US 20050265582A1

(19) **United States**

(12) **Patent Application Publication**

Buehler et al.

(10) **Pub. No.: US 2005/0265582 A1**

(43) **Pub. Date: Dec. 1, 2005**

(54) **METHOD AND SYSTEM FOR TRACKING AND BEHAVIORAL MONITORING OF MULTIPLE OBJECTS MOVING THROUGH MULTIPLE FIELDS-OF-VIEW**

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(21) Appl. No.: **11/191,128**

(22) Filed: **Jul. 27, 2005**

Related U.S. Application Data

(63) Continuation of application No. 10/706,850, filed on Nov. 12, 2003.

(60) Provisional application No. 60/425,267, filed on Nov. 12, 2002.

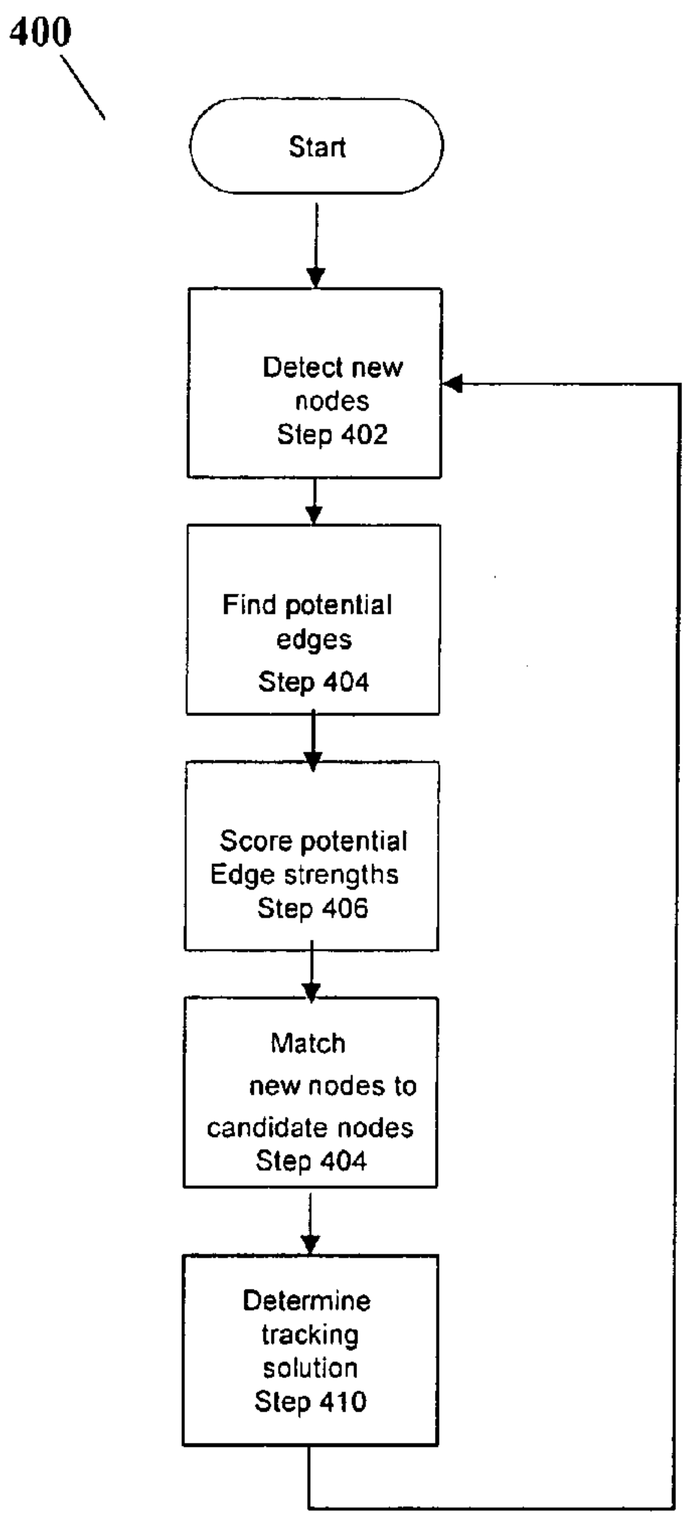
Publication Classification

(51) **Int. Cl.**[7] **G06K 9/00**

(52) **U.S. Cl.** **382/103**; 382/143

(57) **ABSTRACT**

A computerized method of video analysis that includes receiving several series of video frames generated by a number of image sensors. Each image sensor has a field-of-view. The image sensors monitor a portion of a monitored environment. The computerized method also includes concurrently tracking, independent of calibration, multiple objects within the monitored environment as the objects move between fields-of-view, at least two of which overlap, and multiple objects within one field-of-view. The tracking is based on the plurality of received series of video frames



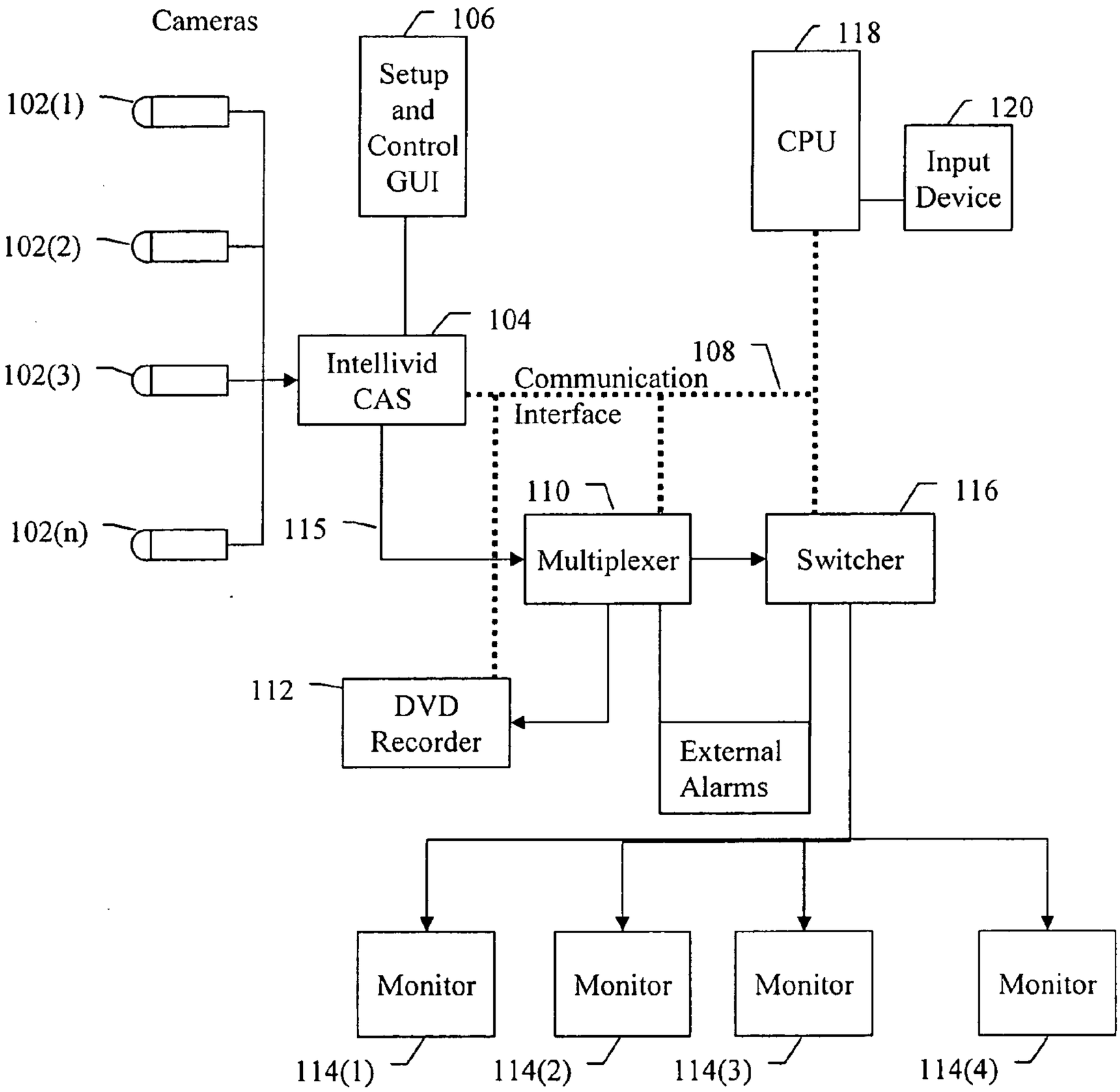

Cameras
106
Setup and Control GUI
118
CPU
120
Input Device
102(1)
102(2)
102(3)
102(n)
104
Intellivid CAS
108
Communication Interface
110
Multiplexer
115
116
Switcher
112
DVD Recorder
External Alarms
Monitor
Monitor
Monitor
Monitor
114(1)
114(2)
114(3)
114(4)

