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(54) **OBJECT DETECTION SYSTEM BASED ON A POOL OF ADAPTIVE FEATURES**

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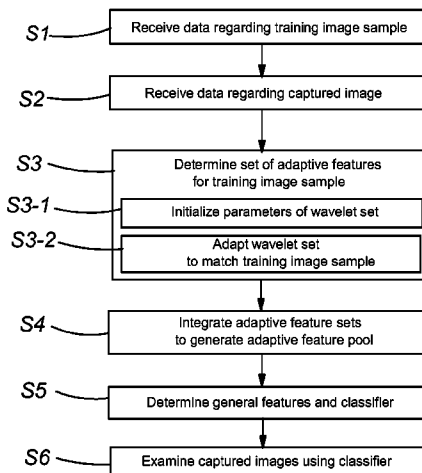
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(57) **ABSTRACT**

A method, system and computer program product for detecting presence of an object in an image are disclosed. According to an embodiment, a method for detecting a presence of an object in an image comprises: receiving multiple training image samples; determining a set of adaptive features for each training image sample, the set of adaptive features matching the local structure of each training image sample; integrating the sets of adaptive features of the multiple training image samples to generate an adaptive feature pool; determining a general feature based on the adaptive feature pool; and examining the image using a classifier determined based on the general feature to detect the presence of the object.

18 Claims, 3 Drawing Sheets



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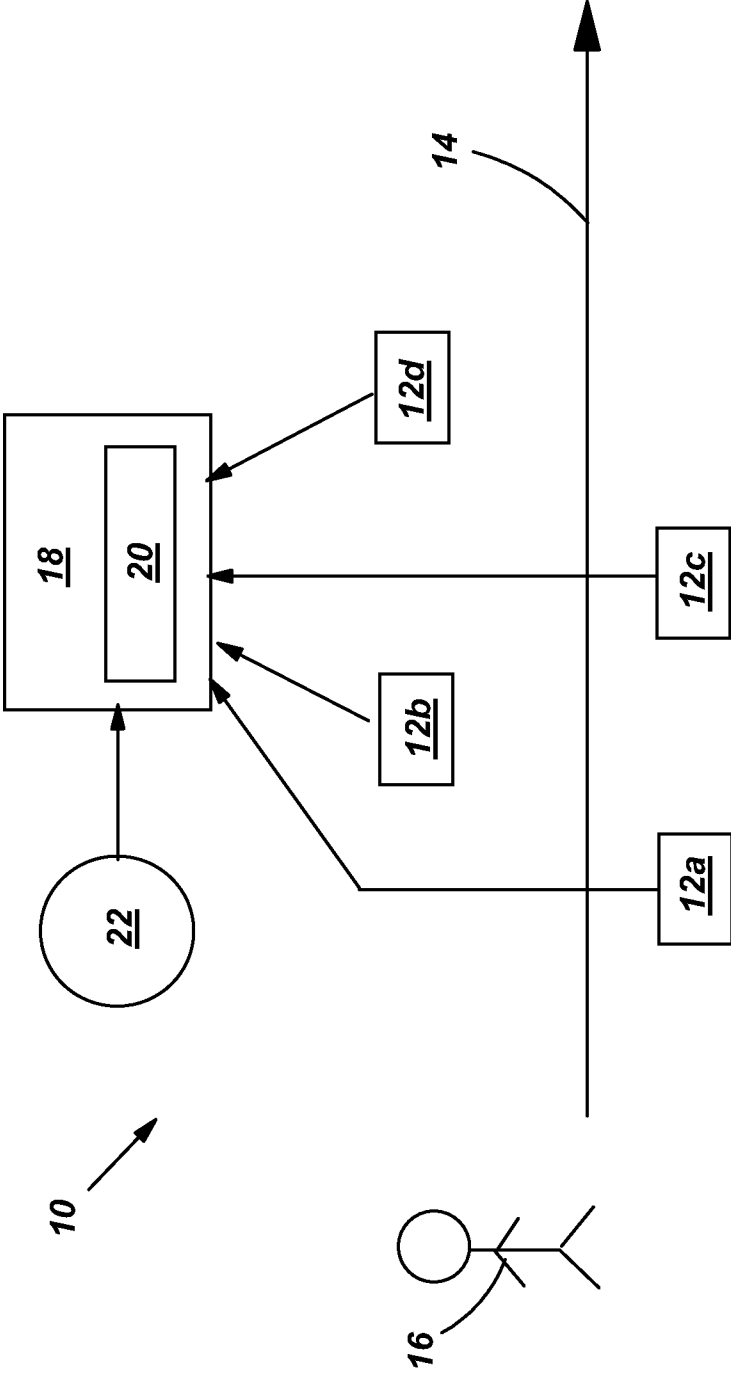
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FIG. 1



