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(54) **ADVERSARIAL MASKS FOR SCENE-CUSTOMIZED FALSE DETECTION REMOVAL**

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G06V 10/98	(2022.01)
G06V 10/70	(2022.01)

(Continued)

(52) **U.S. Cl.**
CPC ***G06V 10/98*** (2022.01); ***G06V 10/70*** (2022.01); ***G06V 10/7715*** (2022.01);
(Continued)

(58) **Field of Classification Search**
CPC G06V 10/98; G06V 10/707715; G06V 10/774; G06V 10/82; G06V 10/25; G06V 20/20; G06V 20/52
See application file for complete search history.

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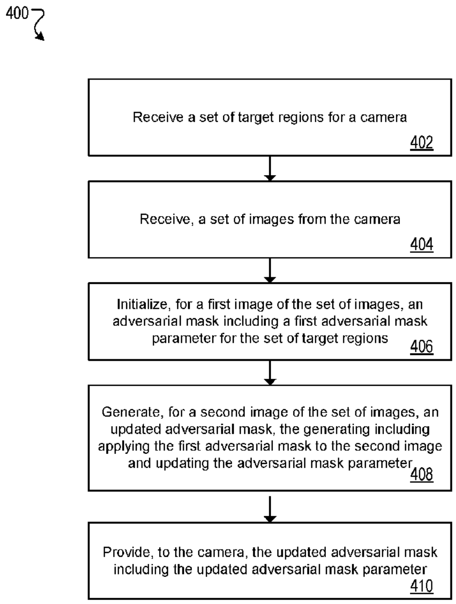
(57) **ABSTRACT**

Methods, systems, and apparatus, including computer programs encoded on a computer storage medium, for receiving multiple images from a camera, each image of the multiple images representative of a detection of an object within the image. For each image of the multiple images the methods include: determining a set of detected objects within the image, each object defined by a respective bounding box, and determining, from the set of detected objects within the image and ground truth labels, a false detection of a first object. The methods further include determining that a target object threshold is met based on a number of false detections of the first object in the multiple images, generating, based on the number of false detections for the first object meeting the target object threshold, an adversarial mask for the first object, and providing, to the camera, the adversarial mask.

20 Claims, 7 Drawing Sheets


400
Receive a set of target regions for a camera
402
Receive, a set of images from the camera
404
Initialize, for a first image of the set of images, an adversarial mask including a first adversarial mask parameter for the set of target regions
406
Generate, for a second image of the set of images, an updated adversarial mask, the generating including applying the first adversarial mask to the second image and updating the adversarial mask parameter
408
Provide, to the camera, the updated adversarial mask including the updated adversarial mask parameter
410

Related U.S. Application Data

(60) Provisional application No. 63/112,800, filed on Nov. 12, 2020.

(51) **Int. Cl.**

G06V 10/77	(2022.01)
G06V 10/774	(2022.01)
G06V 20/20	(2022.01)
G06V 20/52	(2022.01)

(52) **U.S. Cl.**
CPC ***G06V 10/774*** (2022.01); ***G06V 20/20*** (2022.01); *G06V 20/52* (2022.01)

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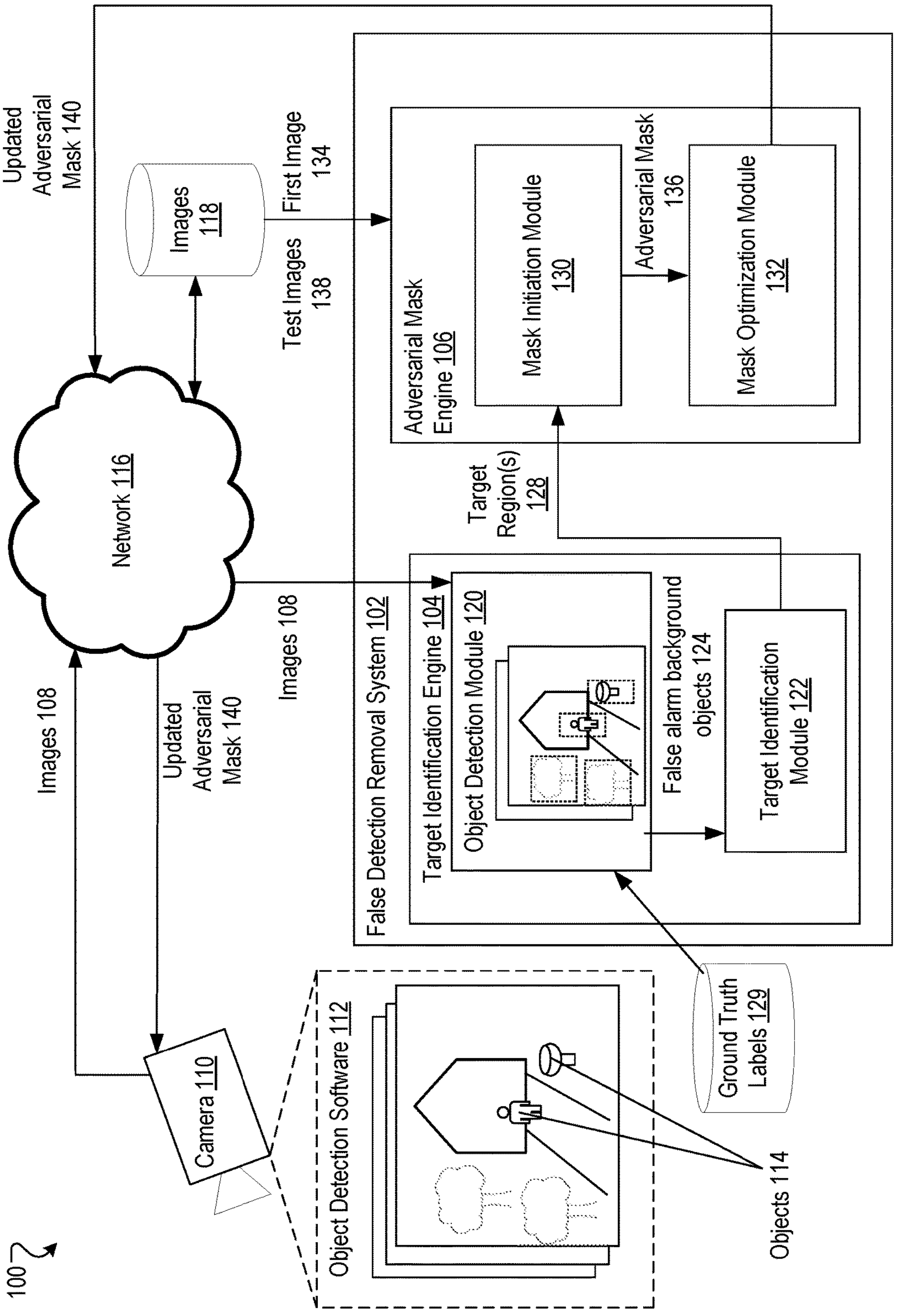
100
Camera 110
Object Detection Software 112
Objects 114
Images 108
Updated Adversarial Mask 140
Network 116
Images 118
Test Images 138
First Image 134
Updated Adversarial Mask 140
Images 108
False Detection Removal System 102
Target Identification Engine 104
Object Detection Module 120
False alarm background objects 124
Target Identification Module 122
Target Region(s) 128
Adversarial Mask Engine 106
Mask Initiation Module 130
Adversarial Mask 136
Mask Optimization Module 132
Ground Truth Labels 129

FIG. 1

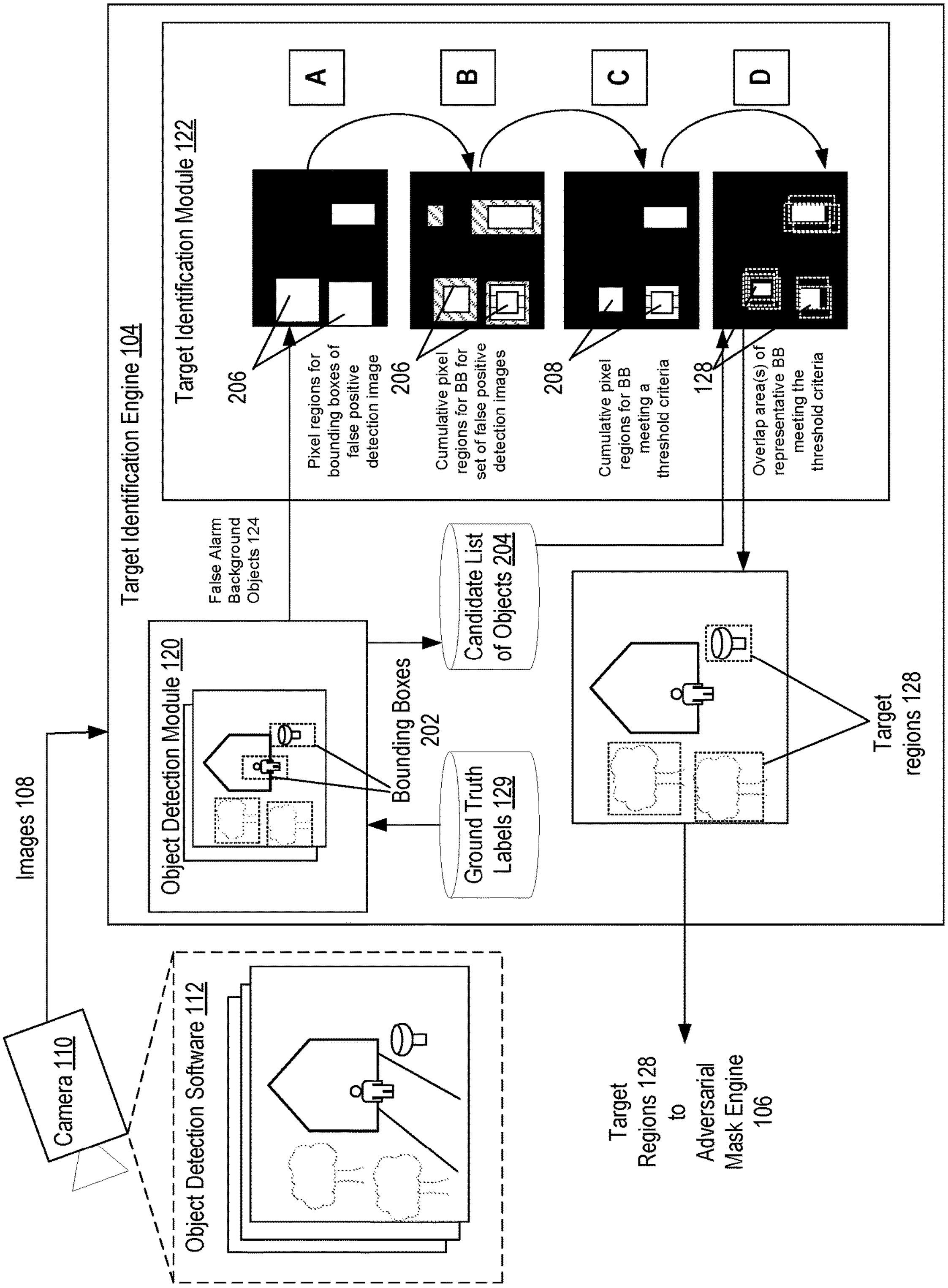
Target Identification Engine 104
Target Identification Module 122
A
B
C
D
206
Pixel regions for bounding boxes of false positive detection image
206
Cumulative pixel regions for BB for set of false positive detection images
208
Cumulative pixel regions for BB meeting a threshold criteria
128
Overlap area(s) of representative BB meeting the threshold criteria
False Alarm Background Objects 124
Object Detection Module 120
Bounding Boxes 202
Candidate List of Objects 204
Ground Truth Labels 129
Target regions 128
Images 108
Camera 110
Object Detection Software 112
Target Regions 128 to Adversarial Mask Engine 106

