image dataset **316**, train a CNN-based user-presence/absence classifier within transfer learning module **308** based on the labeled training image dataset **316**, and subsequently generate trained user-presence/absence classifier **310** as output. In some embodiments, transfer learning module **308** employs a trained CNN-based image-recognition model to perform transfer learning for user-presence/absence recognition purposes. More specifically, transfer learning module **308** can be configured to "freeze" all layers in the trained CNN-based image-recognition model except for the last few layers. Note that the trained CNN-based image-recognition model can be a well-known or otherwise previously-established image recognition model for other objection recognition applications, such as for face recognition. In some embodiments, the phrase "freezing all layers in the trained model except for the last few layers" means freezing all layers from the very first layer of the trained CNN-based model up to the bottleneck layer of the trained CNN-based model, except for the final two layers: i.e., a fully-connected layer and a Softmax layer after the bottleneck layer. Note that the term "freezing a given layer" in the trained CNN-based image-recognition model herein means fixing the previously-established parameters in the given layer, including the weights and biases of the given layer in the disclosed transfer learning module **308**. In the above example, performing transfer learning using the trained CNN-based image-recognition model within transfer learning module **308** means fixing the previously-established weights and biases of all network layers of the trained CNN-based model up to and including the bottleneck layer, but without fixing the trainable parameters in the final fully-connected layer and Softmax layer of the trained CNN-based model.

[0061] FIG. **6** illustrates an exemplary implementation **600** of transfer learning module **308** based on using the Inception-v3 image-recognition model in accordance with some embodiments described herein. As can be seen in FIG. **6**, transfer learning module **600** includes a feature extractor **602** which is composed of the entire Inception-v3 image-recognition model (or "Inception-v3 model" hereinafter) except the final fully-connected (FC) layer and Softmax layer of the original Inception-v3 model. More specifically, feature extractor **602** includes CNN **604** of the Inception-v3 model that includes all layers of the Inception-v3 model up to and before the bottleneck layer. Note that CNN **604** is composed of a stack of feature-extraction layers including a sequence of convolutional layers interleaved with a sequence of pooling layers. For transfer learning purposes in transfer learning module **600**, parameters such as weights and biases in all layers within CNN **604** are fixed to the trained values of the Inception-v3 model. In feature extractor **602**, CNN **604** of feature extractor **602** is followed by the bottleneck layer **606** of the original Inception-v3 model. For performing transfer learning in transfer learning module **600**, parameters such as weights and biases in bottleneck layer **606** are also fixed to the trained values of the Inception-v3 model.

[0062] Feature extractor **602** of transfer learning module **600** receives the labeled training image dataset **316** (in reference to the same items in FIG. **3**) as inputs, wherein each input image in the labeled training image dataset **316** has been resized to 299×299×3 (**3** channels) based on the input-size requirements of the Inception-v3 model. Using feature extractor **602** with fixed parameters, transfer learning module **600** extracts a set of feature maps **608** as the outputs of bottleneck layer **606** for each input training image **316**. In some embodiments, feature maps **608** for each input training image **316** has a dimension of 8×82048.

[0063] Note that because the parameters in feature extractor **602** are fixed, feature extractor **602** will always generate the same set of feature maps **608** for the same input training image **316**. In some embodiments, transfer learning module **600** can use the same labeled training image dataset **316** multiple times, referred to as multiple "epochs of trainings," and in epoch of training, the same labeled training image dataset **316** is used to train the user presence/absence classifier. Because the outputted sets of feature maps **608** do not change in different epochs of trainings based on the same training image dataset **316**, the sets of feature maps **608** of the labeled training image dataset **316** can be stored as two-dimensional (2D) images in a memory or a hard disk after the first epoch of training. As a result, during the second and subsequent epochs of trainings, the sets of feature maps **608** can be simply retrieved from the memory or the disk instead of having to be recalculated by passing the same training image dataset **316** through feature extractor **602**, thereby saving both training time and computational resources during the transfer learning.