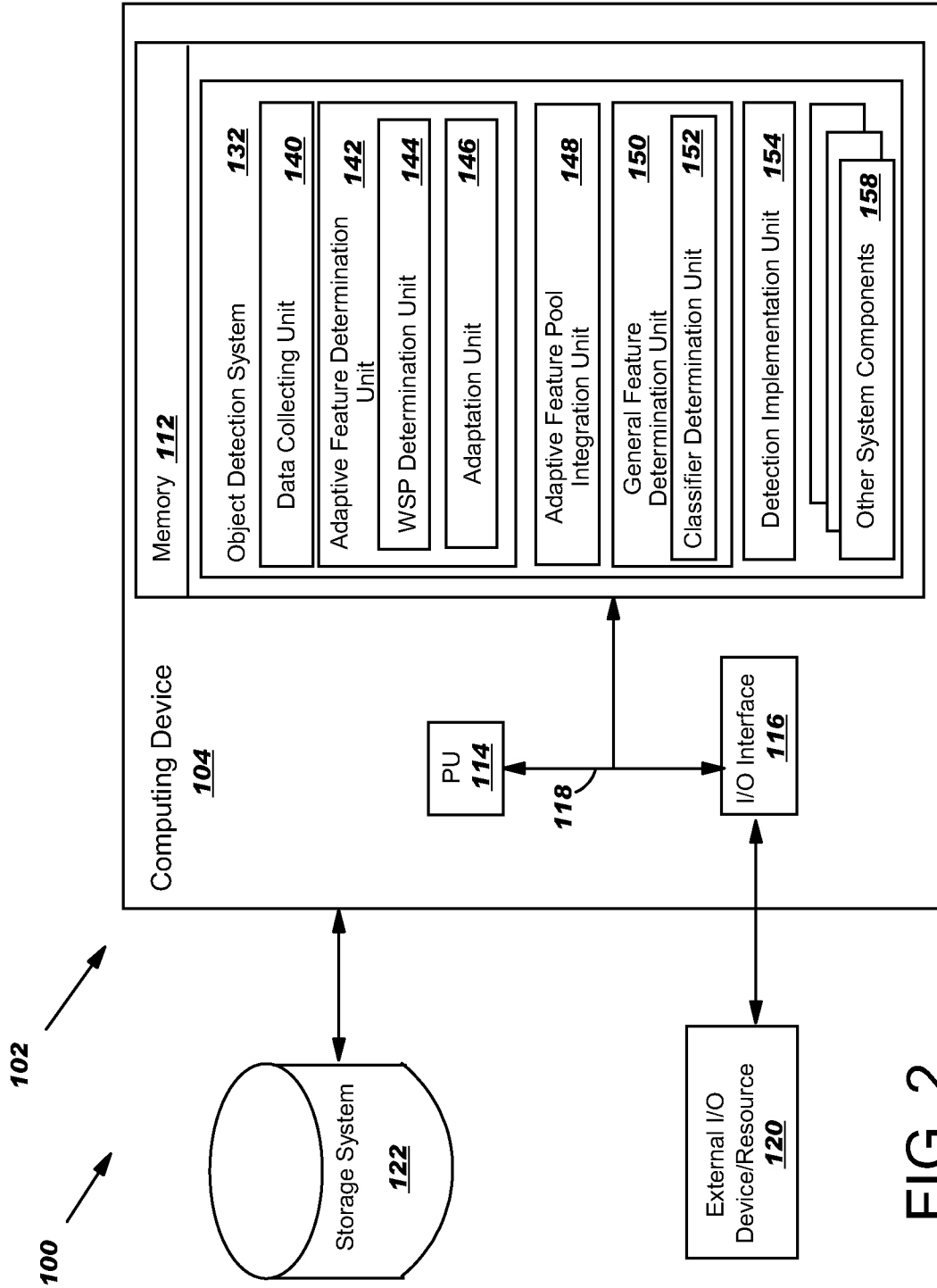
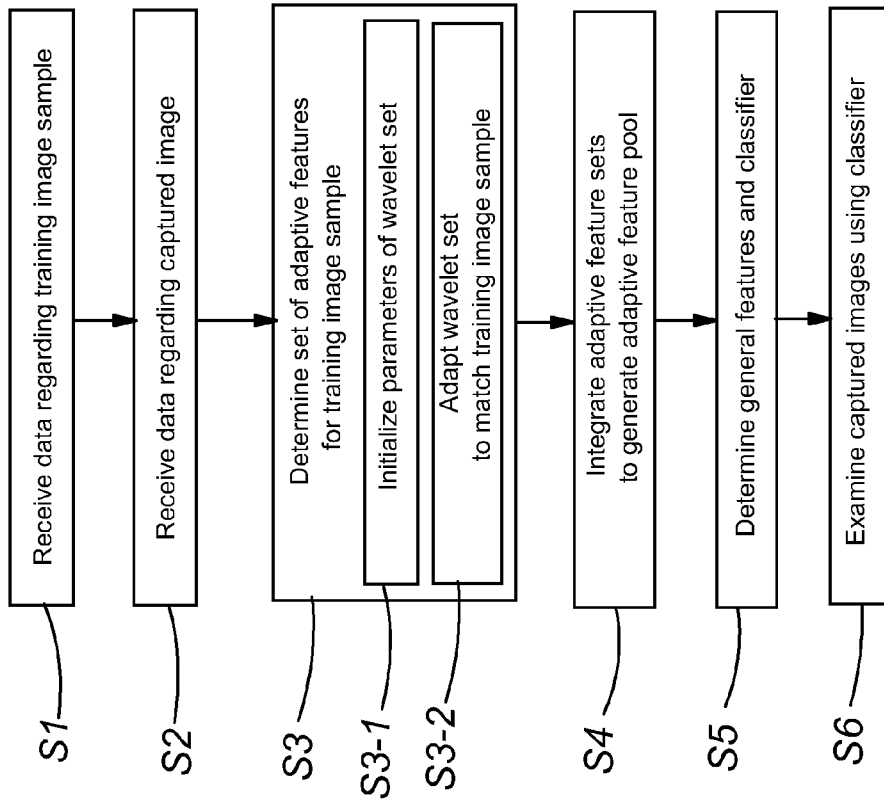