FIG. 2A

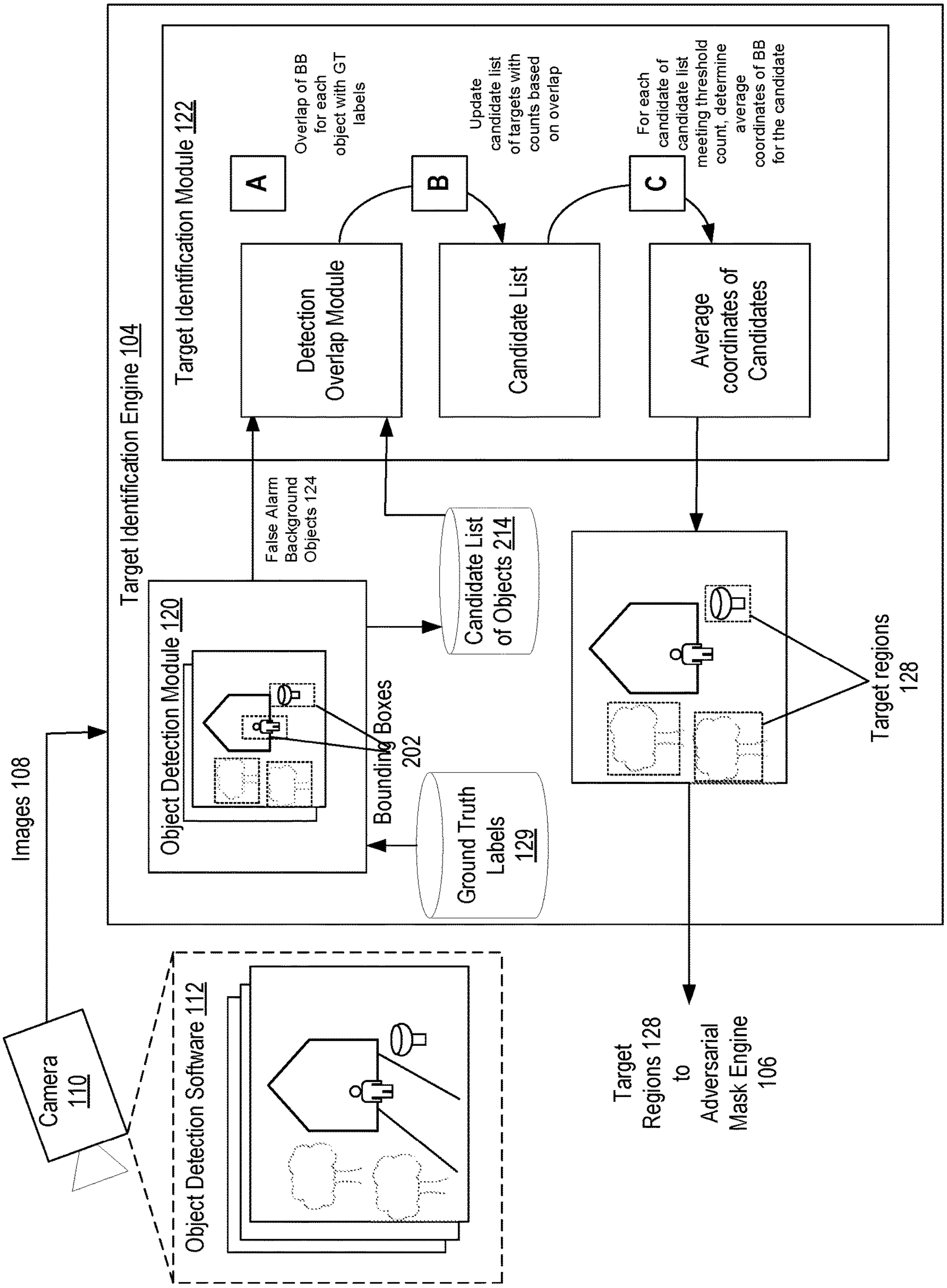
Camera 110
Object Detection Software 112
Images 108
Target Identification Engine 104
Object Detection Module 120
Bounding Boxes 202
Ground Truth Labels 129
Candidate List of Objects 214
False Alarm Background Objects 124
Target Identification Module 122
Detection Overlap Module
Candidate List
Average coordinates of Candidates
A
Overlap of BB for each object with GT labels
B
Update candidate list of targets with counts based on overlap
C
For each candidate of candidate list meeting threshold count, determine average coordinates of BB for the candidate
Target regions 128
Target Regions 128 to Adversarial Mask Engine 106

FIG. 2B

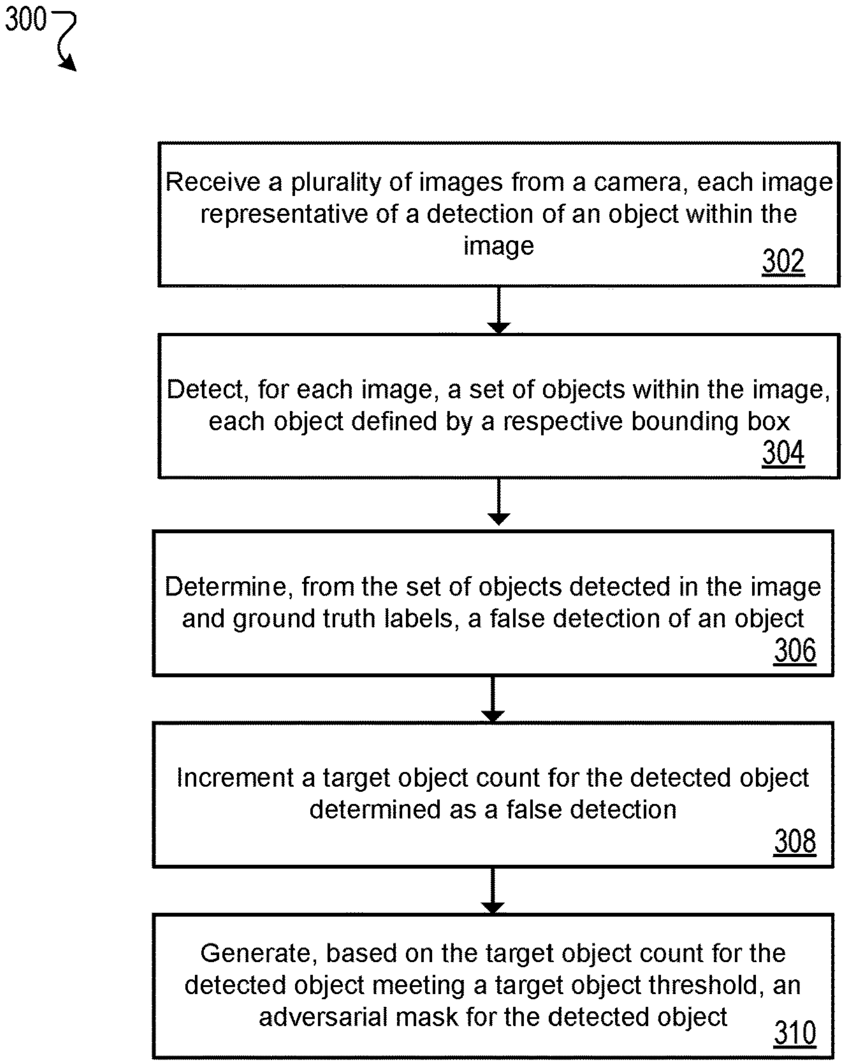
300
Receive a plurality of images from a camera, each image representative of a detection of an object within the image
302
Detect, for each image, a set of objects within the image, each object defined by a respective bounding box
304
Determine, from the set of objects detected in the image and ground truth labels, a false detection of an object
306
Increment a target object count for the detected object determined as a false detection
308
Generate, based on the target object count for the detected object meeting a target object threshold, an adversarial mask for the detected object
310

FIG. 3A

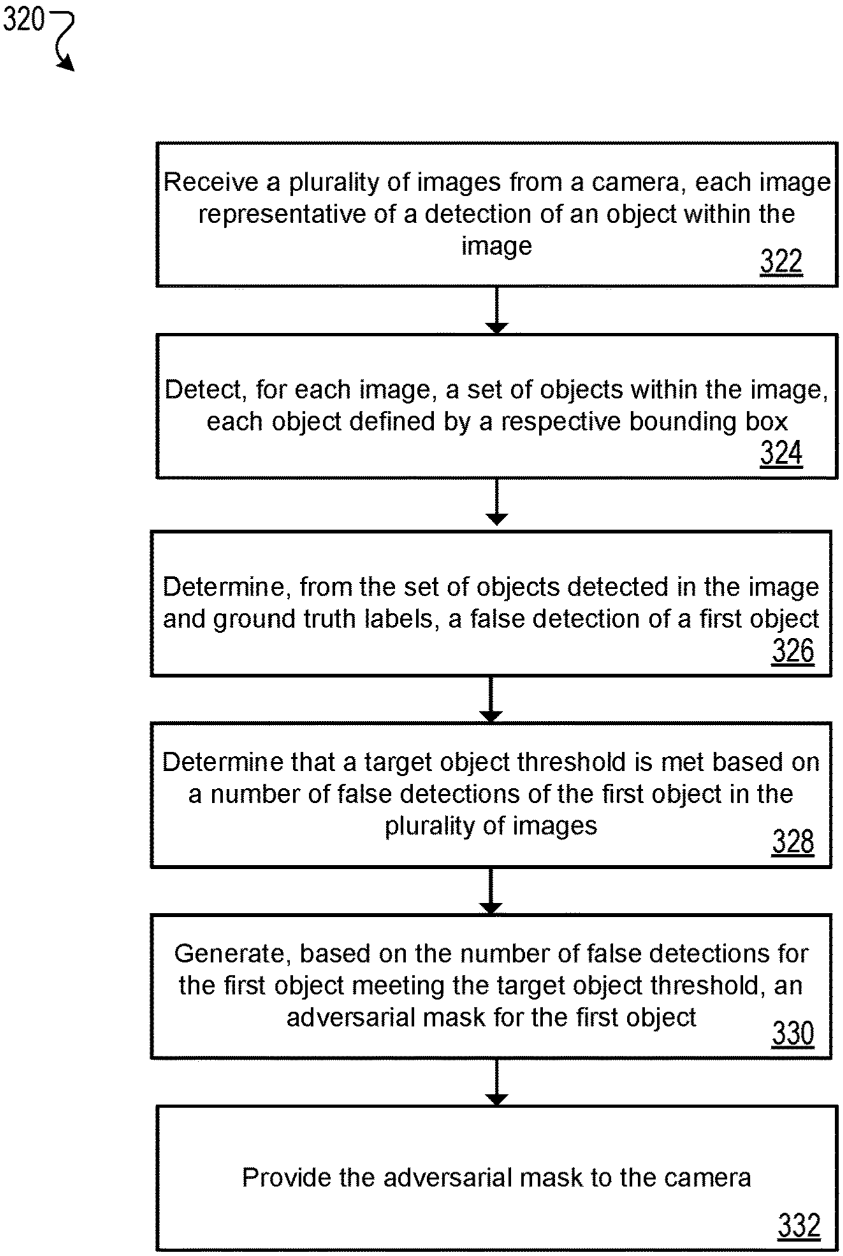
320
Receive a plurality of images from a camera, each image representative of a detection of an object within the image
322
Detect, for each image, a set of objects within the image, each object defined by a respective bounding box
324
Determine, from the set of objects detected in the image and ground truth labels, a false detection of a first object
326
Determine that a target object threshold is met based on a number of false detections of the first object in the plurality of images
328
Generate, based on the number of false detections for the first object meeting the target object threshold, an adversarial mask for the first object
330
Provide the adversarial mask to the camera
332

FIG. 3B

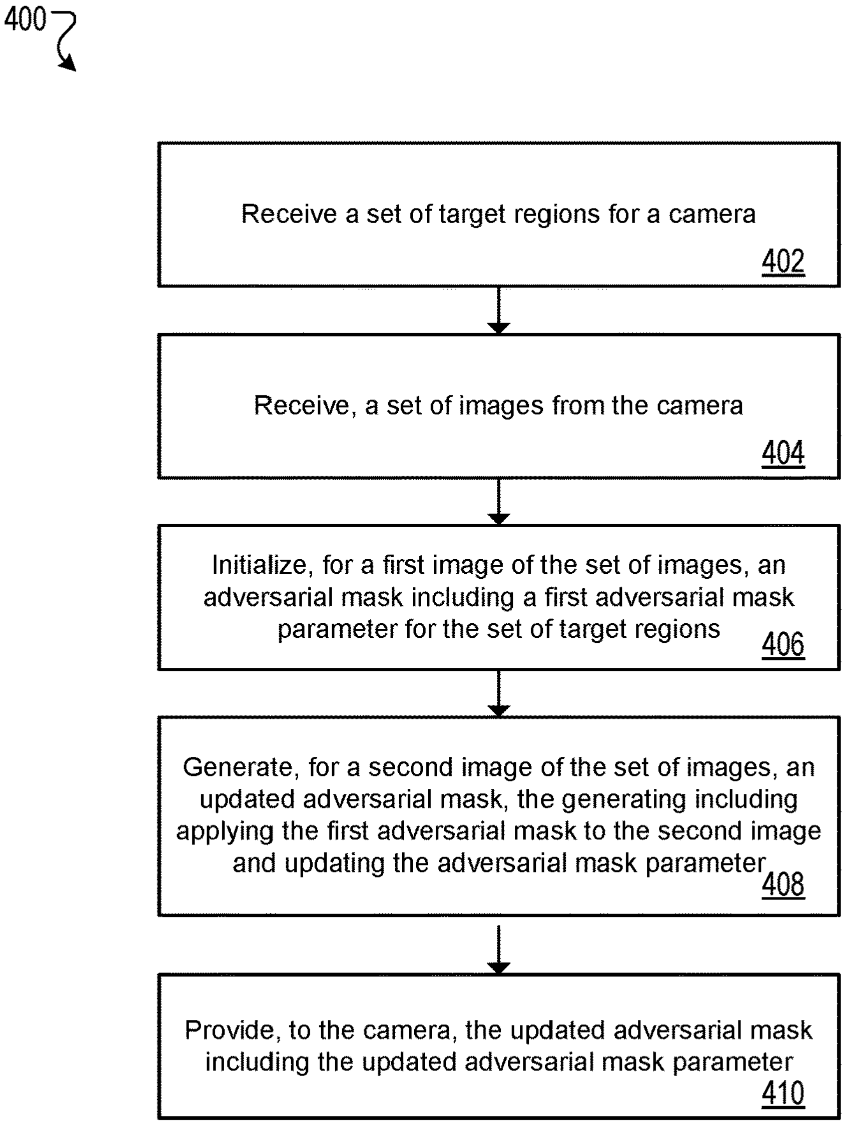
400
Receive a set of target regions for a camera
402
Receive, a set of images from the camera
404
Initialize, for a first image of the set of images, an adversarial mask including a first adversarial mask parameter for the set of target regions
406
Generate, for a second image of the set of images, an updated adversarial mask, the generating including applying the first adversarial mask to the second image and updating the adversarial mask parameter
408
Provide, to the camera, the updated adversarial mask including the updated adversarial mask parameter
410