FIG. 1

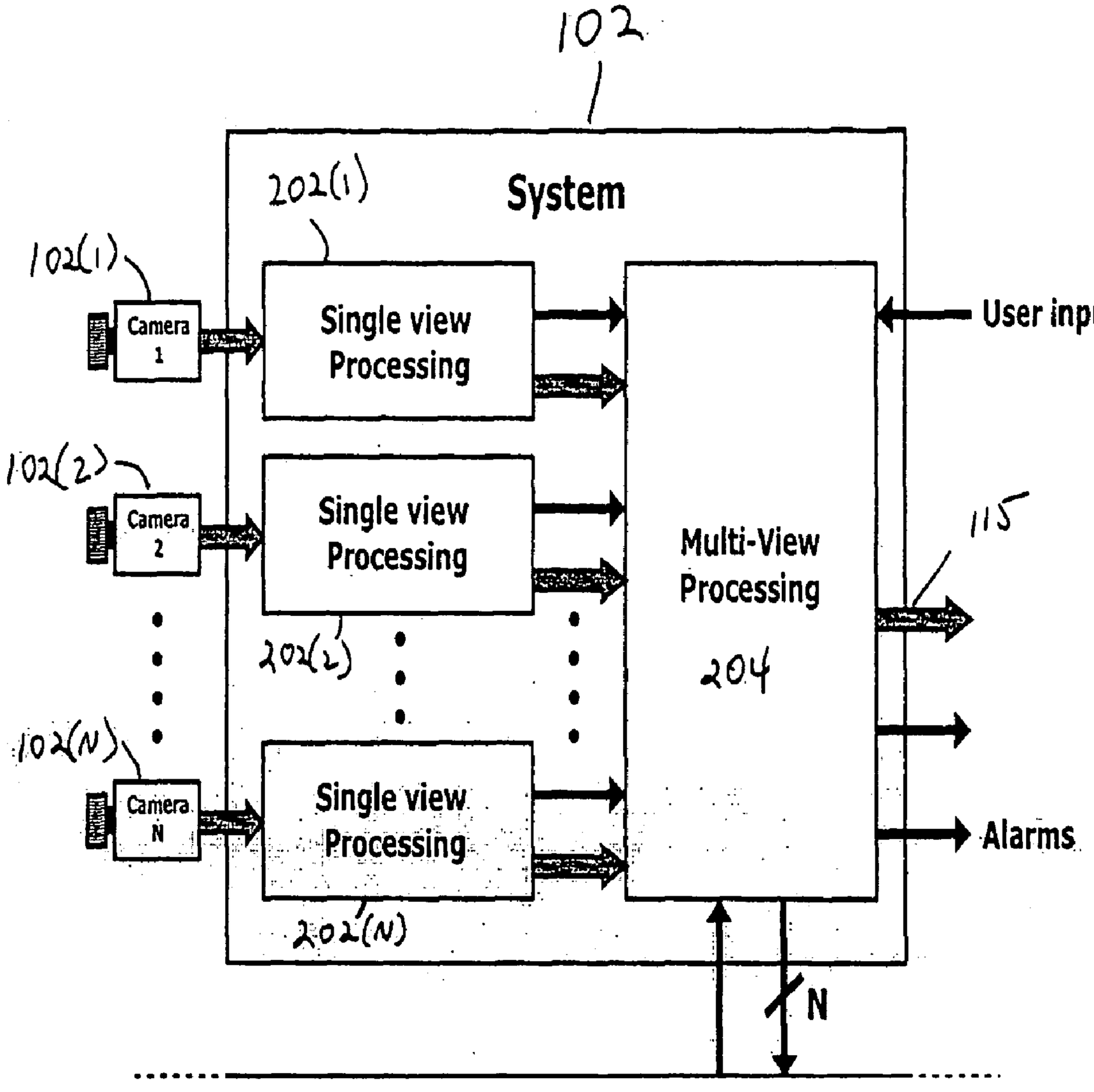

102
System
202(1)
102(1)
Camera 1
Single view Processing
User input
102(2)
Camera 2
Single view Processing
Multi-View Processing
204
115
202(2)
102(N)
Camera N
Single view Processing
Alarms
202(N)
N

Fig. 2

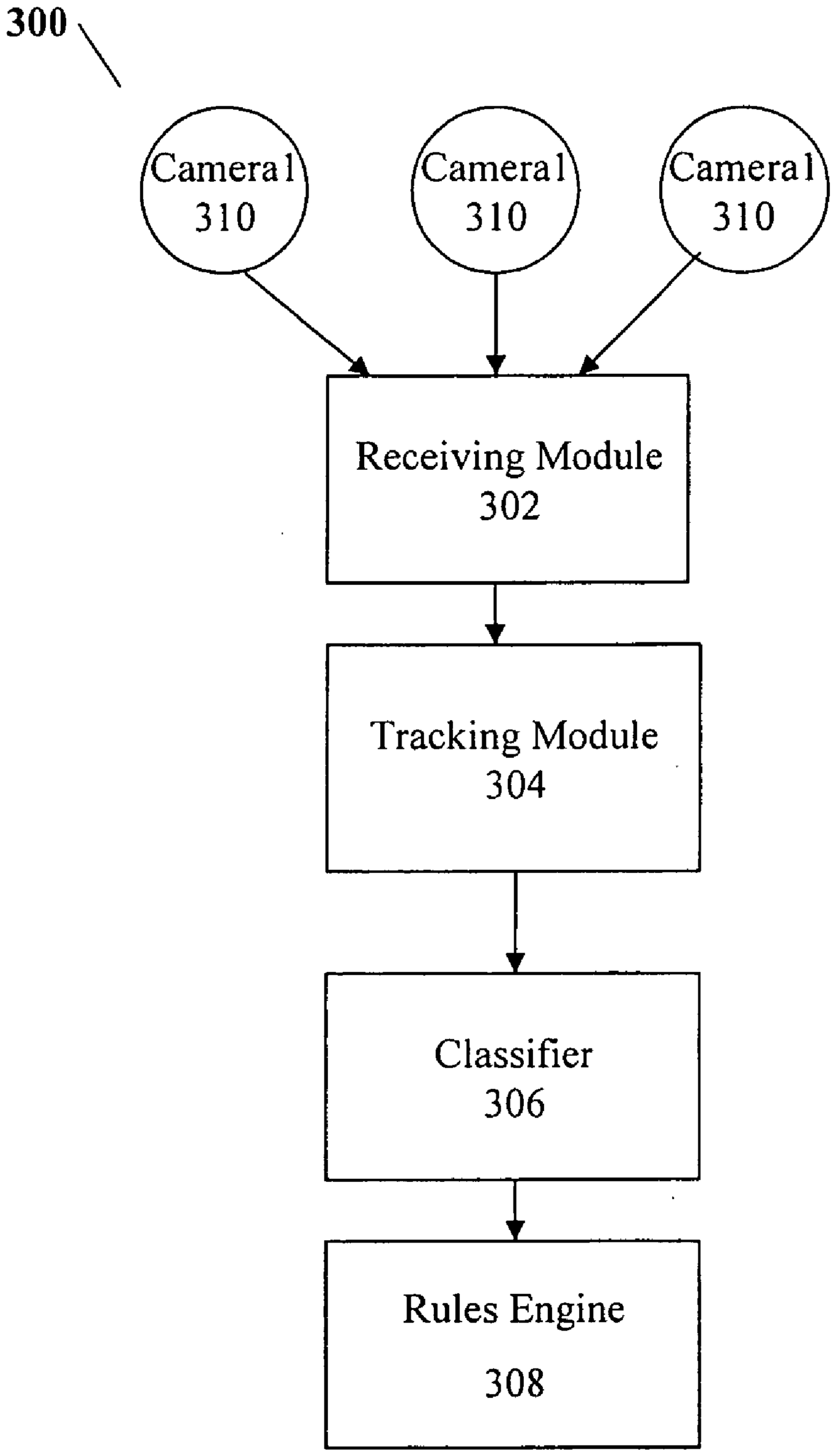

300
Camera 1
310
Camera 1
310
Camera 1
310
Receiving Module
302
Tracking Module
304
Classifier
306
Rules Engine
308

Fig. 3

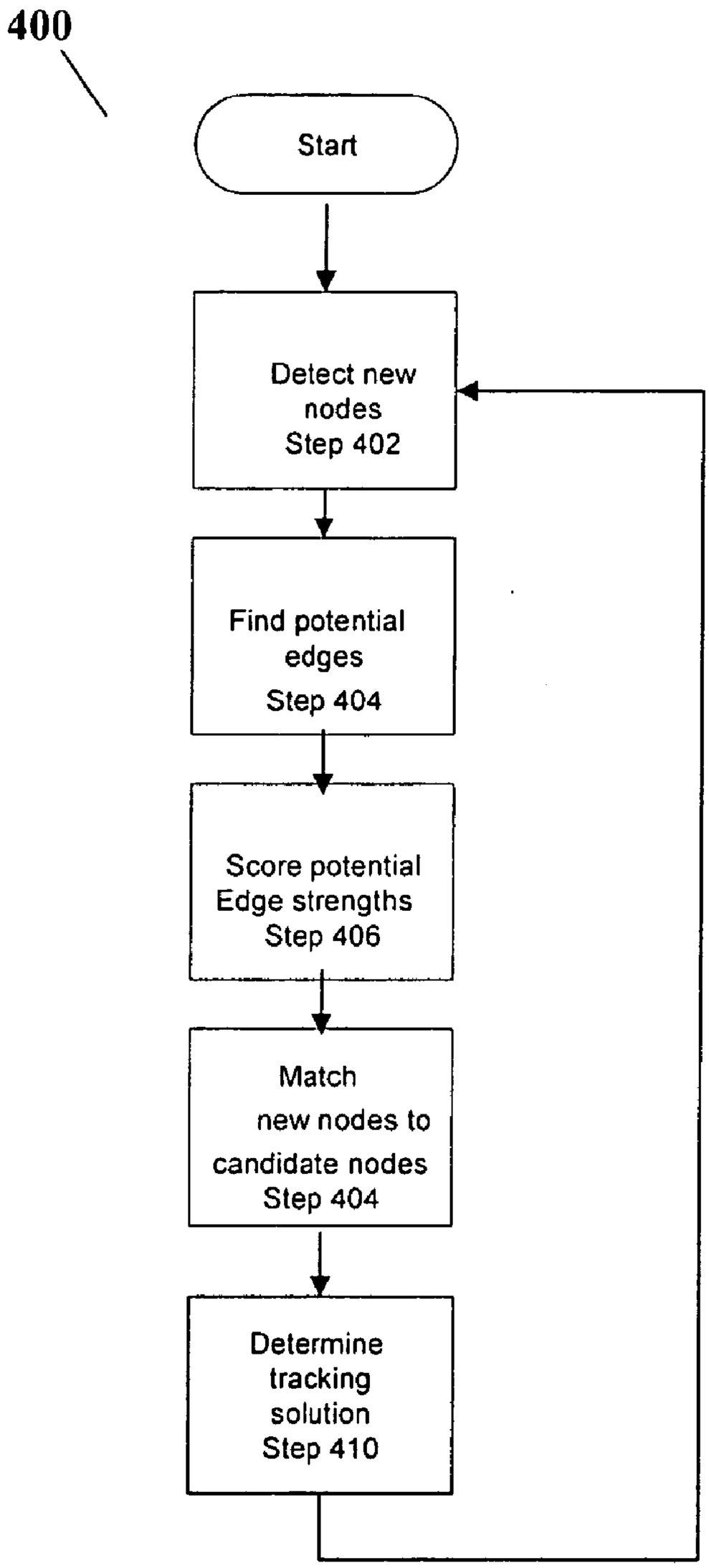

400
Start
Detect new nodes Step 402
Find potential edges Step 404
Score potential Edge strengths Step 406
Match new nodes to candidate nodes Step 404
Determine tracking solution Step 410