FIG. 2

FIG. 3



OBJECT DETECTION SYSTEM BASED ON A POOL OF ADAPTIVE FEATURES

The current application is a continuation application of co-pending U.S. patent application Ser. No. 11/688,372 filed on Mar. 20, 2007, which is hereby incorporated by reference.

FIELD OF THE INVENTION

The present disclosure relates in general to object detection, and more particularly to determining a classifier for object detection based on an adaptive feature pool.

BACKGROUND OF THE INVENTION

In the past few years, considerable progress has been made on learning-based methods for determining a classifier for object detection. In a learning based method, a set of training image samples, including object and non-object instances, are used to learn the classifier. A classifier uses a set of features to distinguish an object from a non-object. For example, Viola and Jones, *Rapid Object Detection Using a Boosted Cascade of Simple Features*, IEEE CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR'01), Kauai, Hi., December 2001, use Adaboost learning to select features and learn a classifier from a large pool of simple, computationally efficient features.

Following Viola and Jones, different extensions of the Viola and Jones method have been proposed, both on the learning algorithm level and on the feature level. For example, on the learning algorithm level, GentleBoost, Real Adaboost, and Vector Boosting algorithms have been proposed to replace the Adaboost algorithm of Viola and Jones. On the feature level, an extended set of Haar-like features, edge orientation histograms, and a sparse feature set have been proposed to be used to learn a classifier. In addition, Principal Component Analysis and Fisher Subspace Analysis have been used as part of the feature pool.

SUMMARY OF THE INVENTION

A first aspect of the invention is directed to a method for detecting a presence of an object in an image, the method comprising: receiving multiple training image samples; using at least one computing device to determine a set of adaptive features for each training image sample, wherein the determining includes: initializing parameters for a set of wavelets; and optimizing the set of wavelets by adapting the parameters to match one-by-one to image structures of the respective training image sample by minimizing the error between the training image sample and the set of wavelets; using at least one computing device to integrate the sets of adaptive features of the multiple training image samples to generate an adaptive feature pool; using at least one computing device to determine a general feature based on the adaptive feature pool, wherein the general feature encodes a common characteristic of all of the training image samples; and using at least one computing device to examine the image using a classifier determined based on the general feature to detect the presence of the object.

A second aspect of the invention is directed to a system comprising: a computer system, including at least one computing device, for performing a method for detecting a presence of an object in an image, the method comprising: obtaining multiple training image samples; determining a set of adaptive features for each training image sample, wherein the determining includes: initializing parameters for a set of

wavelets; and optimizing the set of wavelets by adapting the parameters to match one-by-one to image structures of the respective training image sample by minimizing the error between the training image sample and the set of wavelets; integrating the sets of adaptive features of the multiple training image samples to generate an adaptive feature pool; determining a general feature based on the adaptive feature pool, wherein the general feature encodes a common characteristic of all of the training image samples; and examining the image using a classifier determined based on the general feature to detect the presence of the object.

A third aspect of the invention is directed to a computer program product comprising program code embodied in at least one computer-readable storage medium, which when executed, enables a computer system to implement a method for detecting a presence of an object in an image, the method comprising: receiving multiple training image samples; determining a set of adaptive features for each training image sample, wherein the determining includes: initializing parameters for a set of wavelets; and optimizing the set of wavelets by adapting the parameters to match one-by-one to image structures of the respective training image sample by minimizing the error between the training image sample and the set of wavelets; integrating the sets of adaptive features of the multiple training image samples to generate an adaptive feature pool; determining a general feature based on the adaptive feature pool, wherein the general feature encodes a common characteristic of all of the training image samples; and examining the image using a classifier determined based on the general feature to detect the presence of the object.