FIG. 4

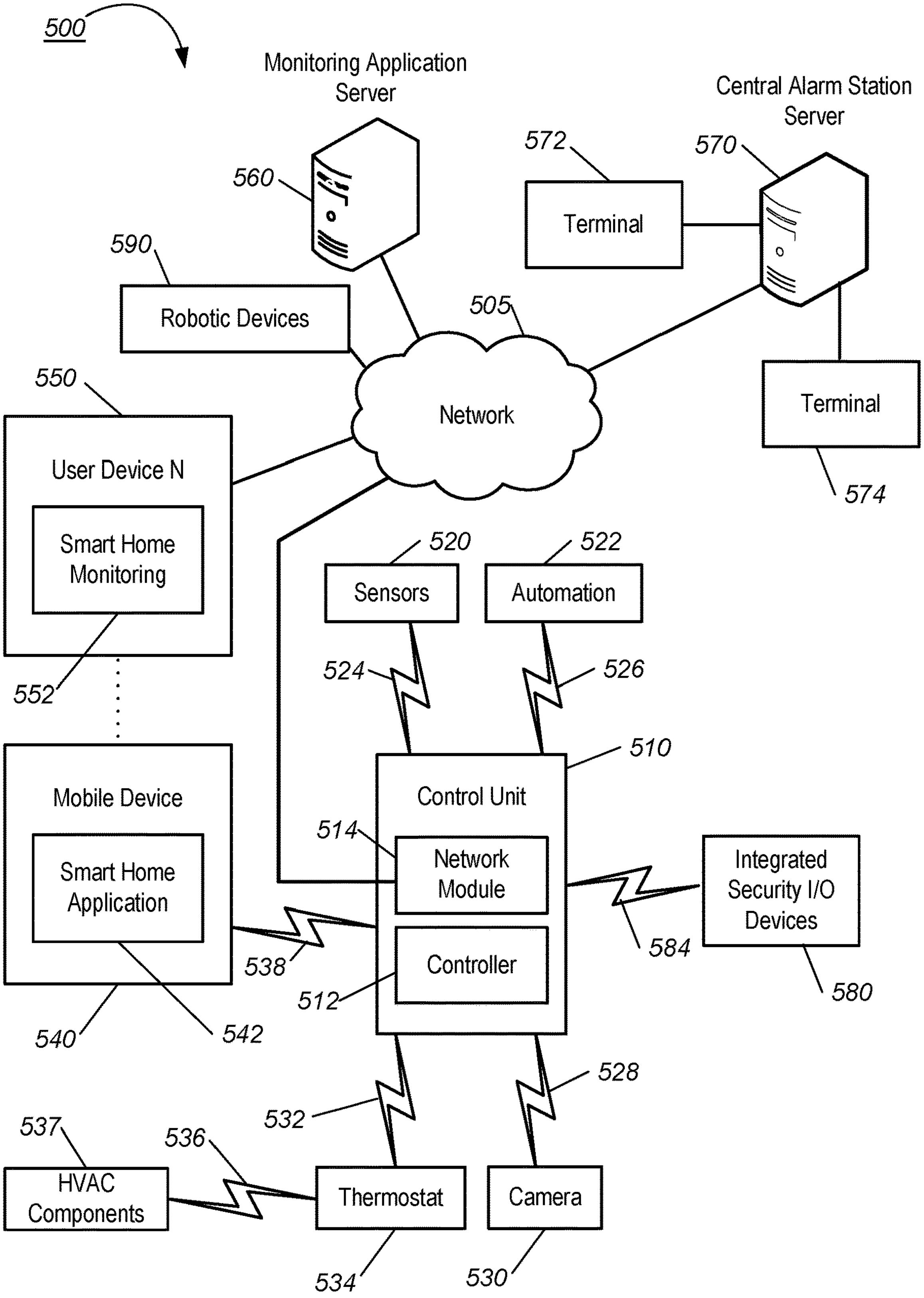
500
Monitoring Application Server
560
Central Alarm Station Server
570
572
Terminal
590
Robotic Devices
505
Network
Terminal
574
550
User Device N
Smart Home Monitoring
552
520
Sensors
522
Automation
524
526
510
Control Unit
514
Network Module
Controller
512
Mobile Device
Smart Home Application
538
540
542
Integrated Security I/O Devices
584
580
528
532
537
HVAC Components
536
Thermostat
Camera
534
530

FIG. 5

ADVERSARIAL MASKS FOR SCENE-CUSTOMIZED FALSE DETECTION REMOVAL

CROSS-REFERENCE TO RELATED APPLICATIONS

This application is a continuation of U.S. application Ser. No. 17/517,114, filed Nov. 2, 2021, which claims the benefit of U.S. Provisional Application No. 63/112,800, filed on Nov. 12, 2020. The disclosure of each of the foregoing applications is incorporated herein by reference.

BACKGROUND

Many properties are equipped with monitoring systems that include sensors and connected system components.

SUMMARY

In general, the subject matter described in this disclosure can be embodied in methods, apparatuses, and systems that generate masks used for false detection removal.

In general, adversarial techniques were traditionally conceived to attack or reduce the quality or accuracy of object detection. Object detection model(s) on a camera can capture and detect objects within a field of view of the camera. False alarm background objects (FABOs), e.g., trees, mailboxes, fountains, etc., can be a source of false positive detections where the object detection model may incorrectly detect a FABO as an object of interest. Techniques are described herein for determining target regions including FABOs within a field of view of a camera that are sources of false positive detections. The areas defining the respective target regions are optimized over a set of multiple images to increase removal of false positive detections due to FABOs while decreasing the impact on true positive detections, where each target region can be an average overlap of areas from images that result in false positive detections. Once the target regions are defined, the target regions can be utilized as a basis for an initial adversarial mask. In some implementations, pixel values for the pixels included in the target regions may be adjusted to generate an adversarial mask that better reduces false positive detections.

An adversarial mask is provided to the camera to utilize during operation by generating an adversarial auxiliary image. The input image is modified by changing values of one or more elements within the input image such as pixels or groups of pixels. The values are changed to produce a corresponding change in the results of a detection algorithm performed on the input image. The adversarial auxiliary image generated using the adversarial mask and the captured image by the camera can prevent an object detection model for the camera from detecting a FABO in the image, thereby reducing false positive detections without necessarily altering the object detection model on the camera.

One innovative aspect of the subject matter described in this specification is embodied in a method that includes receiving multiple images from a camera, each image of the multiple images representative of a detection of an object within the image. For each image of the multiple images the methods include: determining a set of detected objects within the image, each object defined by a respective bounding box, and determining, from the set of detected objects within the image and ground truth labels, a false detection of a first object. The methods further include determining that a target object threshold is met based on a number of false detections of the first object in the multiple images, generating, based on the number of false detections for the first object meeting the target object threshold, an adversarial mask for the first object, and providing, to the camera, the adversarial mask.

Other implementations of this and other aspects include corresponding systems, apparatus, and computer programs, configured to perform the actions of the methods, encoded on computer storage devices. A system of one or more computers can be so configured by virtue of software, firmware, hardware, or a combination of them installed on the system that in operation cause the system to perform the actions. One or more computer programs can be so configured by virtue of having instructions that, when executed by data processing apparatus, cause the apparatus to perform the actions.

The foregoing and other embodiments can each optionally include one or more of the following features, alone or in combination. In some implementations, determining that the target object threshold is met based on the number of false detections of the first object includes, for each determined false detection of the first object: incrementing a target object count for the first object within the image, and determining the target object count for the first object mects a target object threshold.

In some implementations, incrementing a target object count for the first object within the image includes incrementing pixel counts for pixels in a pixel region corresponding to a bounding box defining the first object. In some implementations, determining the target object count for the first object meets the target object threshold includes determining that pixels within the pixel region meet a threshold pixel count, and generating, based on the target object count for the first object meeting the target object threshold, the adversarial mask for the first object can include determining, based on the pixels within the pixel region meeting the threshold pixel count, a target region for the first object, and generating the adversarial mask including the target region.

In some implementations, incrementing a target object for the first object within the image includes: determining, from multiple candidate objects, a candidate object including a bounding box with a threshold overlap with a bounding box of the first object, and incrementing a count for the candidate object. Determining the target object count for the first object meets the target object threshold can include determining the count for the candidate object meets a threshold count, and generating, based on the target object count for the first object meeting the target object threshold, the adversarial mask for the first object can include determining, based on bounding boxes corresponding to each appearance of the candidate object meeting the threshold count in the multiple images, a target region for the candidate object, and generating the adversarial mask including the target region.

In some implementations, the methods further include receiving, from the camera, a second set of multiple images, applying, to a first image of the second set of multiple images, the adversarial mask including an adversarial mask parameter, where applying the adversarial mask to the first image includes modifying one or more pixels of the first image to generate a first auxiliary image, determining, for the first auxiliary image, a gradient and a sign of the gradient, generating, based on the gradient and the sign of the gradient and from the adversarial mask, an updated adversarial mask. Updating the adversarial mask includes: applying the adversarial mask to a second image of the second set of multiple images, and updating the adversarial mask parameter, and providing, to the camera, the updated adversarial mask.

Particular embodiments of the subject matter described in this specification can be implemented so as to realize one or more of the following advantages. Adversarial masks can be utilized to reduce false positive detections triggered by objects that are not of interest within a field of view of a camera. Target objects in images captured by a camera can be identified as sources of false detections and can be used to generate an adversarial mask on a per-image basis, a per-clip basis, or a per-camera basis. The identification of target objects can be performed in an automatic or semi-automatic manner, reducing cost to process and generate an adversarial mask for a camera. An initial adversarial mask can be set as a learnable parameter, where an iterative optimization process can be performed on the initial adversarial mask for multiple images including multiple imaging conditions for a camera, e.g., different lighting, seasons, weather, etc., and can result in a robust adversarial mask that can have minimal impact on true positive detections while maximally reducing false positive detections.

The details of one or more embodiments of the invention are set forth in the accompanying drawings and the description below. Other features and advantages of the invention will become apparent from the description, the drawings, and the claims.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a diagram depicting an example operating environment of a false detection removal system.

FIG. **2**A is a diagram of an example target identification engine of the adversarial mask system.

FIG. **2**B is a diagram of another example target identification engine of the adversarial mask system.

FIG. **3**A is a flow diagram illustrating an example of a process of the adversarial mask system.

FIG. **3**B is a flow diagram illustrating another example of a process of the adversarial mask system.

FIG. **4** is a flow diagram illustrating another example process of the adversarial mask system.

FIG. **5** is a diagram illustrating an example of a property monitoring system.

DETAILED DESCRIPTION

FIG. **1** is a diagram depicting an example operating environment **100** of a false detection removal system **102**. False detection removal system **102** can be hosted on one or more local servers, a cloud-based service, or a combination thereof. False detection removal system **102** includes a target identification engine **104** and an adversarial mask engine **106**. Though described here as a target identification engine **104** and adversarial mask engine **106**, the processes performed by each can be performed by more or fewer engines as part of the false detection removal system **102**.

The system **102** can receive images **108** from a camera **110** as input. Camera **110** can be a surveillance camera located on a property, e.g., a home, and oriented to capture a scene within a field of view of the camera **110**. Camera can include object detection software **112** to detect objects **114** within clips, e.g., video clips, and/or images captured by the camera **110** of the scene.

In some implementations, images **108** from the camera **110** can include representative images from clips captured by camera **110** within a field of view of the camera **110**. For example, camera **110** can capture a clip of a delivery truck passing through the field of view of camera **110** and a representative image including the delivery truck is selected for the clip. The captured images **108** can be processed by object detection software **112**. Object detection software **112** can be located on camera **110** and/or on a cloud-based server and can process the captured images **108** to detect one or more objects within the captured images **108**, e.g., people, animals, vehicles, etc.

In some implementations, object detection software **112** can detect that one or more objects **114** appear within the captured image **108** and provide the captured image **108** to the false detection removal system **102** via a network **116**.

In some implementations, object detection software **112** can include one or more machine-learned models for identifying and classifying objects within the scene. For example, object detection software **112** can include facial recognition software, human/animal models, and the like. Object detection software **112** can detect one or more objects within an image, set of images, or clips captured by camera **110**.

Network **116** is configured to enable the exchange of electronic communications between camera **110** and the system **102**. The network **116** may include, for example, one or more of the Internet, Wide Area Networks (WANs), Local Area Networks (LANs), analog or digital wired and wireless telephone networks (e.g., a public switched telephone network (PSTN), Integrated Services Digital Network (ISDN), a cellular network, and Digital Subscriber Line (DSL), radio, television, cable, satellite, or any other delivery or tunneling mechanism for carrying data. Network **116** may include multiple networks or subnetworks, each of which may include, for example, a wired or wireless data pathway. The network **116** may include a circuit-switched network, a packet-switched data network, or any other network able to carry electronic communications (e.g., data or voice communications). For example, the network **116** may include networks based on the Internet protocol (IP), asynchronous transfer mode (ATM), the PSTN, packet-switched networks based on IP, X.25, or Frame Relay, or other comparable technologies and may support voice using, for example, VoIP, or other comparable protocols used for voice communications. The network **116** may include one or more networks that include wireless data channels and wireless voice channels. The network **116** may be a wireless network, a broadband network, or a combination of networks includes a wireless network and a broadband network.