Fig. 4

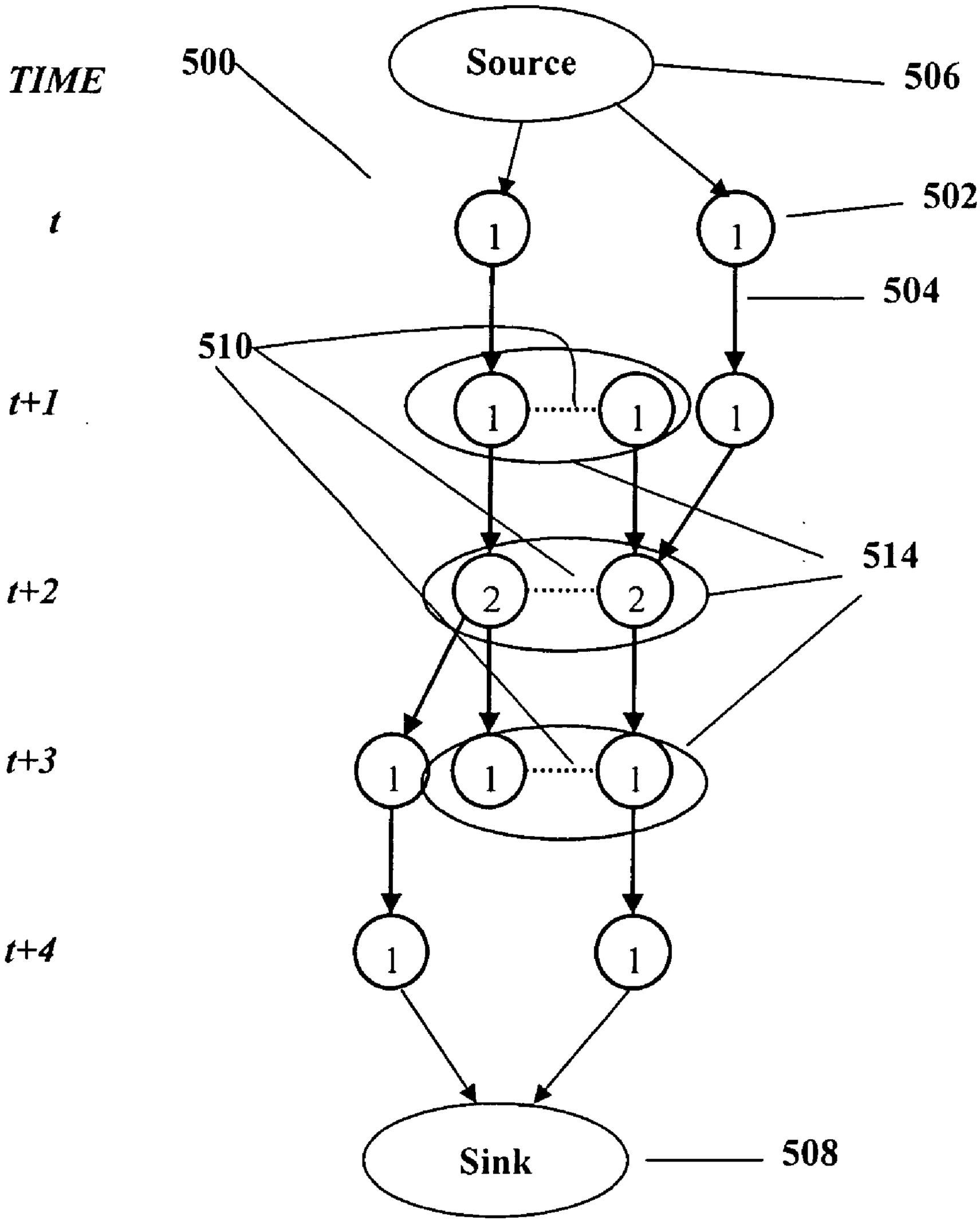


Fig. 5

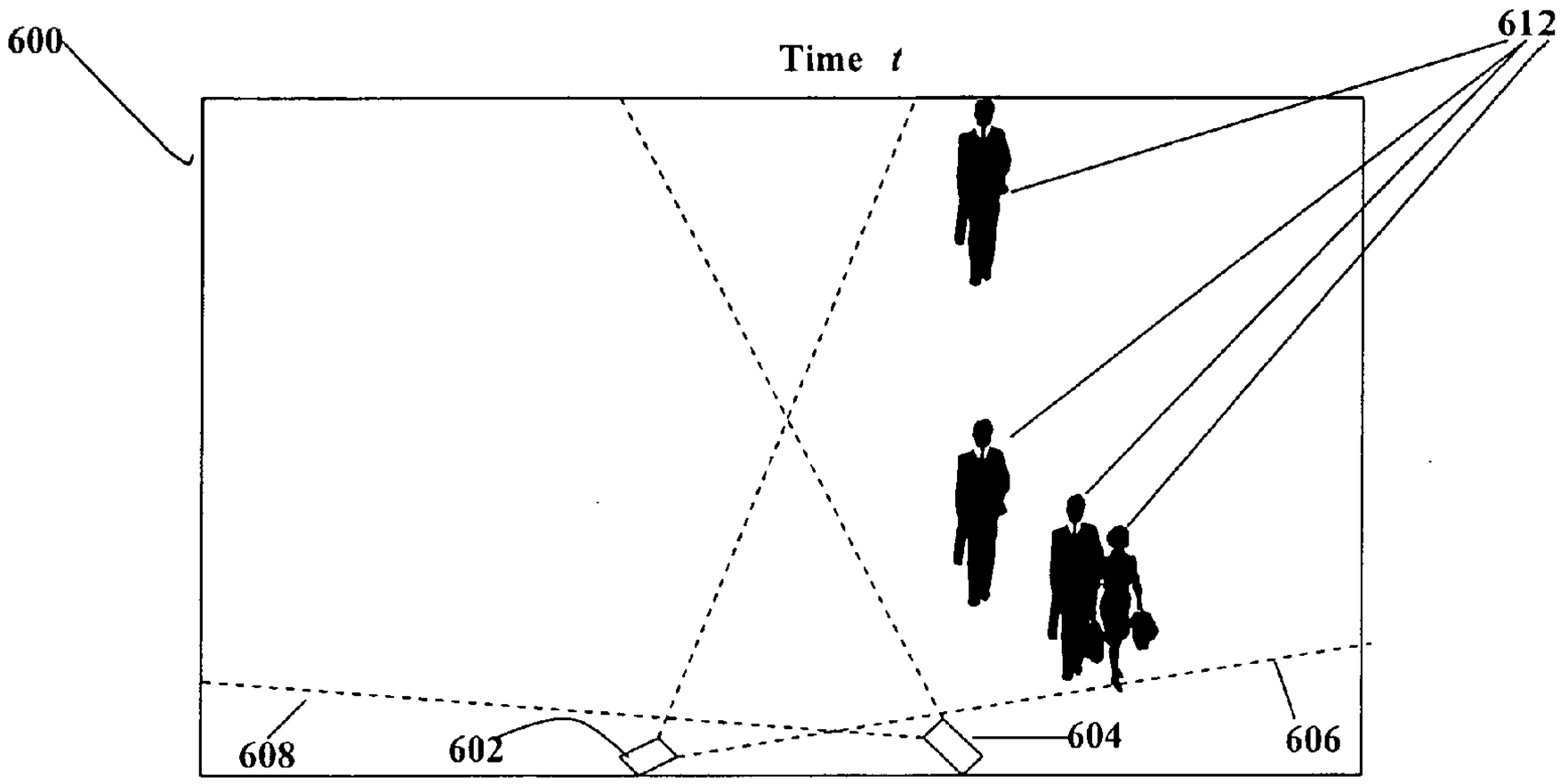


Fig. 6A

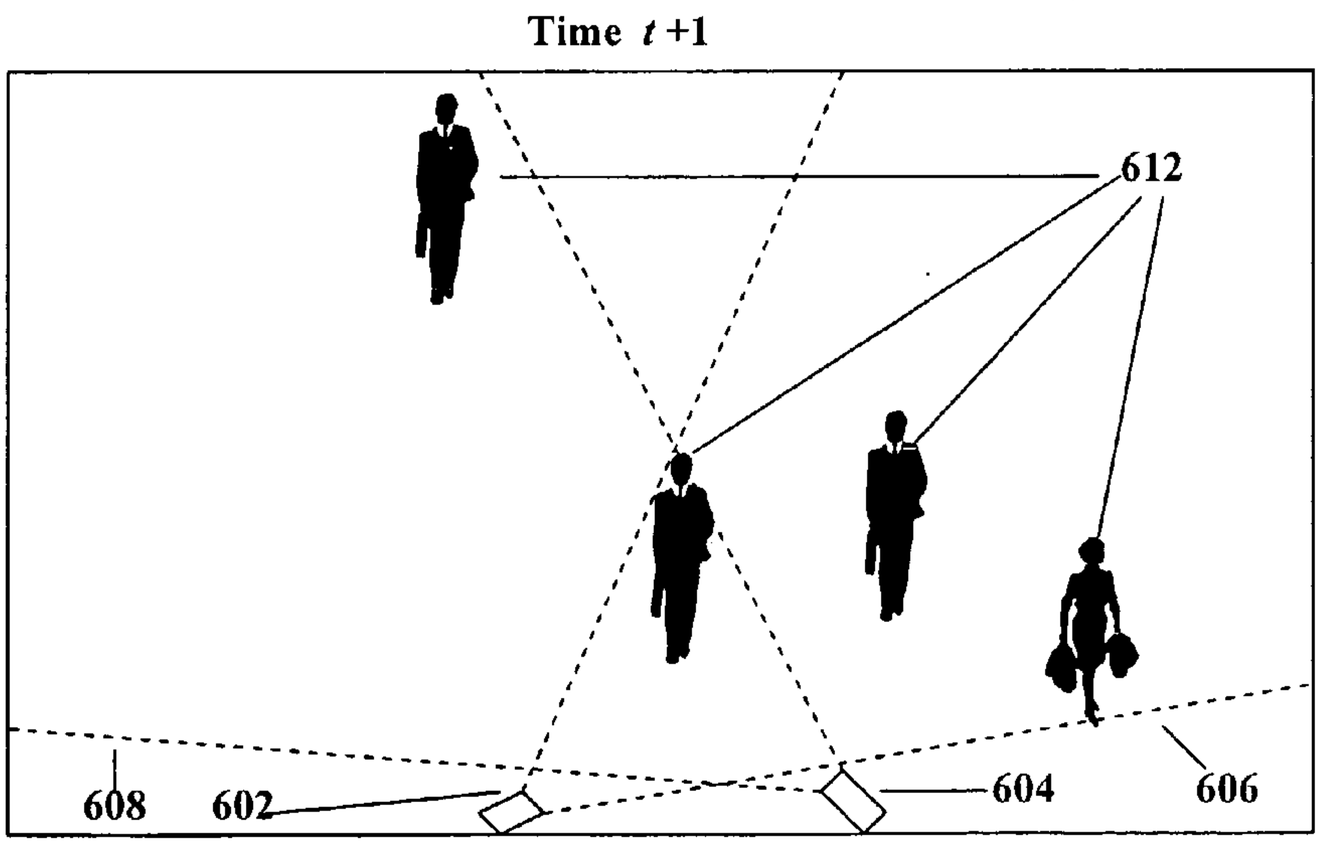
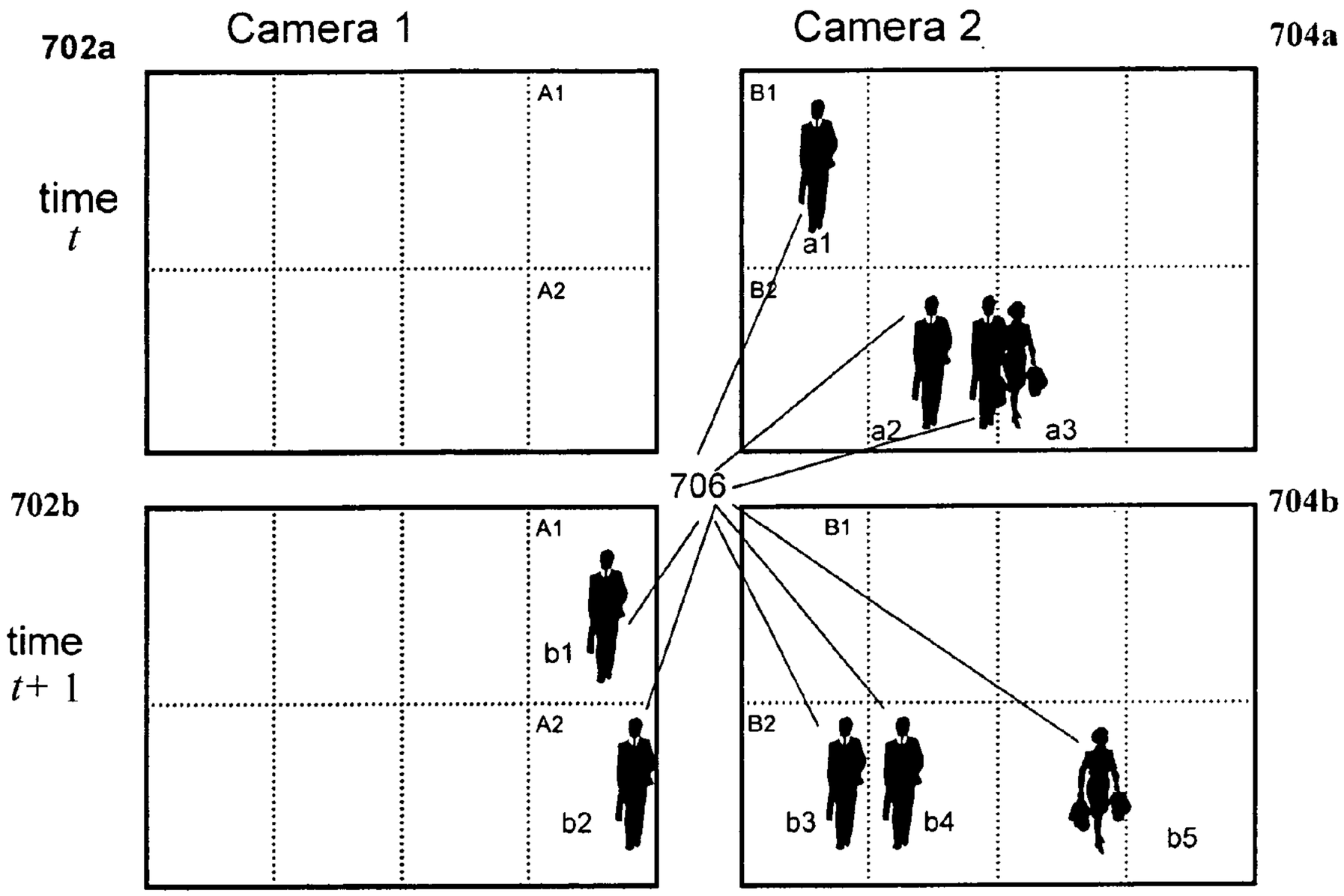


Fig. 6B

Fig. 7A



708

	B1	B2
A1	0	0
A2	0	1

$\Delta t = 0$

710

	B1	B2
A1	.8	0
A2	0	.1

$\Delta t = 1$

Fig. 7B

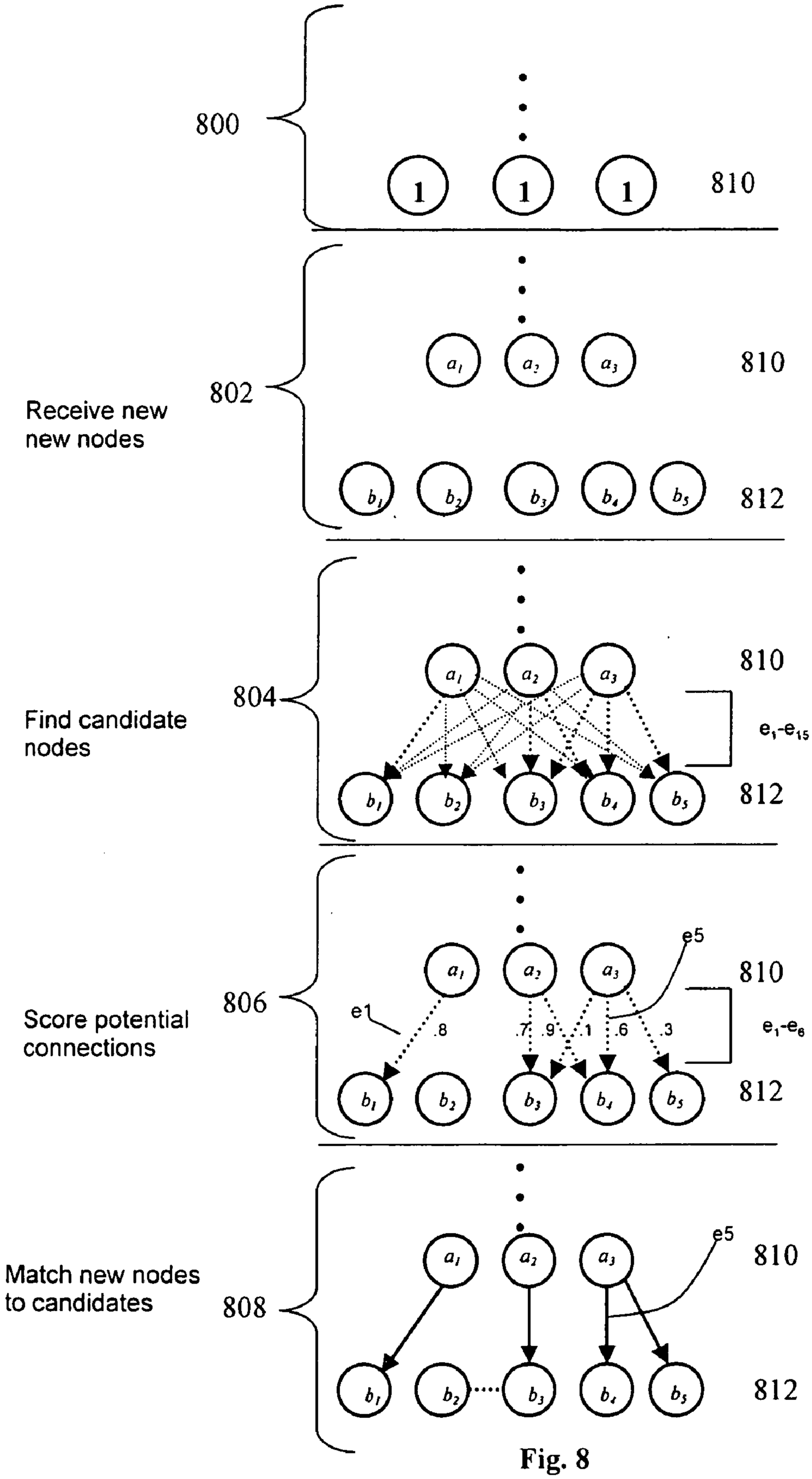

800
1
1
1
810
802
Receive new new nodes
a_1 a_2 a_3
810
b_1 b_2 b_3 b_4 b_5
812
804
Find candidate nodes
a_1 a_2 a_3
810
e_1-e_{15}
b_1 b_2 b_3 b_4 b_5
812
806
Score potential connections
e5
a_1 a_2 a_3
810
e1
.8
.7
.9
.1
.6
.3
e_1-e_6
b_1 b_2 b_3 b_4 b_5
812
808
Match new nodes to candidates
e5
a_1 a_2 a_3
810
b_1 b_2 b_3 b_4 b_5
812