[0064] Note that transfer leaning module **600** does not include the original final FC layer and Softmax layer of the original Inception-v3 model. Instead, transfer leaning module **600** uses a customized FC layer **610** with a set of variables and a customized Softmax layer **612** as the decision layers **616** of the disclosed user-presence/absence classifier **618**. As shown in FIG. **6**, user-presence/absence classifier **618** includes both feature extractor **602** and decision layers **616**.

[0065] As can be seen in FIG. **6**, customized FC layer **610** receives the sets of feature maps **608** of the processed training image dataset **316** as inputs, which are used to train the set of variables within the customized FC layer **610**. In some embodiments, customized FC layer **610** can include 512 nodes, and each of the 512 nodes is associated with a weight variable and a bias variable. As mentioned above, training the customized FC layer **610** can include performing multiple epochs of trainings (e.g., epoch=20) using the same sets of feature maps **608** extracted from the same training image dataset **316**. After performing the multiple epochs of trainings, the customized FC layer **610** will include a set of trained parameters. For the above example of 512 nodes in the FC layer **610**, the set of trained parameters would include 512 trained weight values and 512 trained bias values.

[0066] Finally in transfer leaning module **600**, the outputs from customized FC layer **610** are coupled to Softmax layer **612** which includes a binary Softmax function configured to generate user-presence (e.g., with binary value 1) or user-absence (e.g., with binary value 0) classifications/decisions for each input training image **316**. Note that after the customized FC layer **610** has been sufficiently trained, e.g., through multiple epochs of trainings based on the training image dataset **316**, the trained variables within the customized FC layer **610** can be fixed and the trained user-presence/absence classifier **618** becomes the trained user presence/absence classifier **310** which is the output of user-presence/absence recognition model building system **300**.

[0067] Note that although transfer learning module **308**/**600** has been described based on using the Inception-v3 model as the trained feature extractor, the disclosed transfer learning module within the disclosed user-presence/absence recognition model building system **300** is not meant to be limited to using a particular trained deep-learning framework. Generally speaking, the trained feature extractor within the disclosed transfer learning module **308**/**600** can be implemented with other known image-recognition models including, but are not limited to GGNet, ResNet, DenseNet, AlexNet, Dual Pathway Network, MobileNet, and Inception v1-v2.

[0068] FIG. **7** presents a flowchart illustrating an exemplary process **700** for building a CNN-based user-presence/absence classifier based on captured video images of the user-seating area in accordance with some embodiments described herein. In one or more embodiments, one or more of the steps in FIG. **7** may be omitted, repeated, and/or performed in a different order. Accordingly, the specific arrangement of steps shown in FIG. **7** should not be construed as limiting the scope of the technique.

[0069] Process **700** may begin by collecting a diverse set of raw video images of the user-seating area under various clinically-relevant cases (step **702**). For example, these various clinically-relevant cases can include various backgrounds of the user-seating area; different lighting conditions of the user-seating area; various screen angles and height of the monitor, different distances between the user and the monitor; status of the UIDs; whether the user wears or does not wear one or more of the following items: QR tags, a face mask, a 3D headset, and a scrub; different scrub colors; various headrest angles of the seat; various types of head movements of the user, among others.

[0070] Next, for each raw video image in the diverse set of raw video images of the user-seating area, process **700** generates a diverse set of augmented/preprocessed training images of the raw video image (step **704**). For example, the diverse set of augmented/preprocessed training images of the raw video image can include one or multiple of the following augmented images: (1) one or more cropped images obtained from the raw video image by first randomly placing the largest square bounding box inside the raw image and then cropping the raw image using the bounding box; (2) one or more cropped and zoomed-in images obtained from the raw video image by first randomly placing the largest square bounding box inside the raw image; then randomly zooming in the raw image by a random factor; and finally cropping the zoomed-in image using the bounding box; and (3) one or more cropped, zoomed-in, and possibly flipped images obtained from the raw video image by first randomly placing the largest square bounding box inside the raw video image; then randomly zooming in the raw image by a random factor; next cropping the zoomed-in image using the bounding box, and finally flipping the cropped-out image horizontally with a predetermined probability. In some embodiments, each of the diverse set of augmented/preprocessed training images of a given raw video image is resized to the predetermined dimensions required by the input-size constraints of a downstream CNN classifier to be trained.