In some implementations, images **108** from camera **110** can be provided to the false detection removal system **102** as they are captured. Images **108** can additionally or alternatively be stored in an image database **118**, e.g., on a cloud-based server, on a camera-based data storage, or an edge-based device, and can be provided to and/or accessed by the false detection removal system **102**. For example, camera **110** can upload captured images **108** in image database **118** and false detection removal system **102** can request images **108** from the image database **118** in the process of generating an adversarial mask.

Target identification engine **104** includes an object detection module **120** and a target identification module **122**. Through described here as object detection module **120** and target identification module **122**, the processes described can be performed by more or fewer modules.

Object detection module **120** receives images **108** as input. As described above, images **108** can be provided by camera **110** via network **116**. Additionally, or alternatively, images **108** can be received by the object detection module **120** from image database **118** via the network **116**.

Object detection module **120** can detect, using one or more machine-learned models, objects within each image **108** of a set of images. The object detection module can further identify, by multiple classifiers, the objects appearing in each image **108** of a set of images, and provide the FABOs **124** as output to the target identification module **122**. The target identification module **122** can be located on a cloud-based server, on the camera, or an edge device.

In some implementations, ground truth labels **126** can be applied to each of the objects **114** detected within each image **108**. Each object can be annotated with a ground truth label **126** in an automatic, semi-automatic, or manual manner. For example, objects may be annotated with ground truth labels by a human expert, e.g., "tree, fountain, flag, car, human, animal." In some implementations, the objects may be annotated with ground truth labels using user feedback, e.g., where a homeowner can define a bounding box as a false positive detection.

The annotated objects that are not of interest, e.g., false alarm background objects (FABOs), can be identified from the annotated objects. Images including the FABOs can be identified, and the object detection module **120** can output the FABOs **124**. FABOs **124** can include objects determined to be sources of false positive detections. In other words, objects identified within an image **108** and annotated with ground truth labels can be identified as FABOs **124** as potential sources of false positive detections by camera **110**. For example, an image can include annotated objects "tree" and "fountain" which are examples of false alarm background objects and can result in a determination that the image is a false positive detection. The objects identified in the image **108**, e.g., "tree" and "fountain," are then output as FABOs **124** as possible sources of false positive detections.

In some implementations, FABOs **124** include coordinates for each false detection detected within the image **108**. For example, the object detection module **120**, which can be a form of deep object detector, obtains one or more coordinates that correspond to one or more of the FABOs **124**. The FABOs **124** can include coordinates as well as a classifier for each detection. In some cases, a false detection object class can be used to distinguish the FABOs **124** from objects detected in true positive detection images **108**.

In some implementations, a first false positive detection includes the false detection object class, a first x coordinate, a first y coordinate, a second x coordinate, and a second y coordinate in a given two-dimensional (2D) x-y plane of the image **108**. The first x coordinate and the first y coordinate correspond to a corner of a bounding box that bounds a first false detection. The second x coordinate and the second y coordinate correspond to another corner of a bounding box that bounds the first false detection.

In some implementations, other shapes or identifiers are used to label or define the FABOs **124**. For example, instead of boxes with at least four values corresponding to a first x and y coordinate pair and a second x and y coordinate pair, an oval can be used. A center coordinate point together with a radius length on either the semi-major or semi-minor axis or both can be included. Other common shapes including polygons can be used such as circles, triangles, pentagons, among others.

In some implementations, buffers around bounding shapes can be used. In some cases, shapes can be specified using pixel values or ranges. Bounding shapes can include absolute or relative buffers around particular regions of images. For example, a 2 percent pixel buffer for a rectangular bounding box around a tree can be used to fully capture the tree. Similarly, an absolute buffer of 3 pixels on each of the four sides of the rectangular bounding box can be used to fully capture the tree.

In some implementations, a shape informed by a process similar to the object detection module **120** is used to label or define the FABOs **124**. For example, a tree shown in the image **108** can be detected and a bounding box that labels or defines the detected tree can resemble the shape of the detected tree. In this way, bounding boxes can be dynamic and approximate the shape or appearance of elements which they bound.

In some implementations, FABOs **124** can be representative of objects that result in false positive detections under different imaging conditions by the camera **110**. For example, FABOs **124** can differ under various lighting conditions, e.g., day vs night, weather conditions, e.g., sunny vs. cloudy, and/or seasonal conditions, e.g., fall vs spring. In one example, a tree object within a field of view of a camera can be a FABO under rainy and windy conditions (due to moving branches triggering the camera), but may not be a FABO under sunny, temperate conditions.

Target identification module **122** can receive the FABOs **124** as input and provide, as output, target regions **128**. Target regions **128** represent areas of a scene within the field of view of the camera **110** that are determined to be sources of false positive detections, and which can include at least a portion of a FABO **124**. Further details of the target identification module **122** are discussed below with reference to FIGS. **2**A and **2**B.

Adversarial mask engine **106** receives target regions **128** as input. Adversarial mask engine **106** includes a mask initiation module **130** and a mask optimization module **132**. Though described here as mask initiation module **130** and mask optimization module **132**, the processes described can be performed by more or fewer modules.

Mask initiation module **130** receives the target regions **128** and a first image **134** as input and generates, from the target regions **128** and for the first image **134**, an adversarial mask **136**. First image **134** can be an image of the set of images **108** from image database **118**. Adversarial mask **136** is provided by the mask initiation module **130** as output.

Mask optimization module **132** receives adversarial mask **136** and a set of test images **138** as input, and performs an iterative optimization process to generate an updated adversarial mask **140**, as output. Further details of the operations of the adversarial mask engine **106** are discussed below with reference to FIG. **4**.

Updated adversarial mask **140** is provided to the camera **110**. The updated adversarial mask **140** is utilized by the camera to alter the images captured by the camera **110**. In other words, the update adversarial mask **140** will prevent the object detection software **112** of the camera **110** from detecting the FABOs within the field of view of the camera **110**. For example, the updated adversarial mask **140** will alter one or more pixels of the FABO such that one or more neural networks and/or machine learned models of the object detection software **112** will not recognize a pattern that may lead to object detection of the FABO.

FIGS. **2**A and **2**B are diagrams of example processes of the target identification engine of the adversarial mask system. As described above with reference to FIG. **1**, target identification engine **104** can receive, images **108** from a camera **110** as input. Each image **108** of the images **108** from the camera **110** can be representative of a detection by the camera **110**, e.g., a detection of one or more objects **114** within the field of view of the camera **110**. Object detection module **120** receives the images **108** and can identify a set of false alarm background images (FABOs) **124** as output. In some implementations, as depicted in FIG. **2**A, the object detection module **120** can utilize a one or more machine-learned models to generate a set of bounding boxes **202** for each image **108**, where each bounding box **202** captures an object **114** detected within the image **108**.

Each object **114** identified by a bounding box **202** can be annotated by a ground truth label **129**, e.g., by a human expert, by an end user, or in an automatic/semi-automatic manner, to generate a set of annotated objects. Images **108** including annotated objects that are not of interest can be labeled as false positive detections. The identified annotated objects in each image **108** that is determined to be a false positive detection can be added to a candidate list of objects **204** that are potential FABOs **124**.

FABOs **124** are provided as input to the target identification module **122**. As described above, FABOs **124** can include bounding boxes and a set of coordinates for the bounding boxes **202**, where the bounding box **202** and set of coordinates can define a pixel region including a set of pixels. In Stage A, pixel regions **206** for each of the bounding boxes **202** for the FABOs **124** for a first image that is a false detection are identified.

In Stage B, the target identification module adds, for each of multiple additional images from a set of images, pixel regions **206** for bounding boxes **202** for FABOs **124** in the multiple additional images to a cumulative pixel count for each identified pixel region **206** in a pixel count matrix. In some implementations, the pixel count matrix is initialized to have a size corresponding to the size of the image **108** used by the system **102**, e.g., 480×480. The pixel count matrix can be initialized with all pixel values equal to zero, where each false positive detection increases corresponding pixels in pixel regions by increments of 1.

In Stage C, the target identification module **122** identifies pixel sub-regions **208**, e.g., seed regions, meeting a threshold pixel count. The pixel sub-regions **208** can include a portion or all of a pixel region **206**, e.g., can be a central portion of the pixel region **206**. In one example, a pixel sub-region **208** can include a smaller number of pixels from an area of pixels defined by pixel region **206**. A threshold pixel count can be any integer number, and can be a percentage of the total number of frames that there are in the camera **110**. In one example, 30% of the total frames of the camera videos can be used to create the matrix, e.g., if a camera video has 1000 frames in total, 300 can be set as the threshold. Thus, if there is an area where the pixel counts in the matrix pass a value of 300 they will pass, otherwise any area with pixels under 300 will be discarded.

In some implementations, a threshold pixel count can be defined relative to an average pixel count for each pixel region **206**.

In Stage D, the target identification module **122** identifies candidates from the candidate list of objects **204**, e.g., a FABO, including bounding boxes **202** for each respective candidate that overlap with pixel sub-regions **208**. The module **122** selects, from the candidate list of object **204**, a set of candidates, e.g., FABOs, with respective bounding boxes **202** that overlap each pixel sub-region **208**. In one example, the set of candidates is at least 20 candidates, at least 10 candidates, at least 30 candidates. In another example, the set of candidates includes candidates that have at least a threshold area overlap between an area of the pixel sub-region **208** and a respective area of the bounding box for the candidate, e.g., at least 50%, at least 75%, at least 95%. In another example, the set of candidates includes a particular number of candidates of all the candidates overlapping with the pixel sub-region having the most area overlap between the area of the pixel sub-region **208** and the respective area of the bounding box **202** for the candidate, e.g., a set of 20 candidates having the most overlap compared to the candidates, a set of 10 candidates having the most overlap compared to the candidates, etc., for the particular pixel sub-region **208**.

The target identification module **122** determines, from the bounding boxes **202** of the set of candidates overlapping the pixel sub-region **208**, a target region **128** that is an area of overlap of the bounding boxes **202**. Target regions **128** can include, for example, a tree, fountain, flag, or another object that is not of interest to a user, e.g., homeowner. The target identification module **122** provides the target regions **128**, as discussed above with reference to FIG. **1**, to the adversarial mask engine **106**.

FIG. **2**B is a diagram of another example process of the target identification engine of the adversarial mask system. As described with reference to FIG. **2**A, the object detection module **120** receives images **108** from camera **110** as input and provides, false alarm background objects **124** as output. In some implementations, as depicted in FIG. **2**B, target identification module **122** receives the FABOs **124** as input. In Stage A, a detection overlap module **212** determines if a bounding box **202** corresponding to a received FABO **124** overlaps with a candidate object including a ground truth label in a stored list of candidate objects **214**. For example, the detection overlap module **212** receives a FABO that is a tree with a particular bounding box. The detection overlap module **212** checks if the bounding box for the FABO overlaps with a candidate object including a bounding box and labeled with a ground truth label "tree."

In Stage B, the target identification module updates the stored list of the candidate objects **214**, based on whether the bounding box **202** for the FABO overlaps with a candidate object in the stored list of candidate objects **214**. Updating the stored list of the candidate objects **214** includes storing bounding box coordinates for each candidate object processed by the target identification module **122**. If the bounding box **202** of the FABO is determined to overlap with a candidate object in the stored list of candidate objects **214**, then the target identification module increments a count for the particular candidate object and stores the bounding box coordinates for the FABO **124** with the particular candidate object. If the bounding box of the FABO is determined to not overlap with a candidate object, then the target identification module adds a new candidate object including bounding box coordinates to the stored list of candidate objects **214** to represent the FABO.

In Stage C, the target identification module **122** identifies each candidate object in the stored list of candidate objects **214** that meets a threshold count, e.g., a threshold number of false positive detections for the candidate object. In other words, each candidate object that is identified as a FABO in a threshold number of images **108** provided by the camera, is identified by the target identification module **122**. In some implementations, a percentage number of a total number of frames, e.g., images **108**, from the camera **110** is used as the threshold count. For example, 30% of the total frames of the camera can be used as the threshold count.

For each of the identified candidate objects meeting the threshold count, an average of bounding box coordinates for each instance of the identified candidate object as one or more FABO **124** identified in images **108** is determined. The average coordinates of the object candidates generates target regions **128**. The target identification module **122** outputs the target regions **128** to the adversarial mask engine **106**.

FIG. **3**A is a flow diagram illustrating an example of a process **300** of the adversarial mask system. The system receives multiple images from a camera, each image representative of a detection of an object within the image (**302**). In some implementations, as depicted in FIG. **1**, the system **102** receives multiple images **108** from camera **110**, where each image **108** represents a detection of an object and/or event, e.g., person, animal, vehicle, etc., within the image **108**. Images **108** can be stored in an image database **118**, e.g., on a cloud-based server, and accessible by the system **102** via network **116**.