Fig. 8

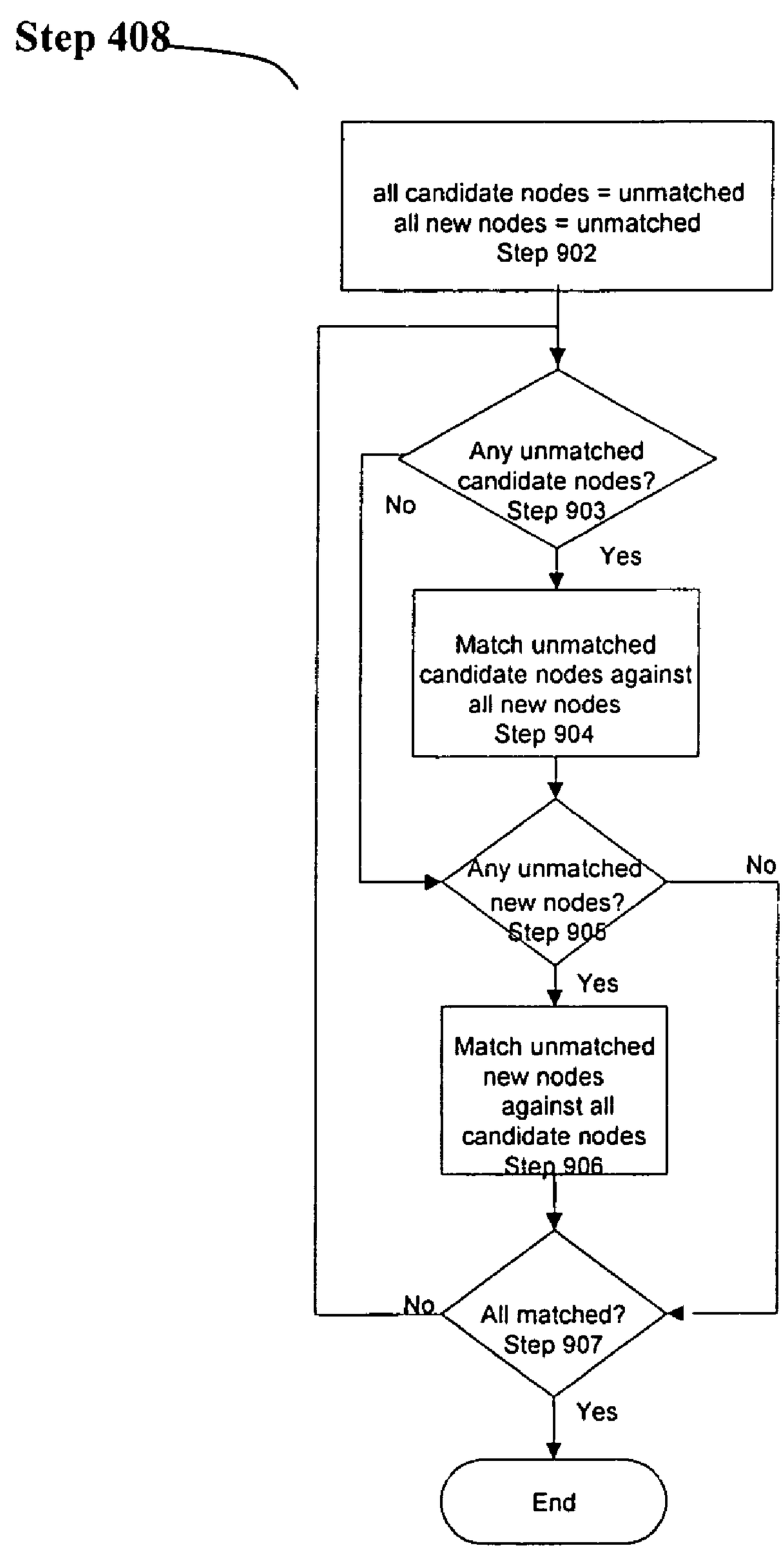

Step 408
all candidate nodes = unmatched
all new nodes = unmatched
Step 902
Any unmatched candidate nodes?
Step 903
No
Yes
Match unmatched candidate nodes against all new nodes
Step 904
Any unmatched new nodes?
Step 905
No
Yes
Match unmatched new nodes against all candidate nodes
Step 906
All matched?
Step 907
No
Yes
End

Fig. 9

1000

	b_1	b_2	b_3	b_4	b_5
a_1	(0.8)	X	X	X	X
a_2	X	X	(0.7)	0.9	X
a_3	X	X	0.1	(0.6)	0.3

Fig. 10A

1002

	b_5
a_1	X
a_2	X
a_3	(0.3)

Fig. 10B

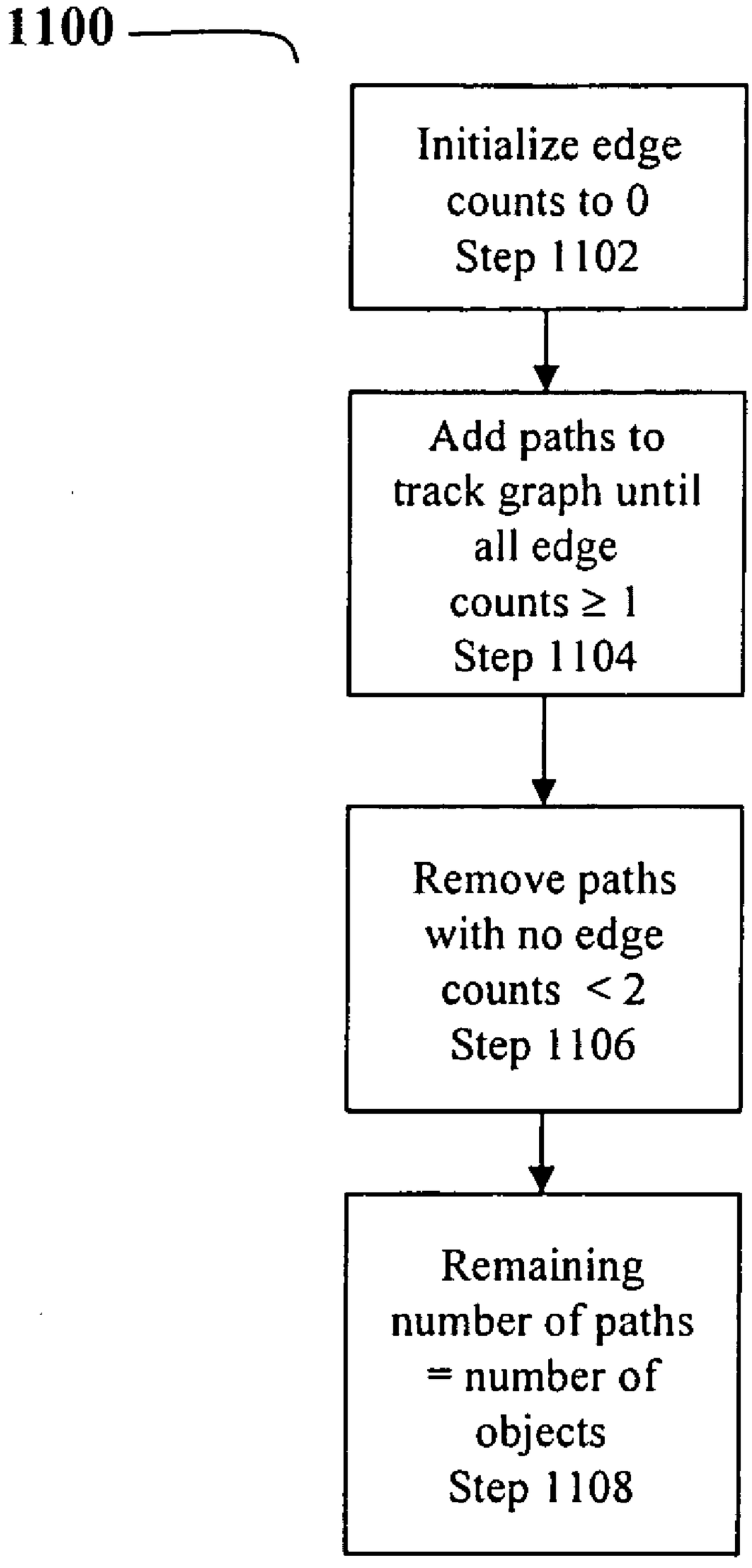

1100
Initialize edge counts to 0 Step 1102
Add paths to track graph until all edge counts ≥ 1 Step 1104
Remove paths with no edge counts < 2 Step 1106
Remaining number of paths = number of objects Step 1108