[0071] Next, for the diverse sets of augmented/preprocessed training images generated from the set of raw video images, process **700** labels each preprocessed training image with either the user-absence classification or the user-presence classification (step **706**). In some embodiments, process **700** labels a preprocessed training image with the user-absence classification if the preprocessed image shows a fully-visible seat; or with the user-presence classification if the preprocessed image shows a partially-visible or non-visible seat. After labeling the set of preprocessed training images, process **700** generates a labeled training image dataset for the downstream user-presence/absence classifier.

[0072] Subsequently, process **700** trains a CNN-based user-presence/absence classifier with the labeled training image dataset through transfer learning. Specifically, process **700** first extracts sets of feature maps from the labeled training image dataset using a trained CNN image-recognition model with fixed network parameters (also referred to as the "feature extractor") (step **708**). In some embodiments, the trained CNN image-recognition model is the Inception-v3 image-recognition model up to the bottleneck layer and without the original final FC layer and Softmax layer of the Inception-v3 model. Next, process **700** trains a customized FC layer containing a set of variables using the extracted sets of feature maps (step **710**). In some embodiments, process **700** trains the customized FC layer by performing multiple epochs of trainings with the same extracted sets of feature maps of the same labeled training image dataset. Finally, process **700** combines the fixed-parameter CNN feature extractor, the customized FC layer with the set of trained variables, and a Softmax binary classifier to obtain a disclosed user-presence/absence image classifier (step **712**).

[0073] FIG. **8** illustrates an exemplary surgical workflow **800** which tracks users at a surgeon console during a surgical session using the disclosed (trained) user-presence/absence classifier in accordance with some embodiments described herein. As can be seen in FIG. **8**, surgical workflow **800** is represented by a time plot with time **802** in the horizontal axis and classifier decisions **804** of the trained user-presence/absence classifier (hereinafter "user-presence/absence classifier") in the vertical axis. More specifically, the user-presence/absence classifier, such as trained user-presence/absence classifier **310** generated by user-presence/absence recognition model building system **300** is used to receive and process real-time video images of the user seating area of the surgeon console. For each frame of the real-time video images, user-presence/absence classifier generates a binary decision **804** of either a user-presence decision (i.e., value 1 in the vertical axis) or a user absence decision (i.e., value 0 in the vertical axis).

[0074] Note that surgical workflow **800** is integrated with a user-switching detection mechanism designed to detect the event when a new user enters the user seating area after a previous user has left the user seating area. As will be discussed below in more detail, the disclosed user-switching detection mechanism can further interact with the user just entering the user seating area to determine whether this user is the same user as the previous user. If the user confirms that he/she is not the same user as the previous user, the disclosed user-switching detection mechanism can trigger recalibration or reconfiguration of surgeon console settings, such as user gaze-tracking settings, user UID-control settings, and user seat settings (e.g., the armrest settings) for the new user. We now begin describing surgical workflow **800** in more detail in conjunction with the user-switching detection mechanism.

[0075] Note that surgical workflow **800** begins with a first time period from t_0 to t_1, during which time user-presence/absence classifier outputs user-presence decisions (1), indicating a user is present at the surgeon console. Next, at or right after time t_1, the first decision change occurs and user-presence/absence classifier begins outputting user-absence decisions (0), indicating the user has left the surgeon console at around time t_1. From time t_1 onward, user-presence/absence classifier continues outputting user-absence decisions (0) until time t_2, at which time the second decision change occurs and user-presence/absence classifier begins outputting user-presence decisions (1). As described above, a transition from user-absence decisions to user-presence decisions can indicate that a user has returned to the surgeon console. In some embodiments, the user-switching detection mechanism detects such a transition in surgical workflow **800**, and subsequently generates a dialog window/box on the monitor of the surgeon console promoting the user to confirm herself/himself as either the same user or a new user. In some embodiments, to avoid false positives, the disclosed user-switching detection mechanism only generates the dialog window/box if a minimum number (e.g., 10) of consecutive user-presence decisions (1) have been generated after time t_2. In surgical workflow **800**, a dialog window/box **806** including a question "Are you the same surgeon?" was generated by user-switching detection mechanism at some time after time t_2.