In some implementations, one or more of the images **108** can be a representative image for a respective clip, e.g., video recording, by the camera **110**. A representative image for a respective clip can be an image capturing one or more objects and/or events that triggered the capturing of the clip. In one example, camera **110** can be triggered to capture a clip by a person walking through the field of view of the camera **110**, where a representative image for the clip includes the person in the frame.

The multiple images **108** can include false positive detections and true positive detections. A false positive detection can include where an object detected in an image is incorrectly detected, for example, where the camera is triggered to capture images/video clips by objects that are not of interest, e.g., a fountain, a mailbox, etc., within a field of view of the camera. A true positive detection can include an image where an object detected is correctly detected, for example, where the camera is triggered to capture images/video clips by an object of interest, e.g., a human, within the field of view of the camera. The objects within the images **108** can be identified by the object detection software **112** on camera **110**, e.g., using multiple classifiers and/or machine-learned models.

For each image, the system detects a set of objects within the image, each object defined by a respective bounding box (**304**). Object detection module **120** of the false detection removal system **102** can apply bounding boxes to objects appearing within an image **108**. Object detection module **120** can include one or more machine-learned models and/or classifiers to identify objects appearing within the image and apply bounding boxes around each of the objects. In some implementations, the object detection module **120** can receive images **108** with bounding boxes ascribed by object detection software **112** on camera **110**.

The system determines false detection of an object from the set of objects detected in the image and utilizing ground truth labels (**306**). Ground truth labels **129** can be applied to the objects detected in the image **108**, e.g., by a human expert. In some implementations, object recognition and clustering techniques can be applied to perform ground truth labeling in a semi-automatic or automatic manner. Ground truth labels **129** applied to each object can be utilized to categorize the object as either a target of interest, e.g., human, vehicle, etc., or a target not of interest, e.g., flag, mailbox, etc. Objects are determined by the system **102** to be targets not of interest, e.g., camera **110** is triggered to capture an image because of a target not of interest within the field of view of the camera **110**, can be labeled by the system **102** as false alarm background objects **124** (FABOs). Images **108** where FABOs triggered the detection can be identified as false positive detections.

The system increments a target object count for the detected object determined as a false detection (**308**). As described with reference to FIGS. **2**A and **2**B, system **102** can increment a target object count for each detected object, e.g., FABO **124**, that is determined to be a source of a false detection. In some implementations, as described with reference to FIG. **2**A, target identification module **122** increments pixel counts for pixels in pixel regions corresponding to bounding boxes for the FABOs identified in the images that are false positive detections. For example, the target identification module **122** can increment pixel counts for pixels corresponding to a bounding box for a tree that is determined to be a FABO by increasing a corresponding pixel count stored for each pixel within the bounding box for the tree. In some implementations, as described with reference to FIG. **2**B, target identification module **122** can increment a count associated with a candidate from a candidate list of objects **214** for which a bounding box of a FABO in an image that is a false positive detection overlaps with the candidate. For example, the target identification module **122** can increment a stored count for a tree from a list of candidate objects (e.g., bird feeder, mailbox, sprinkler, etc.) when the bounding box of the falsely detected object is determined to overlap with the bounding box of the tree.

In some implementations, incrementing the target object count (i.e., a number of false positive detections for the detected object) can be increasing the target object count by 1 such that each false positive detection increases the count by 1 (e.g., 0, 1, 2, 3 . . . etc.). In some implementations, incrementing the target object count can be increasing the target object count by a different integer, e.g., by 2, 3, n, etc. In some implementations, incrementing the target object count can be increasing the target object count by doubling the target object count for each false positive detection (e.g., from 2 to 4), or by multiplying the target object count by another value. In some implementations, incrementing the target object count can be decreasing the target object count for each false positive detection of the target object such that each false positive detection decreases the count by a value (e.g., decreases the count by 1).

Based on the target object count for the detected object meeting a target object threshold, the system generates an adversarial mask for the detected object (**310**). The system **102** can determine, for each detected object, that the detected object meets a target object threshold and provides target regions **128** for the target objects meeting the target object threshold to the adversarial mask engine **106** to generate an adversarial mask for the detected objects meeting the target object threshold. In some implementations, as described with reference to FIG. **2**A, a set of representative bounding boxes, e.g., 20 bounding boxes, a top 5% of bounding boxes, or the like, corresponding to pixel regions **208** that meet a threshold criterion (e.g., a threshold pixel count), are overlapped and an area of overlap is determined as a target region **128**.

In some implementations, as described with reference to FIG. **2**B, average coordinates for the bounding boxes corresponding to candidates in the candidate list of objects that meet a target object threshold, e.g., a number of counts of appearance of the candidate in false positive detections, are utilized to determine a target region **128** for each candidate meeting the threshold.

FIG. **3**B is a flow diagram illustrating another example of a process **320** of the adversarial mask system. The system receives multiple images from a camera, each image representative of a detection of an object within the image (**322**). In some implementations, as depicted in FIG. **1**, the system **102** receives multiple images **108** from camera **110**, where each image **108** represents a detection of an object and/or event, e.g., person, animal, vehicle, etc., within the image

108. Images **108** can be stored in an image database **118**, e.g., on a cloud-based server, and accessible by the system **102** via network **116**.

In some implementations, one or more of the images **108** can be a representative image for a respective clip, e.g., video recording, by the camera **110**. A representative image for a respective clip can be an image capturing one or more objects and/or events that triggered the capturing of the clip. In one example, camera **110** can be triggered to capture a clip by a person walking through the field of view of the camera **110**, where a representative image for the clip includes the person in the frame.

The multiple images **108** can include false positive detections and true positive detections. A false positive detection can include where an object detected in an image is incorrectly detected, for example, where the camera is triggered to capture images/video clips by objects that are not of interest, e.g., a fountain, a mailbox, etc., within a field of view of the camera. A true positive detection can include an image where an object detected is correctly detected, for example, where the camera is triggered to capture images/video clips by an object of interest, e.g., a human, within the field of view of the camera. The objects within the images **108** can be identified by the object detection software **112** on camera **110**, e.g., using multiple classifiers and/or machine-learned models.

For each image, the system detects a set of objects within the image, each object defined by a respective bounding box (**324**). Object detection module **120** of the false detection removal system **102** can apply bounding boxes to objects appearing within an image **108**. Object detection module **120** can include one or more machine-learned models and/or classifiers to identify objects appearing within the image and apply bounding boxes around each of the objects. In some implementations, the object detection module **120** can receive images **108** with bounding boxes ascribed by object detection software **112** on camera **110**.

The system determines false detection of an object from the set of objects detected in the image and utilizing ground truth labels (**326**). Ground truth labels **129** can be applied to the objects detected in the image **108**, e.g., by a human expert. In some implementations, object recognition and clustering techniques can be applied to perform ground truth labeling in a semi-automatic or automatic manner. Ground truth labels **129** applied to each object can be utilized to categorize the object as either a target of interest, e.g., human, vehicle, etc., or a target not of interest, e.g., flag, mailbox, etc. Objects are determined by the system **102** to be targets not of interest, e.g., camera **110** is triggered to capture an image because of a target not of interest within the field of view of the camera **110**, can be labeled by the system **102** as false alarm background objects **124** (FABOs). Images **108** where FABOs triggered the detection can be identified as false positive detections.

The system determines that a target object threshold is met based on a number of false detections of the first object in the plurality of images (**328**). As described with reference to FIGS. **2**A and **2**B, system **102** can track a number of false positive detections for each detected object, e.g., FABO **124**, and compare the number of false positive detections for each detected object to a target object threshold. In some implementations, the system can determine that a number of false positive detections of an object (e.g., a bird bath within a field of view of the camera) meets or exceeds a target object threshold that is a total number of false positive detections. In some implementations, the system can determine that a number of false positive detections of the detected object

compared to a total number of detections meets the target object threshold (i.e., a percentage of the total number of detections are false positive detections due to the detected object meets or exceeds a threshold value).

Based on the number of false detections for the first object meeting the target object threshold, the system generates an adversarial mask for the first object (**330**). The system **102** can generate, for each detected object meeting the target object threshold, an adversarial mask. Generating the adversarial mask can include providing target regions **128** for the target objects meeting the target object threshold to the adversarial mask engine **106** to generate an adversarial mask for the detected objects meeting the target object threshold. In some implementations, as described with reference to FIG. **2**A, a set of representative bounding boxes, e.g., 20 bounding boxes, a top 5% of bounding boxes, or the like, corresponding to pixel regions **208** that meet a threshold criterion (e.g., a threshold pixel count), are overlapped and an area of overlap is determined as a target region **128**.

In some implementations, as described with reference to FIG. **2**B, average coordinates for the bounding boxes corresponding to candidates in the candidate list of objects that meet a target object threshold, e.g., a number of counts of appearance of the candidate in false positive detections, are utilized to determine a target region **128** for each candidate meeting the threshold.

The system provides the adversarial mask to the camera (**332**). The system **102** can provide the adversarial mask to the camera **110**. The camera **110** can receive the adversarial mask and apply the adversarial mask to images captured to reduce a number of false detections of FABOs within a field of view of the camera **110**.

An adversarial mask for camera **110** can be generated from the target regions **128**. The system **102** can perform an iterative optimization process that maximizes the removal of false positive detections while minimizing the impact on true positive detections. FIG. **4** is a flow diagram illustrating another example process of the adversarial mask system for generating and optimizing an adversarial mask for a camera.

The system receives a set of target regions for a camera (**402**). The adversarial mask engine **106** of the adversarial mask system **102** can receive the set of target regions **128** as input. Target identification engine **104** can provide the set of target regions **128** to the adversarial mask engine **106**, where the target identification engine **104** generates the set of target regions **128** from a set of images **108** received from camera **110**. Each target region **128** of the set of target regions **128** can define a pixel region including a set of pixels and coordinates for the pixel region, e.g., coordinates of the relative location of the pixels within the field of view of the camera **110**. As described above, the target regions **128** represent regions within the field of view of the camera **110** that the system **102** determines are associated with false positive detections, e.g., due to false alarm background objects triggering detections by the camera **110**.

The system receives a set of images from the camera (**404**). Camera **110** can provide test images **138** to the false detection removal system **102** via network **116**. In some implementations, image database **118** can store images **108** from camera **110** and provide the test images **138** to the adversarial mask engine **106**.

Test images **138** can include at least one image for each clip captured by the camera **110** over a period of time, e.g., a day, a week, two weeks. The test images **138** can include at least an overlap of the target regions **128** with true positive detection images and false positive detection images. In some implementations, test images **138** can include images captured under different imaging conditions, e.g., different lighting conditions, different weather conditions, different seasons. In one example, test images **138** can include 10 images, 100 images, 200 images, or the like.

For a first image of the set of images, the system initializes an adversarial mask including a first adversarial mask parameter for the set of target regions (**406**). The system **102** receives a first image **134** of the test images **138** and initializes an adversarial mask **136** including the first adversarial mask parameter. The initialized adversarial mask **136** includes a noise mask learnable parameter applied to the first image **134**, where the noise mask includes modification to one or more pixels included in the target regions **128**. To initialize the adversarial mask **136**, the mask initialization module **130** calculates an altered version of the first image **134** using, for example, a fast gradient sign method (FGSM). Module **130** performs a forward pass and a backward pass on the adversarial mask **136** using FGSM to determine a gradient sign and then uses the gradient sign as an initialization value of the adversarial mask learnable parameter for the adversarial mask **136**. The resulting gradient sign is cropped by the target regions **128**.

In some implementations, the adversarial mask engine **106** can perform calculations related to computing the gradient of a loss function and the sign of the gradient of the loss function. For example, the calculation of the adversarial mask engine **106** can follow a form similar to $adv_x=x+\epsilon*\text{sign}(\nabla_x J(\theta,x,y))$ where adv_x is a resulting adversarially generated image or mask, x is an original input image, y is a label related to x that includes one or more false detections among the test images **138**, ϵ is used to control the level of perturbations applied to the original input image x, θ includes one or more model parameters for a model such as the object detection module **120**, J is a loss function that operates on elements of the input image. As discussed above, the gradient, ∇_x, is taken with regard to the loss function operating on elements of the system **102**.

The adversarial mask engine **106** calculates noise based on the gradient sign calculated previously and a system defined parameter, E. In some implementations, the adversarial mask engine **106** can additionally optimize an epsilon parameter E, either as a separate learnable parameter or integrated in the adversarial mask learnable parameter. The system defined parameter can be user or programmatically set and controls a level of magnitude of noise generated based on the input image.

In some implementations, the epsilon parameter e can be set based on a number of times an end user reports a false positive, where the reported count can be utilized as an indication of a level of annoyance or how strongly the system should attempt to correct the issue causing the false positive detections, e.g. by increasing a level of noise being added. Conversely, if an end-user indicates that the system may be over-correcting and missing true positive detections, the epsilon parameter e can be adjusted to reduce a level of noise being added.

In some implementations, a large parameter e increases an amount of noise added to the test image. In other implementations, a different scale can be used to correlate the value of a parameter, such as ϵ, with a level of magnitude of noise generated based on the test image. For example, an ϵ value of 1 may be correlated with a maximum level of noise and an ϵ value of 0 may be correlated with a minimum level of noise. By changing E, a resulting image including the adversarial mask can become more visually dissimilar compared to a test image used to create the adversarial mask.