Other aspects and features of the present invention, as defined solely by the claims, will become apparent to those ordinarily skilled in the art upon review of the following non-limited detailed description of the invention in conjunction with the accompanying figures.

BRIEF DESCRIPTION OF THE DRAWINGS

The embodiments of this disclosure will be described in detail, with reference to the following figures, wherein like designations denote like elements, and wherein:

FIG. 1 shows a block diagram of a system according to an embodiment of the invention.

FIG. 2 shows a block diagram of an illustrative computer environment according to an embodiment of the invention.

FIG. 3 shows an embodiment of the operation of an object detection system.

It is noted that the drawings of the disclosure are not to scale. The drawings are intended to depict only typical aspects of the disclosure, and therefore should not be considered as limiting the scope of the invention. In the drawings, like numbering represents like elements among the drawings.

DETAILED DESCRIPTION OF THE DISCLOSURE

The following detailed description of embodiments refers to the accompanying drawings, which illustrate specific embodiments of the disclosure. Other embodiments having different structures and operations do not depart from the scope of the present invention.

1. SYSTEM OVERVIEW

FIG. 1 shows a block diagram of a system 10 according to an embodiment. System 10 includes multiple image capturing devices (e.g., cameras) 12 (12a-12d are shown) posi-

tioned around a path **14** in a preset pattern. Specifically, cameras **12** are positioned in a sequence to capture different views of an actual three-dimension object **16** in path **14** in a sequence (the arrow of path **14** indicating a presumed direction of movement of actual object **16** in path **14**). For example, camera **12a** captures a frontal view of actual object **16**; subsequent to **12a**, camera **12b** captures a side profile view of actual object **16**; subsequent to **12b**, camera **12c** captures again a frontal view of actual object **16**; and subsequent to **12c**, camera **12d** again captures a side profile view of actual object **16**. The images captured by cameras **12** may be communicated to a processing center **18** to detect whether a target object is present in the images, e.g., processing center **18** determines whether actual object **16** is the target object. In processing the sequence of captured images of actual object **16**, processing center **18** may use different classifiers to examine images of different views of actual object **16**, each of the different classifiers identifying the target object in a different view. For example, a frontal view classifier may be used to examine images captured by cameras **12a** and **12c** and a side profile view identifier may be used to examine images captured by cameras **12b** and **12d**.

It should be appreciated that actual object **16** can be any object in path **14** and captured by a camera **12**. For example, in the case that path **14** is a doorway monitored by surveillance cameras **12**, actual object **16** may be an animal running through the doorway or may be a piece of luggage that is moved through the doorway, or may be the background of the doorway itself, i.e., no additional object except the doorway. A target object may be any object intended to be monitored. For example, target object can be a human-being in general, a human-being with a specific characteristic, e.g., a specific facial complexity, or an automatic weapon. In the following description, a human-being in general will be used as an illustrative example of a target object for descriptive purposes.

The classifiers used in the examination may be determined by a classifier selection unit **20** of processing center **18** based on training image samples **22** input thereto. Details of the selection of a classifier will be described herein together with a computer environment **100** (FIG. 2).

2. COMPUTER ENVIRONMENT

FIG. 2 shows an illustrative environment **100** for detecting the presence of a target object in an image. To this extent, environment **100** includes a computer infrastructure **102** that can perform the various processes described herein for determining whether a target object, e.g., a human-being, is present in the images captured by cameras **12** (FIG. 1). In particular, computer infrastructure **102** is shown including a computing device **104** that comprises an object detection system **132**, which enables computing device **104** to perform the process(es) described herein.

Computing device **104** is shown including a memory **112**, a processing unit (PU) **114**, an input/output (I/O) interface **116**, and a bus **118**. Further, computing device **104** is shown in communication with an external I/O device/resource **120** and a storage system **122**. In general, PU **114** executes computer program code, such as object detection system **132**, that is stored in memory **112** and/or storage system **122**. While executing computer program code, PU **114** can read and/or write data to/from memory **112**, storage system **122**, and/or I/O interface **116**. Bus **118** provides a communications link between each of the components in computing device **104**. I/O interface **116** can comprise any device that enables a user to interact with computing device **104** or any device that

enables computing device **104** to communicate with one or more other computing devices. External I/O device/resource **120** can be coupled to the system either directly or through I/O interface **116**.

In any event, computing device **104** can comprise any general purpose computing article of manufacture capable of executing computer program code installed thereon. However, it is understood that computing device **104** and object detection system **132** are only representative of various possible equivalent computing devices that may perform the various processes of the disclosure. To this extent, in other embodiments, computing device **104** can comprise any specific purpose computing article of manufacture comprising hardware and/or computer program code for performing specific functions, any computing article of manufacture that comprises a combination of specific purpose and general purpose hardware/software, or the like. In each case, the program code and hardware can be created using standard programming and engineering techniques, respectively.