[0076] From time t_2 in surgical workflow **800**, user-presence/absence classifier only outputs user-presence decisions (1) for a brief time interval between t_2 to t_3. This short time interval is immediately followed by the third decision change at time t_3, after which time user-presence/absence classifier begins outputting user-absence decisions (0). Note that this short time interval (t_2, t_3) can be the result of a user enters the user seating area but only for a very brief moment, and subsequently leaves the user seating area. As a result, the user may not respond to dialog window/box **806** during the short time interval (t_2, t_3).

[0077] From time t_3 onward, user-presence/absence classifier continues outputting user-absence decisions (0) until time t_4, at which time the fourth decision change occurs and user-presence/absence classifier again begins outputting user-presence decisions (1). However, as surgical workflow **800** shows, this new user-presence decision period is extremely short and ends at time t_5 almost immediately after it begins at time t_4. In this scenario, the disclosed user-switching detection mechanism does not generate a new dialog window/box because the previously generated dialog window/box **806** has not been answered and therefore remains valid. Note that the user-switching detection mechanism may not generate a dialog window/box even if dialog window/box **806** does not exist for the reason that the time interval (t_4, t_5) may contain fewer than the minimum number (e.g., 10) of consecutive user-presence decisions (1) required to avoid false positives.

[0078] From time t_5 onward, user-presence/absence classifier continues outputting user-absence decisions (0) until time t_6, at which time the fifth decision change occurs and user-presence/absence classifier again begins outputting user-presence decisions (1). From time t_6 onward, user-presence/absence classifier continues outputting user-presence decisions (1) for a prolonged time period indicating a user continues to be present at the surgeon console. Moreover, the returned user may now respond to dialog window/box **806** with a "Yes" answer, confirming that he/she is the same user as the previous user at the user seating area before time t_1. Note that dialog window/box **806** generated around time t_2 remains valid at time t_6 because it has not been responded, so that the disclosed user-switching detection mechanism does not need to generate another dialog window/box around time t_6 for the returned user.

[0079] FIG. **9** presents a flowchart illustrating an exemplary process **900** for tracking users at a surgeon console during a surgical session using a trained user-presence/absence classifier in accordance with some embodiments described herein. In one or more embodiments, one or more of the steps in FIG. **9** may be omitted, repeated, and/or performed in a different order. Accordingly, the specific arrangement of steps shown in FIG. **9** should not be construed as limiting the scope of the technique.

[0080] Process **900** may begin by receiving a first sequence of video images of the user seating area of the surgeon console (step **902**). Process **900** subsequently processes the first sequence of video images to detect an event that a first user in the user seating area exiting the user seating area (step **904**). To detect the event that the first user is exiting the user seating area, process **900** can generate a sequence of user-presence/absence decisions corresponding to the first sequence of video images using the disclosed user-presence/absence image classifier, such as the trained user-presence/absence classifier **310**, and detect a transition that the decision outputs change from user-presence decisions (1) to user-absence decisions (0). Process **900** next receives a second sequence of video images of the user seating area (step **906**). Process **900** subsequently processes the second sequence of video images to detect an event that a second user entering the user seating area (step **908**). To detect the event that the second user entering the user seating area, process **900** can generate a sequence of user-presence/absence decisions corresponding to the second sequence of video images using the disclosed user-presence/absence image classifier, and detect a transition that the decision outputs change from user-absence decisions (0) to user-presence decisions (1).

[0081] Upon detecting the second user entering the user seating area, process **900** subsequently generates a dialog window on the monitor of the surgeon console asking the second user to confirm whether he/she is the same user as the first user (step **910**). In some embodiments, process **900** generates the dialog window only after a minimum number of consecutive user-presence decisions (1) have been generated by the user-presence/absence classifier following the user-absence decisions (0) in order to avoid false positives.