In some implementations, a multiplicative operation can be used to combine e and the gradient sign within a calculation of noise. For example, a calculation containing elements corresponding to e multiplied by elements corresponding to a calculated gradient sign can be used to produce a level of magnitude of noise generated based on the input image. In some cases, a formula version of the calculation can resemble $\epsilon*\text{sign}(\nabla_x)$ where $\text{sign}(\nabla_x)$ is a representation of gradient sign calculated and ϵ is a user defined parameter controlling a level of magnitude of noise generated based on the input image.

In some implementations, a built-in gradient algorithm from a software library can be used to calculate the gradient sign. For example, the software library TensorFlow is an open source software library that can be used for dataflow, differentiable programming, or machine-learning based applications. Gradient and gradient sign functions from TensorFlow can be used to aid in the calculation of the gradient sign. In some implementations, other software libraries can be used. For example, platforms such as PyTorch or MXNet among others can be used within a system such as the system **102** shown in FIG. **1**.

For a second image of the set of images, the system generates an updated adversarial mask, the generating including applying the adversarial mask to the second image and updating the adversarial mask parameter (**408**). Mask optimization module **132** applies adversarial mask **136** to the second image of the set of test images **138** and performs a forward pass and a backward pass. The mask optimization module **132** obtains an object detection loss, e.g., cross entropy, from the forward pass and backward pass, and utilizes the object detection loss to optimize the noise mask learnable parameter of the adversarial mask. Object detection loss can be calculated on a pixel-by-pixel basis, where a detection of an object is calculated per pixel used to detect the object. In one example, the mask optimization module **132** utilizes stochastic gradient descent (SGD) to obtain the object detection loss. The mask optimization module **132** utilizes the optimized noise mask learnable parameter to generate an updated adversarial mask **140**.

In some implementations, step **408** is repeated for K images of the test images **138**, e.g., 10 images, 100 images, 200 images. For each N image of the K images, the mask optimization module **132** adds a current updated adversarial mask **140** to the N image, and performs the forward pass and backward pass. The updated adversarial mask is optimized with the object detection loss calculated for the N image, e.g., using SGD, and the updated adversarial mask is updated. After K iterations are performed, the resulting updated adversarial mask **140** is changed by the mask optimization module **132** to a constant.

The noise is added to the input image in the form of value changes to elements of the input image such as pixels. The result of adding noise to the input image is an adversarial auxiliary image.

In some implementations, the adversarial mask engine **106** can iterate multiple times on a single image or on multiple images in batch. The updated adversarial mask **140** and epsilon values can be made target-region dependent, e.g., a different value is utilized for each target region **128**. To generate a target-region dependent adversarial mask, the adversarial mask engine **106** can perform the same steps described above, but calculate the adversarial mask using different learnable parameters for each target region **128** that are learned independently and without relation between them.

In some implementations, the adversarial mask engine **106** can perform two backward passes in each iteration described above with reference to step **408** in order to calculate two losses, e.g., a first loss (with positive sign) for the detections with regard to the targets in order to maximize their effect, and a second loss (with negative sign) for the detections with regard to the ground truth labels (True Positives) to minimize the target effect on them. This can result in minimizing the effect on true positive detections.

In some implementations, the adversarial mask engine **106** can add a "visibility" factor in the loss calculation to avoid a loss computation when a false positive detection that needs to be removed is not present in a specific test image of a clip used for optimizing the adversarial mask. Additionally, a regularization parameter can be added in the optimization process, e.g., a "Mask Decay" parameter, that can correct the increments or decrements that each iteration does to the optimizable noise mask. Mask decay parameter can behave similarly to a "Weight Decay" parameter in a neural network training processes, for example, by adding a parameter to the loss that forces the trainable parameter e.g., the pixels of the adversarial mask, to be as close as possible to zero in order to reduce its impact.

The system provides, to the camera, the updated adversarial mask including the updated adversarial mask parameter (**410**). The adversarial mask engine **106** provides the updated adversarial mask **140** to the camera **110**. Updated adversarial mask **140** is applied to new captured clips and/or images captured by the camera **110** to obtain an adversarial auxiliary image. The adversarial auxiliary image is a modified version of the captured images.

In some implementations, the adversarial auxiliary image is visually similar to the original portion of the captured image, e.g., can appear visually similar but be modified enough to alter the detections of the object detection software **112** of the camera **110**. The amount of similarity can be controlled, in part, by the value of e discussed above.

FIG. **5** is a diagram illustrating an example of a home monitoring system **500**. The monitoring system **500** includes a network **505**, a control unit **510**, one or more user devices **540** and **550**, a monitoring server **560**, and a central alarm station server **570**. In some examples, the network **505** facilitates communications between the control unit **510**, the one or more user devices **540** and **550**, the monitoring server **560**, and the central alarm station server **570**.

The network **505** is configured to enable exchange of electronic communications between devices connected to the network **505**. For example, the network **505** may be configured to enable exchange of electronic communications between the control unit **510**, the one or more user devices **540** and **550**, the monitoring server **560**, and the central alarm station server **570**. The network **505** may include, for example, one or more of the Internet, Wide Area Networks (WANs), Local Area Networks (LANs), analog or digital wired and wireless telephone networks (e.g., a public switched telephone network (PSTN), Integrated Services Digital Network (ISDN), a cellular network, and Digital Subscriber Line (DSL)), radio, television, cable, satellite, or any other delivery or tunneling mechanism for carrying data. Network **505** may include multiple networks or subnetworks, each of which may include, for example, a wired or wireless data pathway. The network **505** may include a circuit-switched network, a packet-switched data network, or any other network able to carry electronic communications (e.g., data or voice communications). For example, the network **505** may include networks based on the Internet protocol (IP), asynchronous transfer mode (ATM), the PSTN, packet-switched networks based on IP, X.25, or Frame Relay, or other comparable technologies and may support voice using, for example, VoIP, or other comparable protocols used for voice communications. The network **505** may include one or more networks that include wireless data channels and wireless voice channels. The network **505** may be a wireless network, a broadband network, or a combination of networks including a wireless network and a broadband network.

The control unit **510** includes a controller **512** and a network module **514**. The controller **512** is configured to control a control unit monitoring system (e.g., a control unit system) that includes the control unit **510**. In some examples, the controller **512** may include a processor or other control circuitry configured to execute instructions of a program that controls operation of a control unit system. In these examples, the controller **512** may be configured to receive input from sensors, flow meters, or other devices included in the control unit system and control operations of devices included in the household (e.g., speakers, lights, doors, etc.). For example, the controller **512** may be configured to control operation of the network module **514** included in the control unit **510**.

The network module **514** is a communication device configured to exchange communications over the network **505**. The network module **514** may be a wireless communication module configured to exchange wireless communications over the network **505**. For example, the network module **514** may be a wireless communication device configured to exchange communications over a wireless data channel and a wireless voice channel. In this example, the network module **514** may transmit alarm data over a wireless data channel and establish a two-way voice communication session over a wireless voice channel. The wireless communication device may include one or more of a LTE module, a GSM module, a radio modem, cellular transmission module, or any type of module configured to exchange communications in one of the following formats: LTE, GSM or GPRS, CDMA, EDGE or EGPRS, EV-DO or EVDO, UMTS, or IP.

The network module **514** also may be a wired communication module configured to exchange communications over the network **505** using a wired connection. For instance, the network module **514** may be a modem, a network interface card, or another type of network interface device. The network module **514** may be an Ethernet network card configured to enable the control unit **510** to communicate over a local area network and/or the Internet. The network module **514** also may be a voice band modem configured to enable the alarm panel to communicate over the telephone lines of Plain Old Telephone Systems (POTS).

The control unit system that includes the control unit **510** includes one or more sensors. For example, the monitoring system may include multiple sensors **520**. The sensors **520** may include a lock sensor, a contact sensor, a motion sensor, or any other type of sensor included in a control unit system. The sensors **520** also may include an environmental sensor, such as a temperature sensor, a water sensor, a rain sensor, a wind sensor, a light sensor, a smoke detector, a carbon monoxide detector, an air quality sensor, etc. The sensors **520** further may include a health monitoring sensor, such as a prescription bottle sensor that monitors taking of prescriptions, a blood pressure sensor, a blood sugar sensor, a bed mat configured to sense presence of liquid (e.g., bodily fluids) on the bed mat, etc. In some examples, the health-monitoring sensor can be a wearable sensor that attaches to a user in the home. The health-monitoring sensor can collect various health data, including pulse, heart rate, respiration rate, sugar or glucose level, bodily temperature, or motion data.

The sensors **520** can also include a radio-frequency identification (RFID) sensor that identifies a particular article that includes a pre-assigned RFID tag.

The control unit **510** communicates with the home automation controls **522** and a camera **530** to perform monitoring. The home automation controls **522** are connected to one or more devices that enable automation of actions in the home. For instance, the home automation controls **522** may be connected to one or more lighting systems and may be configured to control operation of the one or more lighting systems. In addition, the home automation controls **522** may be connected to one or more electronic locks at the home and may be configured to control operation of the one or more electronic locks (e.g., control Z-Wave locks using wireless communications in the Z-Wave protocol). Further, the home automation controls **522** may be connected to one or more appliances at the home and may be configured to control operation of the one or more appliances. The home automation controls **522** may include multiple modules that are each specific to the type of device being controlled in an automated manner. The home automation controls **522** may control the one or more devices based on commands received from the control unit **510**. For instance, the home automation controls **522** may cause a lighting system to illuminate an area to provide a better image of the area when captured by a camera **530**.

The camera **530** may be a video/photographic camera or other type of optical sensing device configured to capture images. For instance, the camera **530** may be configured to capture images of an area within a building or home monitored by the control unit **510**. The camera **530** may be configured to capture single, static images of the area and also video images of the area in which multiple images of the area are captured at a relatively high frequency (e.g., thirty images per second). The camera **530** may be controlled based on commands received from the control unit **510**.

The camera **530** may be triggered by several different types of techniques. For instance, a Passive Infra-Red (PIR) motion sensor may be built into the camera **530** and used to trigger the camera **530** to capture one or more images when motion is detected. The camera **530** also may include a microwave motion sensor built into the camera and used to trigger the camera **530** to capture one or more images when motion is detected. The camera **530** may have a "normally open" or "normally closed" digital input that can trigger capture of one or more images when external sensors (e.g., the sensors **520**, PIR, door/window, etc.) detect motion or other events. In some implementations, the camera **530** receives a command to capture an image when external devices detect motion or another potential alarm event. The camera **530** may receive the command from the controller **512** or directly from one of the sensors **520**.

In some examples, the camera **530** triggers integrated or external illuminators (e.g., Infra-Red, Z-wave controlled "white" lights, lights controlled by the home automation controls **522**, etc.) to improve image quality when the scene is dark. An integrated or separate light sensor may be used to determine if illumination is desired and may result in increased image quality.

The camera **530** may be programmed with any combination of time/day schedules, system "arming state", or other variables to determine whether images should be captured or not when triggers occur. The camera **530** may enter a low-power mode when not capturing images. In this case, the camera **530** may wake periodically to check for inbound messages from the controller **512**. The camera **530** may be powered by internal, replaceable batteries if located remotely from the control unit **510**. The camera **530** may employ a small solar cell to recharge the battery when light is available. Alternatively, the camera **530** may be powered by the controller's **512** power supply if the camera **530** is co-located with the controller **512**.

In some implementations, the camera **530** communicates directly with the monitoring server **560** over the Internet. In these implementations, image data captured by the camera **530** does not pass through the control unit **510** and the camera **530** receives commands related to operation from the monitoring server **560**.

The system **500** also includes thermostat **534** to perform dynamic environmental control at the home. The thermostat **534** is configured to monitor temperature and/or energy consumption of an HVAC system associated with the thermostat **534**, and is further configured to provide control of environmental (e.g., temperature) settings. In some implementations, the thermostat **534** can additionally or alternatively receive data relating to activity at a home and/or environmental data at a home, e.g., at various locations indoors and outdoors at the home. The thermostat **534** can directly measure energy consumption of the HVAC system associated with the thermostat, or can estimate energy consumption of the HVAC system associated with the thermostat **534**, for example, based on detected usage of one or more components of the HVAC system associated with the thermostat **534**. The thermostat **534** can communicate temperature and/or energy monitoring information to or from the control unit **510** and can control the environmental (e.g., temperature) settings based on commands received from the control unit **510**.

In some implementations, the thermostat **534** is a dynamically programmable thermostat and can be integrated with the control unit **510**. For example, the dynamically programmable thermostat **534** can include the control unit **510**, e.g., as an internal component to the dynamically programmable thermostat **534**. In addition, the control unit **510** can be a gateway device that communicates with the dynamically programmable thermostat **534**. In some implementations, the thermostat **534** is controlled via one or more home automation controls **522**.

A module **537** is connected to one or more components of an HVAC system associated with a home, and is configured to control operation of the one or more components of the HVAC system. In some implementations, the module **537** is also configured to monitor energy consumption of the HVAC system components, for example, by directly measuring the energy consumption of the HVAC system components or by estimating the energy usage of the one or more HVAC system components based on detecting usage of components of the HVAC system. The module **537** can communicate energy monitoring information and the state of the HVAC system components to the thermostat **534** and can control the one or more components of the HVAC system based on commands received from the thermostat **534**.