Similarly, computer infrastructure **102** is only illustrative of various types of computer infrastructures for implementing the invention. For example, in an embodiment, computer infrastructure **102** comprises two or more computing devices that communicate over any type of wired and/or wireless communications link, such as a network, a shared memory, or the like, to perform the various processes of the disclosure. When the communications link comprises a network, the network can comprise any combination of one or more types of networks (e.g., the Internet, a wide area network, a local area network, a virtual private network, etc.). Network adapters may also be coupled to the system to enable the data processing system to become coupled to other data processing systems or remote printers or storage devices through intervening private or public networks. Modems, cable modem and Ethernet cards are just a few of the currently available types of network adapters. Regardless, communications between the computing devices may utilize any combination of various types of transmission techniques.

Object detection system **132** includes a data collecting unit **140**; adaptive feature determination unit **142** including a wavelet set parameter (WSP) initialization unit **144** and an adaptation unit **146**; an adaptive feature pool integration unit **148**; a general feature determination unit **150** including a classifier determination unit **152**; a detection implementation unit **154**; and other system components **158**. Other system components **158** may include any now known or later developed parts of object detection system **132** not individually delineated herein, but understood by those skilled in the art. As should be appreciated, components of computer infrastructure **102** and object detection system **132** may be located at different physical locations or at the same physical location.

According to an embodiment, computer infrastructure **102** and object detection system **132** may be used to implement, inter alia, processing center **18** of system **10** (FIG. 1). For example, adaptive feature determination unit **142**, adaptive feature pool integration unit **148**, and general feature determination unit **150** may be used together to implement classifier selection unit **20** (FIG. 1) of processing center **18**.

Inputs/outputs to computer infrastructure **102**, e.g., through external I/O device/resource **120** and/or I/O interface **116**, may include images of actual object **16** captured by cameras **12** and training image samples **22** of a target object, e.g., a human-being. Training image samples of non-objects may also be required as is appreciated. In the following description, a training image sample **22** refers to a training image sample of the target object for description purposes.

The teaching of the disclosure can also be applied to the processing of non-object training image sample. The operation of system 10 and object detection system 132 are described together herein in detail.

3. OPERATION METHODOLOGY

An embodiment of the operation of object detection system 132 is shown in the flow diagram of FIG. 3. Referring to FIGS. 1-3, in process 51, data collecting unit 140 receives data regarding training image samples 22. Training image samples 22 include sample images of different views of the target object, e.g., human-being. The following description focuses on the processing of training image samples 22 of a specific view, e.g., frontal view, of human-being for simplicity purposes, unless indicated otherwise. It should be appreciated that processing training image samples 22 of other views of the target object are also included, and preferably is implemented in the current invention. Each specific training image sample 22 represents a particular individual of the target object, e.g., a specific person.

In process S2, data collecting unit 140 receives/collects data regarding the images of actual object 16 captured by cameras 12. As described above, different cameras 12 capture different views of actual object 16.

In process S3, adaptive feature determination unit 142 determines a set of adaptive features for each training image sample 22 such that the set of adaptive features together match the respective training image sample 22. According to an embodiment, adaptive feature determination unit 142 adapts a set of wavelets to the training image sample to generate the adaptive feature set. Process S3 includes two sub-processes. In sub-process S3-1, wavelet set parameter (WSP) initialization unit 144 initializes parameters of the wavelet set (6) used to produce the set of adaptive features. $\mathfrak{S} = \{\psi_{n_1} \dots \psi_{n_N}\}$, where $\psi_{n_i}(x, y)$ is a particular mother wavelet function with vector parameters $n_i = (c_x, c_y, \mathfrak{O}, s_x, s_y)^T$, where c_x, c_y indicate the position of the wavelet, \mathfrak{O} the orientation, and s_x, s_y the scale of the wavelets. The wavelet set parameters may include number of wavelets (N), wavelet type, scale initialization, wavelet frequency, group of features treated as a single feature, and initial wavelet vector parameters (n_i), etc. The number of wavelets (N) indicates how many wavelet functions will be used to represent the training image sample. The choice of N is arbitrary and related to the degree of desired representation accuracy. Wavelet type indicates the type of wavelet function used to represent the training image sample. Any type of wavelet functions may be used, and all are included in the invention. According to an embodiment, preferably, Haar and/or Gabor wavelets are used. The scale initialization controls the initial scale of the wavelets. As mentioned before, wavelet vector parameters are defined as $n_i = (c_x, c_y, \mathfrak{O}, s_x, s_y)^T$, where c_x, c_y denote position of the wavelet in x and y axis, s_x, s_y denote scale of the wavelet in x and y axis, and \mathfrak{O} denotes orientation of the wavelet. The frequency parameter controls the number of oscillations of the wavelet filter. WSP initialization unit 144 may select to treat a group of adaptive features as a single feature, which is important to encode global object information with the adaptive features.