[0082] Process **900** next receives a response from the second user through the dialog window (step **912**) and determines if the second user is the same user as the first user based on the response (step **914**). If so, process **900** determines that surgeon console settings do not need to be recalibrated or reconfigured and process **900** terminates. However, if the second user is not the same user as the first user, i.e., the second user being a new user, process **900** determines that surgeon console settings needs to be recalibrated or reconfigured and subsequently launches a surgeon-console-setting recalibrating procedure (step **916**). For example, process **900** can simply generate another dialog window prompting the user to enter his/her identify, which causes robotic surgical system **100** to load new surgeon-console-settings, such as user gaze-tracking settings, user UID-control settings, and user seat settings for the second user.

[0083] FIG. **10** conceptually illustrates a computer system with which some embodiments of the subject technology can be implemented. Computer system **1000** can be a client, a server, a computer, a smartphone, a PDA, a laptop, or a tablet computer with one or more processors embedded therein or coupled thereto, or any other sort of computing device. Such a computer system includes various types of computer-readable media and interfaces for various other types of computer-readable media. Computer system **1000** includes a bus **1002**, processing unit(s) **1012**, a system memory **1004**, a read-only memory (ROM) **1010**, a permanent storage device **1008**, an input device interface **1014**, an output device interface **1006**, and a network interface **1016**. In some embodiments, computer system **1000** is a part of a robotic surgical system.

[0084] Bus **1002** collectively represents all system, peripheral, and chipset buses that communicatively connect the numerous internal devices of computer system **1000**. For instance, bus **1002** communicatively connects processing unit(s) **1012** with ROM **1010**, system memory **1004**, and permanent storage device **1008**.

[0085] From these various memory units, processing unit (s) **1012** retrieves instructions to execute and data to process in order to execute various processes described in this patent disclosure, including the above-described techniques for building a CNN-based user-presence/absence classifier and for tracking users at a surgeon console during a surgical session using the disclosed user-presence/absence classifier described in conjunction with FIGS. **3-9**. The processing unit(s) **1012** can include any type of processor, including, but not limited to, a microprocessor, a graphic processing unit (GPU), a tensor processing unit (TPU), an intelligent processor unit (IPU), a digital signal processor (DSP), a field-programmable gate array (FPGA), and an application-specific integrated circuit (ASIC). Processing unit(s) **1012** can be a single processor or a multi-core processor in different implementations.

[0086] ROM **1010** stores static data and instructions that are needed by processing unit(s) **1012** and other modules of the computer system. Permanent storage device **1008**, on the other hand, is a read-and-write memory device. This device is a non-volatile memory unit that stores instructions and data even when computer system **1000** is off. Some implementations of the subject disclosure use a mass-storage device (such as a magnetic or optical disk and its corresponding disk drive) as permanent storage device **1008**.

[0087] Other implementations use a removable storage device (such as a floppy disk, flash drive, and its corresponding disk drive) as permanent storage device **1008**. Like permanent storage device **1008**, system memory **1004** is a read-and-write memory device. However, unlike storage device **1008**, system memory **1004** is a volatile read-and-write memory, such as a random access memory. System memory **1004** stores some of the instructions and data that the processor needs at runtime. In some implementations, various processes described in this patent disclosure, including the above-described techniques for building a CNN-based user-presence/absence classifier and for tracking users at a surgeon console during a surgical session using the disclosed user-presence/absence classifier described in conjunction with FIGS. **3-9**, are stored in system memory **1004**, permanent storage device **1008**, and/or ROM **1010**. From these various memory units, processing unit(s) **1012** retrieves instructions to execute and data to process in order to execute the processes of some implementations.

[0088] Bus **1002** also connects to input and output device interfaces **1014** and **1006**. Input device interface **1014** enables the user to communicate information to and select commands for the computer system. Input devices used with input device interface **1014** include, for example, alphanumeric keyboards and pointing devices (also called "cursor control devices"). Output device interface **1006** enables, for example, the display of images generated by the computer system **1000**. Output devices used with output device interface **1006** include, for example, printers and display devices, such as cathode ray tubes (CRT) or liquid crystal displays (LCD). Some implementations include devices such as a touchscreen that functions as both input and output devices.