In some examples, the system **500** further includes one or more robotic devices **590**. The robotic devices **590** may be any type of robots that are capable of moving and taking actions that assist in home monitoring. For example, the robotic devices **590** may include drones that are capable of moving throughout a home based on automated control technology and/or user input control provided by a user. In this example, the drones may be able to fly, roll, walk, or otherwise move about the home. The drones may include helicopter type devices (e.g., quad copters), rolling helicopter type devices (e.g., roller copter devices that can fly and roll along the ground, walls, or ceiling) and land vehicle type devices (e.g., automated cars that drive around a home). In some cases, the robotic devices **590** may be devices that are intended for other purposes and merely associated with the system **500** for use in appropriate circumstances. For instance, a robotic vacuum cleaner device may be associated with the monitoring system **500** as one of the robotic devices **590** and may be controlled to take action responsive to monitoring system events.

In some examples, the robotic devices **590** automatically navigate within a home. In these examples, the robotic devices **590** include sensors and control processors that guide movement of the robotic devices **590** within the home. For instance, the robotic devices **590** may navigate within the home using one or more cameras, one or more proximity sensors, one or more gyroscopes, one or more accelerometers, one or more magnetometers, a global positioning system (GPS) unit, an altimeter, one or more sonar or laser sensors, and/or any other types of sensors that aid in navigation about a space. The robotic devices **590** may include control processors that process output from the various sensors and control the robotic devices **590** to move along a path that reaches the desired destination and avoids obstacles. In this regard, the control processors detect walls or other obstacles in the home and guide movement of the robotic devices **590** in a manner that avoids the walls and other obstacles.

In addition, the robotic devices **590** may store data that describes attributes of the home. For instance, the robotic devices **590** may store a floorplan and/or a three-dimensional model of the home that enables the robotic devices **590** to navigate the home. During initial configuration, the robotic devices **590** may receive the data describing attributes of the home, determine a frame of reference to the data (e.g., a home or reference location in the home), and navigate the home based on the frame of reference and the data describing attributes of the home. Further, initial configuration of the robotic devices **590** also may include learning of one or more navigation patterns in which a user provides input to control the robotic devices **590** to perform a specific navigation action (e.g., fly to an upstairs bedroom and spin around while capturing video and then return to a home charging base). In this regard, the robotic devices **590** may learn and store the navigation patterns such that the robotic devices **590** may automatically repeat the specific navigation actions upon a later request.

In some examples, the robotic devices **590** may include data capture and recording devices. In these examples, the robotic devices **590** may include one or more cameras, one or more motion sensors, one or more microphones, one or more biometric data collection tools, one or more temperature sensors, one or more humidity sensors, one or more air flow sensors, and/or any other types of sensors that may be useful in capturing monitoring data related to the home and users in the home. The one or more biometric data collection tools may be configured to collect biometric samples of a person in the home with or without contact of the person. For instance, the biometric data collection tools may include a fingerprint scanner, a hair sample collection tool, a skin cell collection tool, and/or any other tool that allows the robotic devices **590** to take and store a biometric sample that can be used to identify the person (e.g., a biometric sample with DNA that can be used for DNA testing).

In some implementations, the robotic devices **590** may include output devices. In these implementations, the robotic devices **590** may include one or more displays, one or more speakers, and/or any type of output devices that allow the robotic devices **590** to communicate information to a nearby user.

The robotic devices **590** also may include a communication module that enables the robotic devices **590** to communicate with the control unit **510**, each other, and/or other devices. The communication module may be a wireless communication module that allows the robotic devices **590** to communicate wirelessly. For instance, the communication module may be a Wi-Fi module that enables the robotic devices **590** to communicate over a local wireless network at the home. The communication module further may be a 900 MHz wireless communication module that enables the robotic devices **590** to communicate directly with the control unit **510**. Other types of short-range wireless communication protocols, such as Bluetooth, Bluetooth LE, Z-wave, Zigbee, etc., may be used to allow the robotic devices **590** to communicate with other devices in the home. In some implementations, the robotic devices **590** may communicate with each other or with other devices of the system **500** through the network **505**.

The robotic devices **590** further may include processor and storage capabilities. The robotic devices **590** may include any suitable processing devices that enable the robotic devices **590** to operate applications and perform the actions described throughout this disclosure. In addition, the robotic devices **590** may include solid-state electronic storage that enables the robotic devices **590** to store applications, configuration data, collected sensor data, and/or any other type of information available to the robotic devices **590**.

The robotic devices **590** are associated with one or more charging stations. The charging stations may be located at predefined home base or reference locations in the home. The robotic devices **590** may be configured to navigate to the charging stations after completion of tasks needed to be performed for the monitoring system **500**. For instance, after completion of a monitoring operation or upon instruction by the control unit **510**, the robotic devices **590** may be configured to automatically fly to and land on one of the charging stations. In this regard, the robotic devices **590** may automatically maintain a fully charged battery in a state in which the robotic devices **590** are ready for use by the monitoring system **500**.

The charging stations may be contact based charging stations and/or wireless charging stations. For contact based charging stations, the robotic devices **590** may have readily accessible points of contact that the robotic devices **590** are capable of positioning and mating with a corresponding contact on the charging station. For instance, a helicopter type robotic device may have an electronic contact on a portion of its landing gear that rests on and mates with an electronic pad of a charging station when the helicopter type robotic device lands on the charging station. The electronic contact on the robotic device may include a cover that opens to expose the electronic contact when the robotic device is charging and closes to cover and insulate the electronic contact when the robotic device is in operation.

For wireless charging stations, the robotic devices **590** may charge through a wireless exchange of power. In these cases, the robotic devices **590** need only locate themselves closely enough to the wireless charging stations for the wireless exchange of power to occur. In this regard, the positioning needed to land at a predefined home base or reference location in the home may be less precise than with a contact based charging station. Based on the robotic devices **590** landing at a wireless charging station, the wireless charging station outputs a wireless signal that the robotic devices **590** receive and convert to a power signal that charges a battery maintained on the robotic devices **590**.

In some implementations, each of the robotic devices **590** has a corresponding and assigned charging station such that the number of robotic devices **590** equals the number of charging stations. In these implementations, the robotic devices **590** always navigate to the specific charging station assigned to that robotic device. For instance, a first robotic device may always use a first charging station and a second robotic device may always use a second charging station.

In some examples, the robotic devices **590** may share charging stations. For instance, the robotic devices **590** may use one or more community charging stations that are capable of charging multiple robotic devices **590**. The community charging station may be configured to charge multiple robotic devices **590** in parallel. The community charging station may be configured to charge multiple robotic devices **590** in serial such that the multiple robotic devices **590** take turns charging and, when fully charged, return to a predefined home base or reference location in the home that is not associated with a charger. The number of community charging stations may be less than the number of robotic devices **590**.

In addition, the charging stations may not be assigned to specific robotic devices **590** and may be capable of charging any of the robotic devices **590**. In this regard, the robotic devices **590** may use any suitable, unoccupied charging station when not in use. For instance, when one of the robotic devices **590** has completed an operation or is in need of battery charge, the control unit **510** references a stored table of the occupancy status of each charging station and instructs the robotic device to navigate to the nearest charging station that is unoccupied.

The system **500** further includes one or more integrated security devices **580**. The one or more integrated security devices may include any type of device used to provide alerts based on received sensor data. For instance, the one or more control units **510** may provide one or more alerts to the one or more integrated security input/output devices **580**. Additionally, the one or more control units **510** may receive one or more sensor data from the sensors **520** and determine whether to provide an alert to the one or more integrated security input/output devices **580**.

The sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the integrated security devices **580** may communicate with the controller **512** over communication links **524**, **526**, **528**, **532**, **538**, and **584**. The communication links **524**, **526**, **528**, **532**, **538**, and **584** may be a wired or wireless data pathway configured to transmit signals from the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the integrated security devices **580** to the controller **512**. The sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the integrated security devices **580** may continuously transmit sensed values to the controller **512**, periodically transmit sensed values to the controller **512**, or transmit sensed values to the controller **512** in response to a change in a sensed value.

The communication links **524**, **526**, **528**, **532**, **538**, and **584** may include a local network. The sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the integrated security devices **580**, and the controller **512** may exchange data and commands over the local network. The local network may include 802.11 "Wi-Fi" wireless Ethernet (e.g., using low-power Wi-Fi chipsets), Z-Wave, Zigbee, Bluetooth, "Homeplug" or other "Powerline" networks that operate over AC wiring, and a Category 5 (CAT5) or Category 6 (CAT6) wired Ethernet network. The local network may be a mesh network constructed based on the devices connected to the mesh network.

The monitoring server **560** is an electronic device configured to provide monitoring services by exchanging electronic communications with the control unit **510**, the one or more user devices **540** and **550**, and the central alarm station server **570** over the network **505**. For example, the monitoring server **560** may be configured to monitor events generated by the control unit **510**. In this example, the monitoring server **560** may exchange electronic communications with the network module **514** included in the control unit **510** to receive information regarding events detected by the control unit **510**. The monitoring server **560** also may receive information regarding events from the one or more user devices **540** and **550**.

In some examples, the monitoring server **560** may route alert data received from the network module **514** or the one or more user devices **540** and **550** to the central alarm station server **570**. For example, the monitoring server **560** may transmit the alert data to the central alarm station server **570** over the network **505**.

The monitoring server **560** may store sensor and image data received from the monitoring system and perform analysis of sensor and image data received from the monitoring system. Based on the analysis, the monitoring server **560** may communicate with and control aspects of the control unit **510** or the one or more user devices **540** and **550**.

The monitoring server **560** may provide various monitoring services to the system **500**. For example, the monitoring server **560** may analyze the sensor, image, and other data to determine an activity pattern of a resident of the home monitored by the system **500**. In some implementations, the monitoring server **560** may analyze the data for alarm conditions or may determine and perform actions at the home by issuing commands to one or more of the controls **522**, possibly through the control unit **510**.

The monitoring server **560** can be configured to provide information (e.g., activity patterns) related to one or more residents of the home monitored by the system **500** (e.g., a user). For example, one or more of the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the integrated security devices **580** can collect data related to a resident including location information (e.g., if the resident is home or is not home) and provide location information to the thermostat **534**.

The central alarm station server **570** is an electronic device configured to provide alarm monitoring service by exchanging communications with the control unit **510**, the one or more user devices **540** and **550**, and the monitoring server **560** over the network **505**. For example, the central alarm station server **570** may be configured to monitor alerting events generated by the control unit **510**. In this example, the central alarm station server **570** may exchange communications with the network module **514** included in the control unit **510** to receive information regarding alerting events detected by the control unit **510**. The central alarm station server **570** also may receive information regarding alerting events from the one or more user devices **540** and **550** and/or the monitoring server **560**.

The central alarm station server **570** is connected to multiple terminals **572** and **574**. The terminals **572** and **574** may be used by operators to process alerting events. For example, the central alarm station server **570** may route alerting data to the terminals **572** and **574** to enable an operator to process the alerting data. The terminals **572** and **574** may include general-purpose computers (e.g., desktop personal computers, workstations, or laptop computers) that are configured to receive alerting data from a server in the central alarm station server **570** and render a display of information based on the alerting data. For instance, the controller **512** may control the network module **514** to transmit, to the central alarm station server **570**, alerting data indicating that a sensor **520** detected motion from a motion sensor via the sensors **520**. The central alarm station server **570** may receive the alerting data and route the alerting data to the terminal **572** for processing by an operator associated with the terminal **572**. The terminal **572** may render a display to the operator that includes information associated with the alerting event (e.g., the lock sensor data, the motion sensor data, the contact sensor data, etc.) and the operator may handle the alerting event based on the displayed information.

In some implementations, the terminals **572** and **574** may be mobile devices or devices designed for a specific function. Although FIG. **5** illustrates two terminals for brevity, actual implementations may include more (and, perhaps, many more) terminals.

The one or more authorized user devices **540** and **550** are devices that host and display user interfaces. For instance, the user device **540** is a mobile device that hosts or runs one or more native applications (e.g., the home monitoring application **542**). The user device **540** may be a cellular phone or a non-cellular locally networked device with a display. The user device **540** may include a cell phone, a smart phone, a tablet PC, a personal digital assistant ("PDA"), or any other portable device configured to communicate over a network and display information. For example, implementations may also include Blackberry-type devices (e.g., as provided by Research in Motion), electronic organizers, iPhone-type devices (e.g., as provided by Apple), iPod devices (e.g., as provided by Apple) or other portable music players, other communication devices, and handheld or portable electronic devices for gaming, communications, and/or data organization. The user device **540** may perform functions unrelated to the monitoring system, such as placing personal telephone calls, playing music, playing video, displaying pictures, browsing the Internet, maintaining an electronic calendar, etc.

The user device **540** includes a home monitoring application **552**. The home monitoring application **542** refers to a software/firmware program running on the corresponding mobile device that enables the user interface and features described throughout. The user device **540** may load or install the home monitoring application **542** based on data received over a network or data received from local media. The home monitoring application **542** runs on mobile devices platforms, such as iPhone, iPod touch, Blackberry, Google Android, Windows Mobile, etc. The home monitoring application **542** enables the user device **540** to receive and process image and sensor data from the monitoring system.