Fig. 11

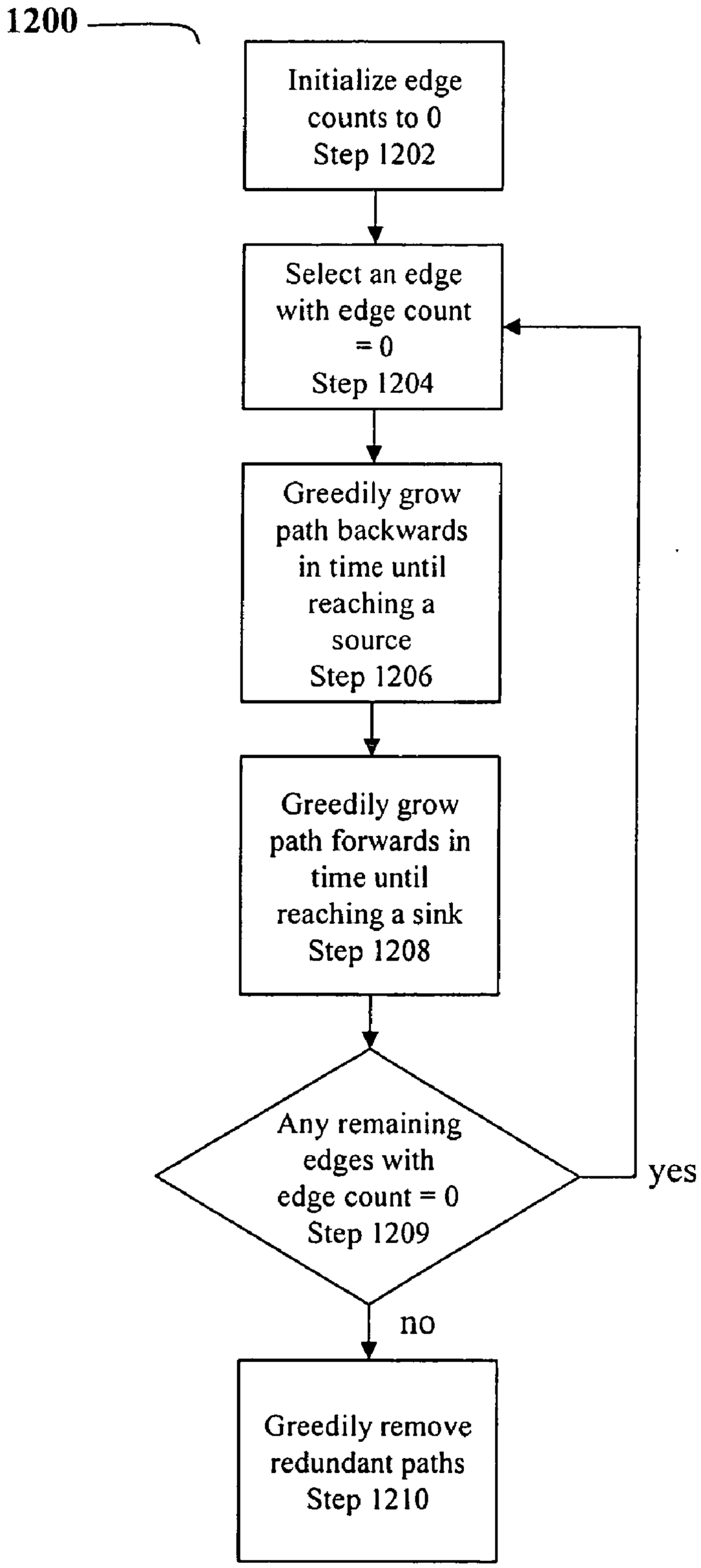

1200
Initialize edge counts to 0 Step 1202
Select an edge with edge count = 0 Step 1204
Greedily grow path backwards in time until reaching a source Step 1206
Greedily grow path forwards in time until reaching a sink Step 1208
Any remaining edges with edge count = 0 Step 1209
yes
no
Greedily remove redundant paths Step 1210

Fig. 12

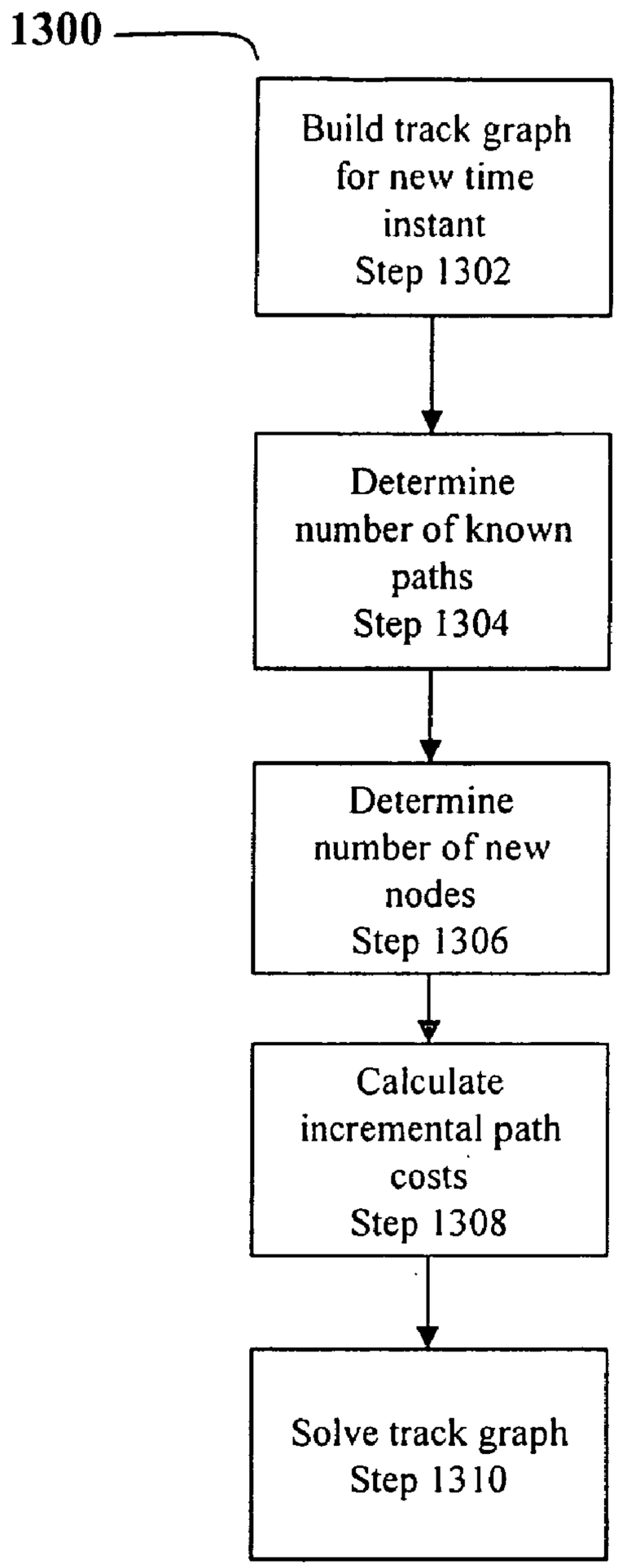

1300
Build track graph for new time instant Step 1302
Determine number of known paths Step 1304
Determine number of new nodes Step 1306
Calculate incremental path costs Step 1308
Solve track graph Step 1310

Fig. 13

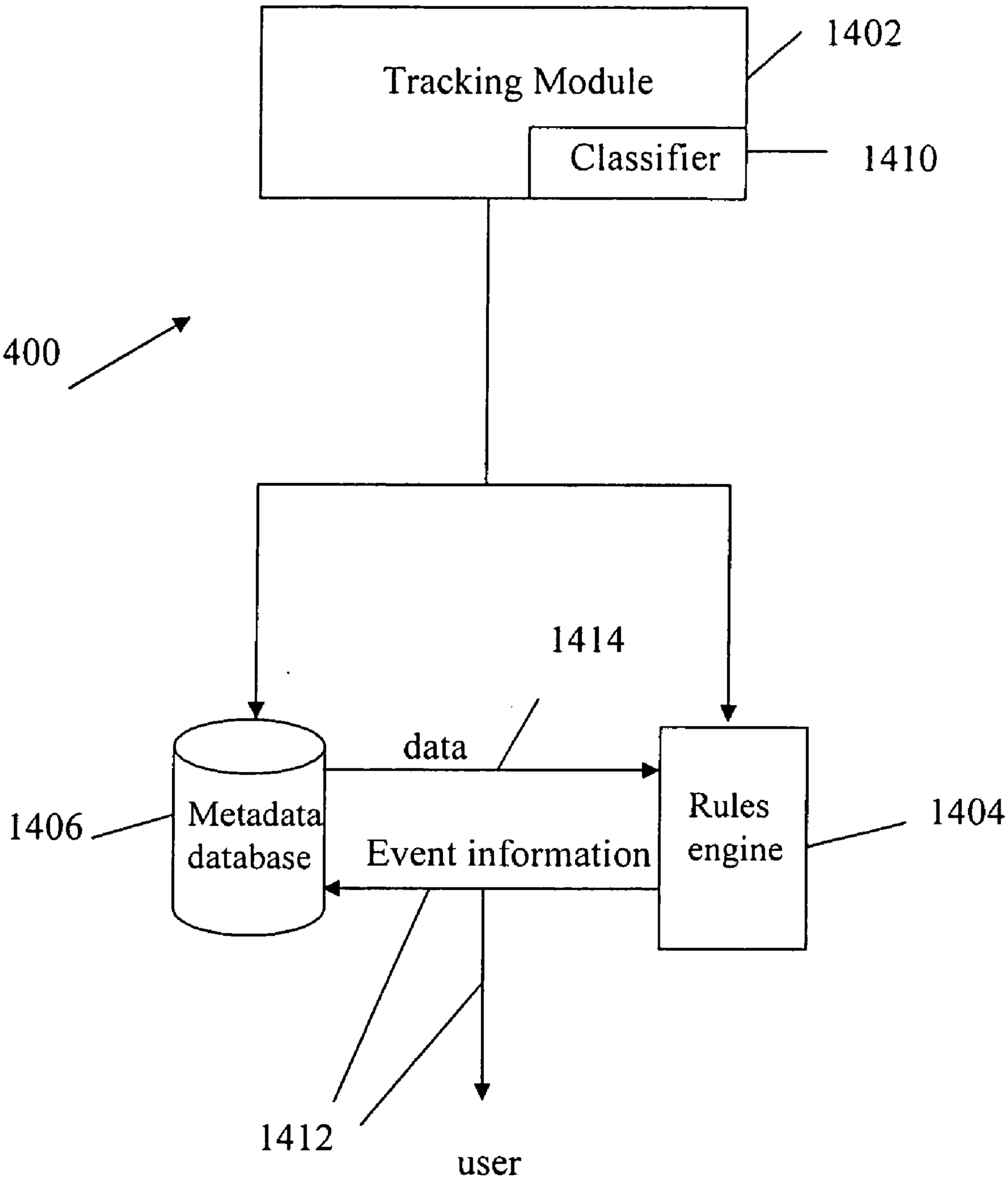

Tracking Module
1402
Classifier
1410
1400
1414
data
1406
Metadata database
Rules engine
1404
Event information
1412
user