[0089] Finally, as shown in FIG. **10**, bus **1002** also couples computer system **1000** to a network (not shown) through a network interface **1016**. In this manner, the computer can be a part of a network of computers (such as a local area network ("LAN"), a wide area network ("WAN"), an intranet, or a network of networks, such as the Internet. Any or all components of computer system **1000** can be used in conjunction with the subject disclosure.

[0090] The various illustrative logical blocks, modules, circuits, and algorithm steps described in connection with the embodiments disclosed in this patent disclosure may be implemented as electronic hardware, computer software, or combinations of both. To clearly illustrate this interchangeability of hardware and software, various illustrative components, blocks, modules, circuits, and steps have been described above generally in terms of their functionality. Whether such functionality is implemented as hardware or software depends upon the particular application and design constraints imposed on the overall system. Skilled artisans may implement the described functionality in varying ways for each particular application, but such implementation decisions should not be interpreted as causing a departure from the scope of the present disclosure.

[0091] The hardware used to implement the various illustrative logics, logical blocks, modules, and circuits described in connection with the aspects disclosed herein may be implemented or performed with 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 designed to perform the functions described herein. A general-purpose processor may be a microprocessor, but in the alternative, the processor may be any conventional processor, controller, microcontroller, or state machine. A processor may also be implemented as a combination of receiver devices, e.g., a combination of a DSP and a microprocessor, a plurality of microprocessors, one or more microprocessors in conjunction with a DSP core, or any other such configuration. Alternatively, some steps or methods may be performed by circuitry that is specific to a given function.

[0092] In one or more exemplary aspects, the functions described may be implemented in hardware, software, firmware, or any combination thereof. If implemented in software, the functions may be stored as one or more instructions or code on a non-transitory computer-readable storage medium or non-transitory processor-readable storage medium. The steps of a method or algorithm disclosed herein may be embodied in processor-executable instructions that may reside on a non-transitory computer-readable or processor-readable storage medium. Non-transitory computer-readable or processor-readable storage media may be any storage media that may be accessed by a computer or a processor. By way of example but not limitation, such non-transitory computer-readable or processor-readable storage media may include RAM, ROM, EEPROM, flash memory, CD-ROM or other optical disk storage, magnetic disk storage or other magnetic storage devices, or any other medium that may be used to store desired program code in the form of instructions or data structures and that may be accessed by a computer. Disk and disc, as used herein, includes compact disc (CD), laser disc, optical disc, digital versatile disc (DVD), floppy disk, and Blu-ray disc where disks usually reproduce data magnetically, while discs reproduce data optically with lasers. Combinations of the above are also included within the scope of non-transitory computer-readable and processor-readable media. Additionally, the operations of a method or algorithm may reside as one or any combination or set of codes and/or instructions on a non-transitory processor-readable storage medium and/or computer-readable storage medium, which may be incorporated into a computer-program product.

[0093] While this patent document contains many specifics, these should not be construed as limitations on the scope of any disclosed technology or of what may be claimed, but rather as descriptions of features that may be specific to particular embodiments of particular techniques. Certain features that are described in this patent document in the context of separate embodiments can also be implemented in combination in a single embodiment. Conversely, various features that are described in the context of a single embodiment can also be implemented in multiple embodiments separately or in any suitable subcombination. Moreover, although features may be described above as acting in certain combinations and even initially claimed as such, one or more features from a claimed combination can in some cases be excised from the combination, and the claimed combination may be directed to a subcombination or variation of a subcombination.

[0094] Similarly, while operations are depicted in the drawings in a particular order, this should not be understood as requiring that such operations be performed in the particular order shown or in sequential order, or that all illustrated operations be performed, to achieve desirable results. Moreover, the separation of various system components in the embodiments described in this patent document should not be understood as requiring such separation in all embodiments.

[0095] Only a few implementations and examples are described, and other implementations, enhancements and variations can be made based on what is described and illustrated in this patent document.