According to an embodiment, the wavelet set parameters for the respective training image samples 22 are initialized/controlled to be diversified to achieve a desired diversity of adaptive features in an adaptive feature pool as will be described. For example, the wavelet sets for different training image samples 22 may be initialized with different wavelet parameters. One way to control the diversity is to randomly

assign different wavelet set parameters for the wavelet sets of different training image samples 22. In addition, a user may instruct WSP determination unit 144 regarding how to assign wavelet set parameters for some specific training image samples 22, and/or all training image samples 22.

In sub-process S3-2, adaptation unit 146 adapts the wavelet set for each training image sample 22 such that the wavelets match one-to-one to the image structures of the respective training image sample 22. The goal of the adaptation is to learn the parameters of the wavelets ψ_{n_i} , e.g., position, scale, and orientation, so that they match the image structures of the training image sample 22. The following description focuses on the adaptation of a wavelet set for a specific training image sample 22 for simplicity purposes. The described process may be operated upon each and every training image samples 22 independently.

According to an embodiment, adaptation unit 146 first initializes the set of wavelets ψ_{n_i} along training image sample 22 according to the parameters specified by WSP unit 144.

Subsequently, adaptation unit 146 optimizes wavelets ψ_{n_i} to match the image structures of training image sample 22 by minimizing the error between the training image sample and the wavelets using the following equation:

$$E = \min_{n_i, w_i} \left\| I - \sum_i w_i \psi_{n_i} \right\|^2, \quad (1)$$

where E denotes an energy function, ψ_{n_i} denotes a wavelet with wavelet vector parameters n_i , with $n_i = (c_x, c_y, \mathfrak{O}, s_x, s_y)^T$, where c_x, c_y denote position of the wavelet in x and y axis, s_x, s_y denote scale of the wavelet in x and y axis, and \mathfrak{O} denotes orientation of the wavelet, w_i denotes a weight of the wavelet, and I denotes the training image sample.

Using equation (1), wavelets ψ_{n_i} vector parameters n_i are optimized so that the training sample image 22 may be closely reconstructed by the optimized wavelets ψ_{n_i} and weights w_i using the following equation:

$$\hat{I} = \sum_{i=1}^N w_i \psi_{n_i}, \quad (2)$$

where N indicates the number of wavelets, ψ_{n_i} indicates optimized wavelet i, and w_i indicates the weight of optimized wavelet i.

Rather than relying on equation (1) above, adaptation unit 146 may directly compute wavelet weights w_i once the wavelet vector parameters n_i are optimized. If the wavelet functions ψ_{n_i} are orthogonal, weights w_i may be calculated as the inner product of training image sample 22 (I) with respective wavelet function ψ_{n_i} . That is:

$$w_i = \langle I, \psi_{n_i} \rangle \quad (3)$$

For more a general case where wavelet functions ψ_{n_i} may not be orthogonal, adaptation unit 146 may construct a family of dual wavelets $\tilde{\psi} = \{\tilde{\psi}_{n_1} \dots \tilde{\psi}_{n_N}\}$. Wavelet $\tilde{\psi}_{n_i}$ is dual wavelet of ψ_{n_i} if the bi-orthogonality condition is satisfied, i.e., $\langle \tilde{\psi}_{n_i}, \psi_{n_j} \rangle = \delta_{i,j}$, where $\delta_{i,j}$ is the Kronecker delta function. As such:

$$\tilde{\psi}_{n_i} = \sum_j (A^{-1})_{i,j} \psi_{n_j}, \quad \text{where} \quad (4)$$

$$A_{i,j} = \langle \psi_{n_i}, \psi_{n_j} \rangle. \quad (5)$$

Then, weights w_i may be calculated using the following equation:

$$w_i = \langle I, \tilde{\psi}_{n_i} \rangle \quad (6)$$

where I is the training image sample **22**.

In process **S3**, after the wavelets are optimized to match the training image sample **22**, the optimized wavelets ψ_{n_i} are referred to as “adaptive features” for illustrative purposes.

In process **S4**, adaptive feature pool integration unit **148** integrates the sets of adaptive features for all training image samples **22** to generate an adaptive feature pool. Specifically, according to an embodiment, adaptive feature pool integration unit **148** puts all the adaptive features for all the training image samples **22** into a single pool of adaptive features (Ω) defined as:

$$\Omega = \bigcup_{i=1}^M \psi_i, \quad (7)$$

where ψ_i indicates a set of adaptive features i , and M indicates a total number of training samples **22**.

As described above, adaptive features in the adaptive features pool are diversified because parameters of the wavelet sets for determining the adaptive features of different training image samples **22** are diversified. For example, Haar adaptive features may be used to reconstruct a training image sample **22**, while Gabor adaptive features may be used to reconstruct another training image sample **22**.