Fig. 14

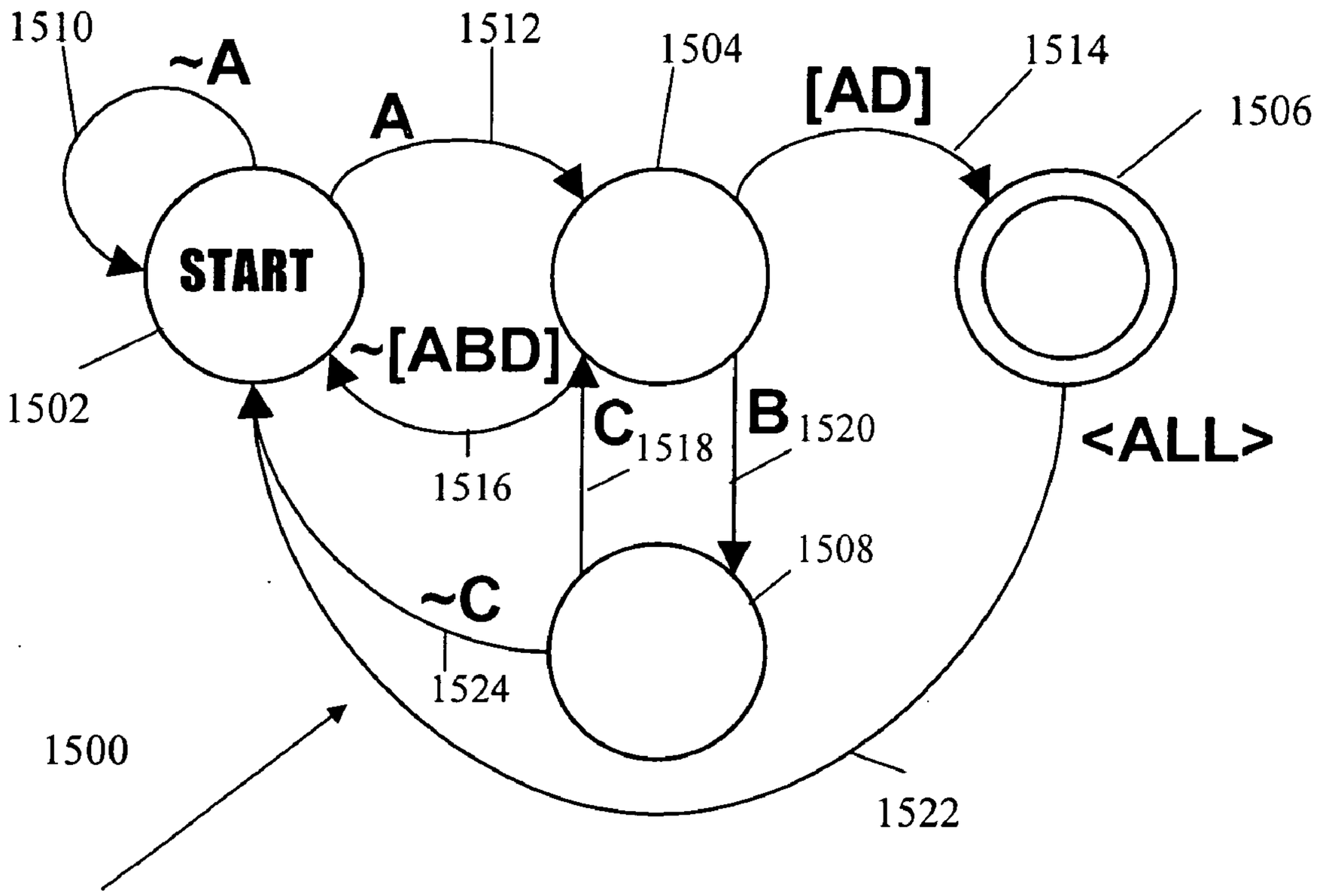

1510
~A
1512
A
1504
[AD]
1514
1506
START
~[ABD]
1502
1516
C 1518
B 1520
<ALL>
1508
~C
1524
1500
1522

Fig. 15

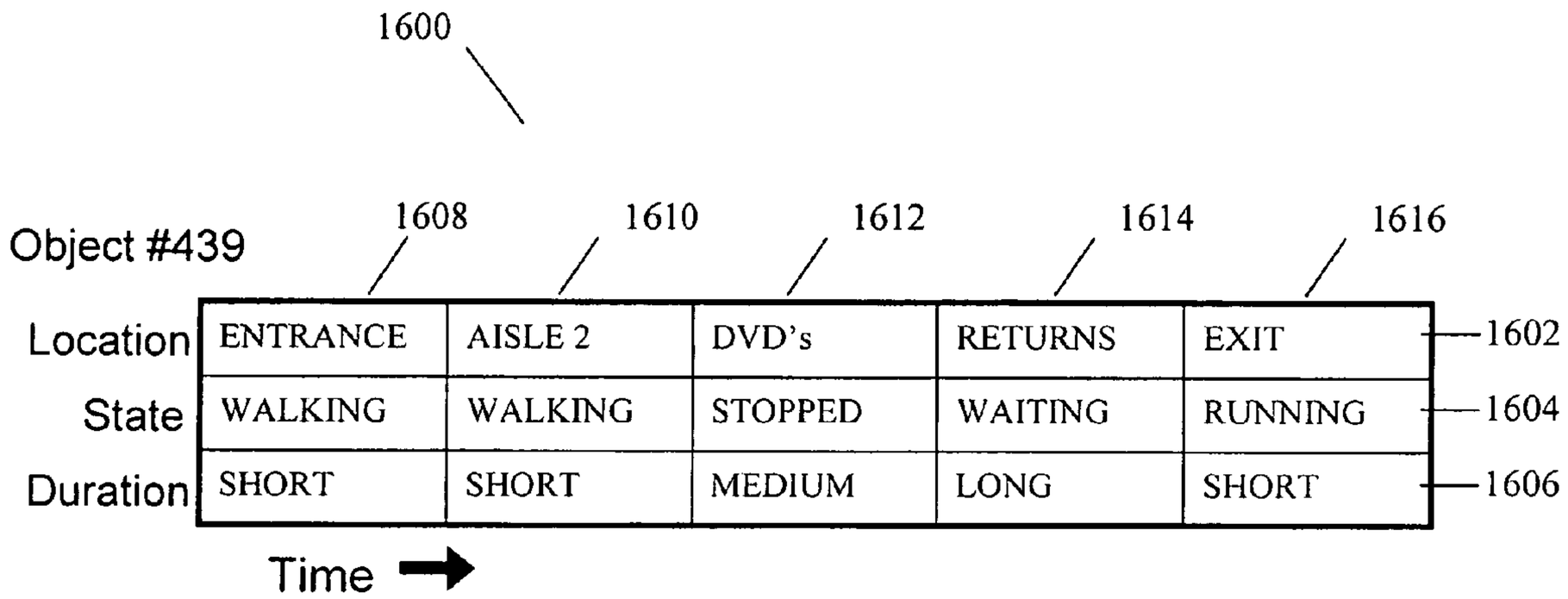

1600
Object #439
1608
1610
1612
1614
1616
Location
State
Duration
ENTRANCE
AISLE 2
DVD's
RETURNS
EXIT
WALKING
WALKING
STOPPED
WAITING
RUNNING
SHORT
SHORT
MEDIUM
LONG
SHORT
1602
1604
1606
Time