The user device **540** may be a general-purpose computer (e.g., a desktop personal computer, a workstation, or a laptop computer) that is configured to communicate with the monitoring server **560** and/or the control unit **510** over the network **505**. The user device **540** may be configured to display a smart home user interface **552** that is generated by the user device **540** or generated by the monitoring server **560**. For example, the user device **540** may be configured to display a user interface (e.g., a web page) provided by the monitoring server **560** that enables a user to perceive images captured by the camera **530** and/or reports related to the monitoring system. Although FIG. **5** illustrates two user devices for brevity, actual implementations may include more (and, perhaps, many more) or fewer user devices.

In some implementations, the one or more user devices **540** and **550** communicate with and receive monitoring system data from the control unit **510** using the communication link **538**. For instance, the one or more user devices **540** and **550** may communicate with the control unit **510** using various local wireless protocols such as Wi-Fi, Bluetooth, Z-wave, Zigbee, HomePlug (ethernet over power line), or wired protocols such as Ethernet and USB, to connect the one or more user devices **540** and **550** to local security and automation equipment. The one or more user devices **540** and **550** may connect locally to the monitoring system and its sensors and other devices. The local connection may improve the speed of status and control communications because communicating through the network **505** with a remote server (e.g., the monitoring server **560**) may be significantly slower.

Although the one or more user devices **540** and **550** are shown as communicating with the control unit **510**, the one or more user devices **540** and **550** may communicate directly with the sensors and other devices controlled by the control unit **510**. In some implementations, the one or more user devices **540** and **550** replace the control unit **510** and perform the functions of the control unit **510** for local monitoring and long range/offsite communication.

In other implementations, the one or more user devices **540** and **550** receive monitoring system data captured by the control unit **510** through the network **505**. The one or more user devices **540**, **550** may receive the data from the control unit **510** through the network **505** or the monitoring server **560** may relay data received from the control unit **510** to the one or more user devices **540** and **550** through the network **505**. In this regard, the monitoring server **560** may facilitate communication between the one or more user devices **540** and **550** and the monitoring system.

In some implementations, the one or more user devices **540** and **550** may be configured to switch whether the one or more user devices **540** and **550** communicate with the control unit **510** directly (e.g., through link **538**) or through the monitoring server **560** (e.g., through network **505**) based on a location of the one or more user devices **540** and **550**. For instance, when the one or more user devices **540** and **550** are located close to the control unit **510** and in range to communicate directly with the control unit **510**, the one or more user devices **540** and **550** use direct communication. When the one or more user devices **540** and **550** are located far from the control unit **510** and not in range to communicate directly with the control unit **510**, the one or more user devices **540** and **550** use communication through the monitoring server **560**.

Although the one or more user devices **540** and **550** are shown as being connected to the network **505**, in some implementations, the one or more user devices **540** and **550** are not connected to the network **505**. In these implementations, the one or more user devices **540** and **550** communicate directly with one or more of the monitoring system components and no network (e.g., Internet) connection or reliance on remote servers is needed.

In some implementations, the one or more user devices **540** and **550** are used in conjunction with only local sensors and/or local devices in a house. In these implementations, the system **500** includes the one or more user devices **540** and **550**, the sensors **520**, the home automation controls **522**, the camera **530**, and the robotic devices **590**. The one or more user devices **540** and **550** receive data directly from the sensors **520**, the home automation controls **522**, the camera **530**, and the robotic devices **590**, and sends data directly to the sensors **520**, the home automation controls **522**, the camera **530**, and the robotic devices **590**. The one or more user devices **540**, **550** provide the appropriate interfaces/processing to provide visual surveillance and reporting.

In other implementations, the system **500** further includes network **505** and the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590**, and are configured to communicate sensor and image data to the one or more user devices **540** and **550** over network **505** (e.g., the Internet, cellular network, etc.). In yet another implementation, the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590** (or a component, such as a bridge/router) are intelligent enough to change the communication pathway from a direct local pathway when the one or more user devices **540** and **550** are in close physical proximity to the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590** to a pathway over network **505** when the one or more user devices **540** and **550** are farther from the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590**.

In some examples, the system leverages GPS information from the one or more user devices **540** and **550** to determine whether the one or more user devices **540** and **550** are close enough to the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590** to use the direct local pathway or whether the one or more user devices **540** and **550** are far enough from the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590** that the pathway over network **505** is required.

In other examples, the system leverages status communications (e.g., pinging) between the one or more user devices **540** and **550** and the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590** to determine whether communication using the direct local pathway is possible. If communication using the direct local pathway is possible, the one or more user devices **540** and **550** communicate with the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590** using the direct local pathway. If communication using the direct local pathway is not possible, the one or more user devices **540** and **550** communicate with the sensors **520**, the home automation controls **522**, the camera **530**, the thermostat **534**, and the robotic devices **590** using the pathway over network **505**.

In some implementations, the system **500** provides end users with access to images captured by the camera **530** to aid in decision making. The system **500** may transmit the images captured by the camera **530** over a wireless WAN network to the user devices **540** and **550**. Because transmission over a wireless WAN network may be relatively expensive, the system **500** can use several techniques to reduce costs while providing access to significant levels of useful visual information (e.g., compressing data, down-sampling data, sending data only over inexpensive LAN connections, or other techniques).

In some implementations, a state of the monitoring system and other events sensed by the monitoring system may be used to enable/disable video/image recording devices (e.g., the camera **530**). In these implementations, the camera **530** may be set to capture images on a periodic basis when the alarm system is armed in an "away" state, but set not to capture images when the alarm system is armed in a "home" state or disarmed. In addition, the camera **530** may be triggered to begin capturing images when the alarm system detects an event, such as an alarm event, a door-opening event for a door that leads to an area within a field of view of the camera **530**, or motion in the area within the field of view of the camera **530**. In other implementations, the camera **530** may capture images continuously, but the captured images may be stored or transmitted over a network when needed.

The described systems, methods, and techniques may be implemented in digital electronic circuitry, computer hardware, firmware, software, or in combinations of these elements. Apparatus implementing these techniques may include appropriate input and output devices, a computer processor, and a computer program product tangibly embodied in a machine-readable storage device for execution by a programmable processor. A process implementing these techniques may be performed by a programmable processor executing a program of instructions to perform desired functions by operating on input data and generating appropriate output. The techniques may be implemented in one or more computer programs that are executable on a programmable system including at least one programmable processor coupled to receive data and instructions from, and to transmit data and instructions to, a data storage system, at least one input device, and at least one output device.

Each computer program may be implemented in a high-level procedural or object-oriented programming language, or in assembly or machine language if desired; and in any case, the language may be a compiled or interpreted language. Suitable processors include, by way of example, both general and special purpose microprocessors. Generally, a processor will receive instructions and data from a read-only memory and/or a random access memory. Storage devices suitable for tangibly embodying computer program instructions and data include all forms of non-volatile memory, including by way of example semiconductor memory devices, such as Erasable Programmable Read-Only Memory (EPROM), Electrically Erasable Programmable Read-Only Memory (EEPROM), and flash memory devices; magnetic disks such as internal hard disks and removable disks; magneto-optical disks; and Compact Disc Read-Only Memory (CD-ROM). Any of the foregoing may be supplemented by, or incorporated in, specially designed ASICs (application-specific integrated circuits).

It will be understood that various modifications may be made. For example, other useful implementations could be achieved if steps of the disclosed techniques were performed in a different order and/or if components in the disclosed systems were combined in a different manner and/or replaced or supplemented by other components. Accordingly, other implementations are within the scope of the disclosure.

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What is claimed is:

1. A computer-implemented method comprising:
   - accessing a set of target regions for a camera;
   - accessing a set of images that were captured by the camera;
   - initializing, for a first image of the set of images, an adversarial mask including a first value for an adversarial mask parameter for the set of target regions;
   - generating, for a second image of the set of images, an updated adversarial mask, the generating including:
     - applying the adversarial mask to the second image, and
     - updating the first value to a second value for the adversarial mask parameter using a result of applying the adversarial mask to the second image; and
   - providing, to the camera, the updated adversarial mask for use by an object detection model.

2. The method of claim **1**, comprising accessing data representing the set of target regions that indicate regions within a field of view of the camera in which there was a false positive detection.

3. The method of claim **1**, comprising detecting, from a plurality of regions within a field of view of the camera, the set of target regions that are associated with false positive detections.

4. The method of claim **1**, comprising:
   - detecting, in a first image, a first bounding box for a first object that was a false positive detection;
   - detecting, in a second image, a second bounding box for a second object that was a true positive detection;
   - determining that the first bounding box and the second bounding box overlap in an image region represented by the same coordinates in the respective images; and
   - assigning the image region as a target region in the set of target regions that are associated with false positive detections.

5. The method of claim **1**, wherein initializing the adversarial mask comprises determining an altered version of the first image.

6. The method of claim **1**, wherein initializing the adversarial mask including the first value for the adversarial mask parameter comprises:
   - performing a forward pass on the adversarial mask using a fast gradient sign method;
   - performing a backward pass on the adversarial mask using the fast gradient sign method;
   - determining a sign of a gradient of a loss function associated with an object detection model; and
   - using the sign of the gradient as an initialization value of a noise mask learnable parameter for the adversarial mask.

7. The method of claim **1**, wherein applying the adversarial mask to the second image comprises:
   - performing a forward pass on the second image using a fast gradient sign method;
   - performing a backward pass on the second image using the fast gradient sign method;
   - determining, using the forward and backward passes, an object detection loss; and
   - determining, using the object detection loss, a noise mask learnable parameter of the updated adversarial mask.

8. A system comprising one or more computers and one or more storage devices on which are stored instructions that are operable, when executed by the one or more computers, to cause the one or more computers to perform operations comprising:
   - accessing by the one or more computers, a set of target regions for a camera;
   - accessing, by the one or more computers, a set of images from the camera;
   - initializing, for a first image of the set of images, an adversarial mask including a first value for an adversarial mask parameter for the set of target regions;
   - generating, for a second image of the set of images, an updated adversarial mask, the generating including:
     - applying the adversarial mask to the second image, and
     - updating the first value to a second value for the adversarial mask parameter using a result of applying the adversarial mask to the second image; and
   - providing, to the camera, the updated adversarial mask for use by an object detection model.

9. The system of claim **8**, wherein the operations comprise accessing data representing the set of target regions that indicate regions within a field of view of the camera that are associated with false positive detections.

10. The system of claim **8**, wherein the operations comprise detecting, from a plurality of regions within a field of view of the camera, the set of target regions that are associated with false positive detections.

11. The system of claim **8**, wherein:
   - the set of images comprise at least a first image that includes a first representation of a first object and a second representation of a second object,
   - a first bounding box for the first representation of the first object overlaps a second bounding box for the second representation of the second object,
   - and the second object is an object of interest.

12. The system of claim **8**, wherein initializing the adversarial mask comprises determining an altered version of the first image.

13. The system of claim **8**, wherein initializing the adversarial mask including a first adversarial mask parameter comprises:
   - performing a forward pass on the adversarial mask using a fast gradient sign method;
   - performing a backward pass on the adversarial mask using the fast gradient sign method;
   - determining a sign of a gradient of a loss function associated with an object detection model; and
   - using the sign of the gradient as an initialization value of a noise mask learnable parameter for the adversarial mask.

14. The system of claim **8**, wherein applying the adversarial mask to the second image comprises:
   - performing a forward pass on the second image using a fast gradient sign method;
   - performing a backward pass on the second image using the fast gradient sign method;
   - determining, using the forward and backward passes, an object detection loss; and
   - determining, using the object detection loss, a noise mask learnable parameter of the updated adversarial mask.

15. The system of claim **8**, wherein the operations comprise:
   - detecting, in a first image, a first bounding box for a first object that was a false positive detection;
   - detecting, in a second image, a second bounding box for a second object that was a true positive detection;

determining that the first bounding box and the second bounding box overlap in an image region represented by the same coordinates in the respective images; and

assigning the image region as a target region in the set of target regions that are associated with false positive detections.

16. One or more non-transitory computer storage media encoded with instructions that, when executed by one or more computers, cause the one or more computers to perform the following operations:

accessing by the one or more computers, a set of target regions for a camera;

accessing, by the one or more computers, a set of images from the camera;

initializing, for a first image of the set of images, an adversarial mask including a first value for an adversarial mask parameter for the set of target regions;

generating, for a second image of the set of images, an updated adversarial mask, the generating including:

applying the adversarial mask to the second image, and

updating the first value to a second value for the adversarial mask parameter using a result of applying the adversarial mask to the second image; and

providing, to the camera, the updated adversarial mask for use by an object detection model.

17. The non-transitory computer storage media of claim **16**, wherein the operations comprise accessing data representing the set of target regions that indicate regions within a field of view of the camera that are associated with false positive detections.

18. The non-transitory computer storage media of claim **16**, wherein the operations comprise detecting, from a plurality of regions within a field of view of the camera, the set of target regions that are associated with false positive detections.

19. The non-transitory computer storage media of claim **16**, wherein:

the set of images comprise at least a first image that includes a first representation of a first object and a second representation of a second object,

a first bounding box for the first representation of the first object overlaps a second bounding box for the second representation of the second object,

and the second object is an object of interest.

20. The non-transitory computer storage media of claim **16**, wherein initializing the adversarial mask comprises determining an altered version of the first image.

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