In process **S5**, general feature determination unit **150** determines general features based on the adaptive feature pool (Ω). A general feature(s) is the feature(s) from the adaptive feature pool that encodes common characteristics of all training image samples **22**. In addition, classifier determination unit **152** further determines a classifier based on the general features, which is to be used to detect whether a target object is present in the images captured by cameras **12**. Any method may be used to determine general features and/or a classifier and all are included in the invention. For example, Adaboost learning of Viola and Jones may be used to select general features and classifiers. According to an embodiment, multiple general features and classifiers may be determined based on different views of training image samples **22** for identifying different views of training image samples **22**.

In process **S6**, detection implementation unit **154** examines the images captured by cameras **12** to detect whether a target object is present in the images. According to an embodiment, detection implementation unit **154** uses different classifiers to examine the respective views of actual object **16**. For example, a side profile view classifier (to identify a side profile view of the target object) will be used to examine the images captured by cameras **12b** and **12d**; and a frontal view classifier (to identify a frontal view of the target object) will be used to examine the images captured by cameras **12a** and **12c**.

4. CONCLUSION

While shown and described herein as a method and system for detecting presence of an object in an image, it is understood that the disclosure further provides various alternative embodiments. For example, in an embodiment, the invention provides a program product stored on a computer-readable medium, which when executed, enables a computer infrastructure to detect presence of an object in an image. To this extent, the computer-readable medium includes program

code, such as object detection system **132** (FIG. 2), which implements the process described herein. It is understood that the term “computer-readable medium” comprises one or more of any type of physical embodiment of the program code. In particular, the computer-readable medium can comprise program code embodied on one or more portable storage articles of manufacture (e.g., a compact disc, a magnetic disk, a tape, etc.), on one or more data storage portions of a computing device, such as memory **112** (FIG. 2) and/or storage system **122** (FIG. 2), and/or as a data signal traveling over a network (e.g., during a wired/wireless electronic distribution of the program product).

It should be appreciated that the teachings of the present invention could be offered as a business method on a subscription or fee basis. For example, a system **10** (FIG. 1), a computing device **104** comprising object detection system **132** (FIG. 2) could be created, maintained and/or deployed by a service provider that offers the functions described herein for customers. That is, a service provider could offer to provide a service to encourage a virtual world user to perform a conduct as described above.

As used herein, it is understood that the terms “program code” and “computer program code” are synonymous and mean any expression, in any language, code or notation, of a set of instructions that cause a computing device having an information processing capability to perform a particular function either directly or after any combination of the following: (a) conversion to another language, code or notation; (b) reproduction in a different material form; and/or (c) decompression. To this extent, program code can be embodied as one or more types of program products, such as an application/software program, component software/a library of functions, an operating system, a basic I/O system/driver for a particular computing and/or I/O device, and the like. Further, it is understood that the terms “component” and “system” are synonymous as used herein and represent any combination of hardware and/or software capable of performing some function(s).

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

The terminology used herein is for the purpose of describing particular embodiments only and is not intended to be limiting of the invention. As used herein, the singular forms “a”, “an” and “the” are intended to include the plural forms as well, unless the context clearly indicates otherwise. It will be

further understood that the terms “comprises” and/or “comprising,” when used in this specification, specify the presence of stated features, integers, steps, operations, elements, and/or components, but do not preclude the presence or addition of one or more other features, integers, steps, operations, elements, components, and/or groups thereof.

Although specific embodiments have been illustrated and described herein, those of ordinary skill in the art appreciate that any arrangement which is calculated to achieve the same purpose may be substituted for the specific embodiments shown and that the invention has other applications in other environments. This application is intended to cover any adaptations or variations of the present invention. The following claims are in no way intended to limit the scope of the invention to the specific embodiments described herein.

What is claimed is:

1. A method for detecting a presence of an object in an image, the method comprising:

receiving multiple training image samples of the object;
using at least one computing device to determine a set of adaptive features for each training image sample of the object, wherein the determining includes:

initializing parameters for a set of wavelets; and
optimizing the set of wavelets by adapting the parameters to match one-by-one to image structures of the respective training image sample by minimizing the error between the training image sample and the set of wavelets;

using at least one computing device to integrate the sets of adaptive features of the multiple training image samples to generate an adaptive feature pool;

using at least one computing device to determine a general feature based on the adaptive feature pool, wherein the general feature encodes a common characteristic of all of the training image samples of the object; and

using at least one computing device to examine the image using a classifier determined based on the general feature to detect the presence of the object.

2. The method of claim 1, wherein the adapting is implemented approximately using formula:

$$E = \min_{n_i, w_i} \left\| I - \sum_i w_i \psi_{n_i} \right\|^2,$$

where E denotes an energy function, denotes a wavelet with a wavelet vector parameter n_i , with $n_i = (cx, cy, sx, sy)T$, where cx, cy denote position of the wavelet in x and y axis, sx, sy denote scale of the wavelet in x and y axis, and denotes orientation of the wavelet, w_i denotes a weight of the wavelet, and I denotes the training image sample.