What is claimed is:

1. A computer-implemented method for detecting user presence/absence at a surgeon console in a robotic surgical system, the method comprising:

receiving a set of raw video images capturing a user seating area of the surgeon console;

processing the set of raw video images to generate a set of training images;

training a convolutional neural network (CNN) model using the set of training images, wherein the CNN model includes an image classifier configured to output a binary classification for each input image, and wherein the binary classification is either a user-presence classification or a user-absence classification;

receiving a set of real-time video images of the user seating area captured during a surgical session; and

applying the trained CNN model to the set of real-time video images to automatically classify each video image in the set of real-time video images as either a user-presence classification or a user-absence classification.

2. The computer-implemented method of claim **1**, wherein processing the set of raw video images to generate the set of training images includes, for each raw video image in the set raw of video images:

generating a plurality of augmented images of the raw video image using a set of image augmentation techniques; and

including one or more of the plurality of augmented images in the set of training images.

3. The computer-implemented method of claim **2**, wherein generating the plurality of augmented images of the raw video image using the set of image augmentation techniques include:

placing a bounding box of first predetermined dimensions within the frame of the raw video image;

cropping the raw image with the bounding box to generate a first augmented image of the raw image having the first predetermined dimensions.

4. The computer-implemented method of claim **3**, wherein the method further comprises:

zooming in on the first augmented image with a random zoom-in factor to generate a second augmented image of the raw image having the first predetermined dimensions.

5. The computer-implemented method of claim **4**, wherein the method further comprises:

flipping the second augmented image horizontally to generate a third augmented image of the raw image having the first predetermined dimensions.

6. The computer-implemented method of claim **3**, wherein the first predetermined dimensions include a vertical dimension and a horizontal dimension which are both equal to the smaller dimension of the raw image.

7. The computer-implemented method of claim **1**, wherein after generating the set of training images, the method further comprises automatically annotating each training image in the set of training images with either a user-presence label indicating the presence of a user in the training image or a user-absence label indicating the absence of any user in the training image.

8. The computer-implemented method of claim **7**, wherein automatically annotating the training image in the set of training images includes:

detecting a seat object within the training image using an image recognition technique;

determining if a part of the detected seat object is blocked by another object in the training image; and

if so,

labeling the training image with the user-presence label;

otherwise,

labeling the training image with the user-absence label.

9. The computer-implemented method of claim **7**, wherein annotating the training image in the set of training images further includes labeling the training image with the user-presence label if the image recognition technique fails to detect a seat object.

10. The computer-implemented method of claim **1**, wherein the CNN model comprises a stack of feature-extraction layers including a sequence of convolutional layers and a sequence of pooling layers having a first set of parameters, which is followed a fully-connected layer having a second set of parameters, which is further followed by a final output layer, and wherein training the CNN model using the set of training images includes:

for each training image in the set of training images, using the stack of feature-extraction layers to extract a set of two-dimensional (2D) feature maps of the training image while fixing the first set of parameters; and

training the second set of parameters of the fully-connected layer based at least on the sets of extracted 2D feature maps extracted from the set of training images to obtain a trained fully-connected layer; and

fixing both the first set of parameters and the trained second set of parameters in the CNN model to obtain the trained CNN model.

11. The computer-implemented method of claim **10**, wherein the stack of feature-extraction layers includes a portion of a Inception-v3 image-recognition model from the input layer up to the bottleneck layer, and wherein the Inception-v3 image-recognition model was previously trained to detect and recognize objects unrelated to detecting user presence/absence at the surgeon console.

12. An apparatus for detecting user presence/absence at a surgeon console in a robotic surgical system, the apparatus comprising:

one or more processors;

a memory coupled to the one or more processors, the memory storing instructions that, when executed by the one or more processors, cause the apparatus to;

receive a set of raw video images capturing a user seating area of the surgeon console;

process the set of raw video images to generate a set of training images;

train a deep-learning image classifier using the set of training images, wherein the deep-learning image classifier is configured to receive an input image, process the input image, and output a binary classification for the input image, and wherein the binary classification is either a user-presence classification or a user-absence classification;

receive a set of real-time video images of the user seating area captured during a surgical session; and

apply the trained deep-learning image classifier to the set of real-time video images to automatically classify each video image in the set of real-time video images as either the user-presence classification or the user-absence classification.