3. The method of claim 2, wherein the initialized parameters for the set of wavelets include at least one of: a number of wavelets, a wavelet type, a scale initialization, a wavelet frequency, or a group of features treated as a single feature.

4. The method of claim 3, wherein the initialized parameters of the sets of wavelets for the respective multiple training image samples are configured to diversify the adaptive features in the adaptive feature pool.

5. The method of claim 1, wherein the general feature is determined from the adaptive features of the multiple training image samples.

6. The method of claim 1, further comprising examining a sequence of images to detect a presence of a moving three-dimensional object, multiple different classifiers being used

sequentially in examining the sequence of images, wherein each of the multiple different classifiers identifies the three-dimensional object in a different view.

7. A system comprising:

a computer system, including at least one computing device, for performing a method for detecting a presence of an object in an image, the method comprising:

obtaining multiple training image samples of the object;

determining a set of adaptive features for each training image sample of the object, wherein the determining includes:

initializing parameters for a set of wavelets; and

optimizing the set of wavelets by adapting the parameters to match one-by-one to image structures of the respective training image sample by minimizing the error between the training image sample and the set of wavelets;

integrating the sets of adaptive features of the multiple training image samples to generate an adaptive feature pool;

determining a general feature based on the adaptive feature pool, wherein the general feature encodes a common characteristic of all of the training image samples of the object; and

examining the image using a classifier determined based on the general feature to detect the presence of the object.

8. The system of claim 7, wherein the adapting is implemented approximately using formula:

$$E = \min_{n_i, w_i} \left\| I - \sum_i w_i \psi_{n_i} \right\|^2,$$

where E denotes an energy function, denotes a wavelet with a wavelet vector parameter n_i , with $n_i = (cx, cy, sx, sy)T$, where cx, cy denote position of the wavelet in x and y axis, sx, sy denote scale of the wavelet in x and y axis, and denotes orientation of the wavelet, w_i denotes a weight of the wavelet, and I denotes the training image sample.

9. The system of claim 7, wherein the initialized parameters for the set of wavelets include at least one of: a number of wavelets, a wavelet type, a scale initialization, a wavelet frequency, or a group of features treated as a single feature.

10. The system of claim 9, wherein the initialized parameters of the sets of wavelets for the respective multiple training image samples are configured to diversify the adaptive features in the adaptive feature pool.

11. The system of claim 7, wherein the general feature is determined from the adaptive features of the multiple training image samples.

12. The system of claim 7, wherein the examining includes examining a sequence of images to detect a presence of a moving three-dimensional object using multiple different classifiers sequentially, wherein each of the multiple different classifiers identifies the three-dimensional object in a different view.

13. A computer program product comprising program code embodied in at least one non-transitory computer-readable storage medium, which when executed, enables a computer system to implement a method for detecting a presence of an object in an image, the method comprising:

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receiving multiple training image samples of the object;
determining a set of adaptive features for each training
image sample of the object, wherein the determining
includes:
initializing parameters for a set of wavelets; and
optimizing the set of wavelets by adapting the parameters
to match one-by-one to image structures of the respec-
tive training image sample by minimizing the error
between the training image sample and the set of wave-
lets;
integrating the sets of adaptive features of the multiple
training image samples to generate an adaptive feature
pool;
determining a general feature based on the adaptive feature
pool, wherein the general feature encodes a common
characteristic of all of the training image samples of the
object; and
examining the image using a classifier determined based
on the general feature to detect the presence of the
object.
14. The program product of claim **13**, wherein the adapting
is implemented approximately using formula:

$$E = \min_{n_i, w_i} \left\| I - \sum_i w_i \psi_{n_i} \right\|^2,$$

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where E denotes an energy function, ψ_{n_i} denotes a wavelet
with a wavelet vector parameter n_i , with $n_i = (cx, cy, sx,$
 $sy)T$, where cx, cy denote position of the wavelet in x and
y axis, sx, sy denote scale of the wavelet in x and y axis,
and θ_i denotes orientation of the wavelet, w_i denotes a
weight of the wavelet, and I denotes the training image
sample.

15. The program product of claim **13**, wherein the initial-
ized parameters for the set of wavelets include at least one of:
a number of wavelets, a wavelet type, a scale initialization, a
wavelet frequency, or a group of features treated as a single
feature.

16. The program product of claim **15**, wherein the initial-
ized parameters of the sets of wavelets for the respective
multiple training image samples are configured to diversify
the adaptive features in the adaptive feature pool.

17. The program product of claim **13**, wherein the general
feature is determined from the adaptive features of the mul-
tiple training image samples.

18. The program product of claim **13**, wherein the exam-
ining includes examining a sequence of images to detect a
presence of a moving three-dimensional object using mul-
tiple different classifiers sequentially, wherein each of the
multiple different classifiers identifies the three-dimensional
object in a different view.

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