13. The apparatus of claim **12**, wherein the memory further stores instructions that, when executed by the one or more processors, cause the apparatus to generate the set of training images by:

for each raw video image in the set raw of video images:

generating a plurality of augmented images of the raw video image using a set of image augmentation techniques; and

including one or more of the plurality of augmented images in the set of training images.

14. The apparatus of claim **13**, wherein the memory further stores instructions that, when executed by the one or more processors, cause the apparatus to generate the plurality of augmented images of the raw video image by:

placing a bounding box of first predetermined dimensions within the frame of the raw video image;

cropping the raw image with the bounding box to generate a first augmented image of the raw image having the first predetermined dimensions.

15. The apparatus of claim **12**, wherein the memory further stores instructions that, when executed by the one or more processors, cause the apparatus to automatically annotate each training image in the set of training images with either a user-presence label indicating the presence of a user in the training image or a user-absence label indicating the absence of any user in the training image.

16. The apparatus of claim **15**, wherein the memory further stores instructions that, when executed by the one or more processors, cause the apparatus to automatically annotate the training image by:

detecting a seat object within the training image using an image recognition technique;

determining if a part of the detected seat object is blocked by another object in the training image; and

if so,

labeling the training image with the user-presence label:

Otherwise,

labeling the training image with the user-absence label.

17. The apparatus of claim **12**, wherein the deep-learning image classifier comprises a stack of feature-extraction layers including a sequence of convolutional layers and a sequence of pooling layers having a first set of parameters, which is followed a fully-connected layer having a second set of parameters, which is further followed by a final output layer, and wherein training the deep-learning image classifier using the set of training images includes:

for each training image in the set of training images, using the stack of feature-extraction layers to extract a set of two-dimensional (2D) feature maps of the training image while fixing the first set of parameters; and

training the second set of parameters of the fully-connected layer based at least on the sets of extracted 2D feature maps extracted from the set of training images to obtain a trained fully-connected layer; and

fixing both the first set of parameters and the trained second set of parameters in the CNN model to obtain the trained deep-learning image classifier.

18. The apparatus of claim **17**, wherein the stack of feature-extraction layers includes a portion of a Inception-v3 image-recognition model from the input layer up to the bottleneck layer, and wherein the Inception-v3 image-recognition model was previously trained to detect and recognize objects unrelated to detecting user presence/absence at the surgeon console.

19. A robotic surgical system, comprising:

a surgeon console including a user seating area; and

a computer at the surgeon console configured to detect user presence/absence/absence at the surgeon console by:

receiving a set of raw video images capturing the user seating area of the surgeon console;

processing the set of raw video images to generate a set of training images;

training a convolutional neural network (CNN) model using the set of training images, wherein the CNN model includes an image classifier configured to output a binary classification for each input image, and wherein the binary classification is either a user-presence classification or a user-absence classification;

receiving a set of real-time video images of the user seating area captured during a surgical session; and

applying the trained CNN model to the set of real-time video images to automatically classify each video image in the set of real-time video images as either the user-presence classification or the user-absence classification.

20. The robotic surgical system of claim **19**, wherein the CNN model comprises a stack of feature-extraction layers including a sequence of convolutional layers and a sequence of pooling layers having a first set of parameters, which is followed a fully-connected layer having a second set of parameters, which is further followed by a final output layer, and wherein training the CNN model using the set of training images includes:

for each training image in the set of training images, using the stack of feature-extraction layers to extract a set of two-dimensional (2D) feature maps of the training image while fixing the first set of parameters; and

training the second set of parameters of the fully-connected layer based at least on the sets of extracted 2D feature maps extracted from the set of training images to obtain a trained fully-connected layer; and

fixing both the first set of parameters and the trained second set of parameters in the CNN model to obtain the trained CNN model.

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