Figure 16

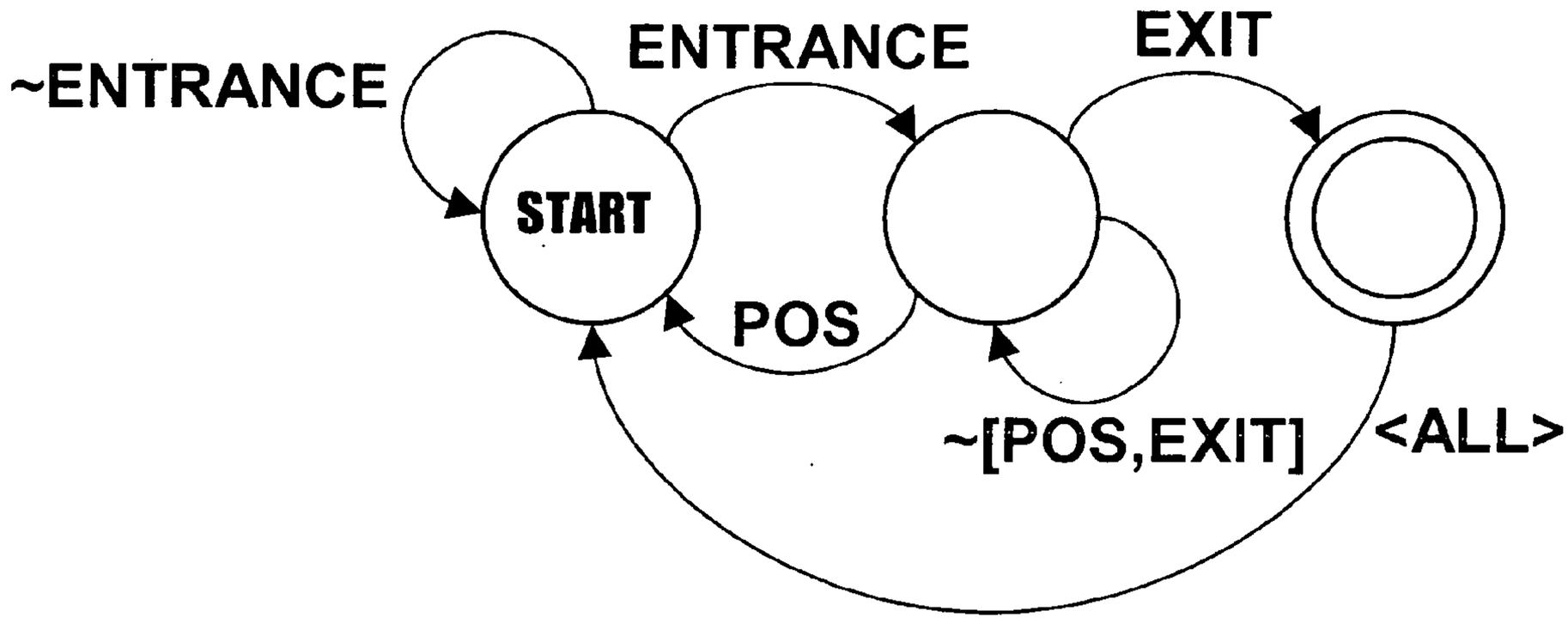


Fig. 17

METHOD AND SYSTEM FOR TRACKING AND BEHAVIORAL MONITORING OF MULTIPLE OBJECTS MOVING THROUGH MULTIPLE FIELDS-OF-VIEW

CROSS-REFERENCE TO RELATED APPLICATION

[0001] This application is a continuation of U.S. patent application Ser. No. 10/706,850, filed on Nov. 12, 2003, which further claims priority to and the benefit of U.S. provisional patent application Ser. No. 60/425,267, filed Nov. 12, 2002, both of which are incorporated herein by reference in their entirety.

TECHNICAL FIELD

[0002] The present invention generally relates to video surveillance, and more specifically to a computer aided surveillance system capable of tracking multiple objects.

BACKGROUND

[0003] The current heightened sense of security and declining cost of camera equipment have resulted in increased use of closed circuit television (CCTV) surveillance systems. Such systems have the potential to reduce crime, prevent accidents, and generally increase security in a wide variety of environments.

[0004] A simple closed-circuit television system uses a single camera connected to a display device. More complex systems can have multiple cameras and/or multiple displays. One known type of system is the security display in a retail store, which switches periodically between different cameras to provide different views of the store. Higher security installations, such as prisons and military installations, use a bank of video displays each displaying the output of an associated camera. A guard or human attendant watches the various screens looking for suspicious activity.

[0005] More recently, inexpensive digital cameras have become popular for security and other applications. "Web cams" may also be used to monitor remote locations. Web cams typically have relatively slow frame rates, but are sufficient for some security applications. Inexpensive cameras that transmit signals wirelessly to remotely located computers or other displays are also used to provide video surveillance.

[0006] As the number of cameras in a surveillance system increases, the amount of raw information that needs to be processed and analyzed also increases. Computer technology can be used to alleviate this raw data processing task, resulting in a new breed of information technology device—the computer-aided surveillance (CAS) system. Computer-aided surveillance technology has been developed for various applications. For example, the military has used computer-aided image processing to provide automated targeting and other assistance to fighter pilots and other personnel. In addition, computer-aided surveillance has been applied to monitor activity in other environments such as swimming pools, stores, and parking lots.

[0007] A CAS system automatically monitors objects (e.g., people, inventory, etc.) as they appear in series of surveillance video frames. One particularly useful monitoring task is tracking the movements of objects in a monitored area. Methods for tracking objects, such as people, moving through an image are known in the art. To achieve more accurate tracking information, the CAS system can utilize knowledge about the basic elements of the images depicted in the series of surveillance video frames.

[0008] Generally, a video surveillance frame depicts an image of a scene in which people and things move and interact. A video frame is composed of a plurality of pixels, often arranged in a grid-like fashion. The number of pixels in an image depends on several factors including the resolution of the camera generating the image, the display on which the image is presented, the capacity of the storage device on which the images are stored, etc. Analysis of a video frame can be conducted either at the pixel level or at the (pixel) group level depending on the processing capability and the desired level of precision. A pixel or group of pixels being analyzed is referred to herein as an "image region."

[0009] Image regions can be categorized as depicting part of the background of the frame or as depicting a foreground object. A set of contiguous pixels determined to depict one or more foreground objects is referred to as "blob." In general, the background remains relatively static in each frame. However, objects are depicted in different image regions in different frames. Several methods for separating objects in a video frame from the background of the frame, referred to as object or blob extraction, are known in the art. A common approach is to use a technique called "background subtraction." Of course, other techniques can be used.

[0010] A robust tracking system faces many difficulties. Changes in scene lighting can affect the quality of object extraction, causing foreground elements to be misshapen or omitted completely. Object occlusions can cause objects to disappear or merge together, leading to difficulties in correspondence between frames. Further, tracked objects can change shape or color over time, preventing correspondence even though the objects were properly extracted.

[0011] In addition, even under ideal conditions, single-view tracking systems invariably lose track of monitored objects that leave the field-of-view of the camera. When multiple cameras are available, as in many close-circuit television systems, it is theoretically possible to reacquire the target when it appears in a different camera. This ability to perform automatic "camera hand-off" is of significant practical interest.

SUMMARY OF THE INVENTION

[0012] In one aspect, the invention relates to a computerized method of video analysis that includes receiving several series of video frames generated by a number of image sensors. In one embodiment, the image sensor is a video camera. Each image sensor has its own field-of-view which can, but does not have to, overlap with another image sensor's field-of-view. The image sensors monitor a portion of a monitored environment. The computerized method also includes concurrently tracking, independent of calibration, multiple objects within the monitored environment as the objects move between fields-of-view, and multiple objects within one field-of-view. The tracking is based on the plurality of received series of video frames.

[0013] In one embodiment, the method of video analysis also includes tracking objects based on a probability that an object included in one video frame generated by a first image sensor at a first point in time will be included in a video frame generated by a second image sensor at a second point in time. In another embodiment, the method of video analysis includes storing a plurality of blob states over time. Each blob state includes a number of objects included in the blob and a blob signature. The method of video analysis can also store a plurality of transition likelihood values representing the probability that objects within one blob at one instant in time correspond to objects within other blobs at other instants in time. In one embodiment, the transition probabilities can be updated as new information is gleaned from subsequent video frames.

[0014] In one embodiment, the method of video analysis includes storing object data indicating correspondences between objects and blob states. The method can also include generating a tracking solution based on the blob states and transition probabilities.

[0015] In one embodiment, the method of video analysis includes generating tracking metadata. Tracking metadata can include, without limitation, object track data, tracking solutions, object feature data and field-of-view data. In another embodiment, the method further includes selecting a rule set to analyze the generated tracking metadata and evaluating the tracking metadata, based on the rule set, using a rules engine. Rule sets may include rules for monitoring parking lot security, detecting property theft, detecting hazards to children, monitoring public safety, and determining merchandizing and operations statistics.

[0016] In another aspect, the invention relates to a computerized system for video analysis which includes a receiving module configured to receive a plurality of series of video frames and a calibration independent tracking module in communication with the receiving module. The series of video frames are generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view. The tracking module is configured to both concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view and to concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames. The tracking module also can output tracking metadata.

[0017] In one embodiment, the video analysis system also includes a rules engine, which is in communication with the tracking module and receiving the tracking metadata.

[0018] In another aspect, the invention relates to a system for monitoring parking lot security which includes a receiving module configured to receive a plurality of series of video frames and a calibration independent tracking module in communication with the receiving module. The series of video frames are generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view. The tracking module is configured to both concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view and to concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames. The tracking module also can output tracking metadata. The system also includes a rules engine utilizing a parking lot security rule set configured to receive and evaluate the tracking metadata.

[0019] In another aspect, the invention relates to a system for property theft detection which includes a receiving module configured to receive a plurality of series of video frames and a calibration independent tracking module in communication with the receiving module. The series of video frames are generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view. The tracking module is configured to both concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view and to concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames. The tracking module also can output tracking metadata. The system also includes a rules engine utilizing a theft detection rule set configured to receive and evaluate the tracking metadata.

[0020] In another aspect, the invention relates to a system for child hazard detection which includes a receiving module configured to receive a plurality of series of video frames and a calibration independent tracking module in communication with the receiving module. The series of video frames are generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view. The tracking module is configured to both concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view and to concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames. The tracking module also can output tracking metadata. The system also includes a rules engine utilizing a child safety rule set configured to receive and evaluate the tracking metadata.

[0021] In another aspect, the invention relates to a system for property theft detection which includes a receiving module configured to receive a plurality of series of video frames and a calibration independent tracking module in communication with the receiving module. The series of video frames are generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view. The tracking module is configured to both concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view and to concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames. The tracking module also can output tracking metadata. The system also includes a rules engine utilizing a public safety monitoring rule set configured to receive and evaluate the tracking metadata.

[0022] In another aspect, the invention relates to a system for merchandizing and operations statistical analysis which includes a receiving module configured to receive a plurality of series of video frames and a calibration independent tracking module in communication with the receiving module. The series of video frames are generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view. The tracking module is configured to both concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view and to concurrently track a plurality of objects within one field-of-view based on the plurality of

received series of video frames. The tracking module also can output tracking metadata. The system also includes a rules engine utilizing a merchandizing and operations statistical rule set configured to receive and evaluate the tracking metadata.

[0023] In another aspect, the invention relates to a method of analyzing video data that includes receiving tracking metadata from a calibration-independent tracking module and analyzing the metadata using a regular expression representation of a specified pattern. An event is generated if a portion of the metadata exhibits the specified pattern. In one embodiment, the method also includes comparing the regular expression of the specified pattern to the portion of the metadata by utilizing a software implemented representation of a finite state machine.

BRIEF DESCRIPTION OF THE DRAWINGS

[0024] The foregoing discussion will be understood more readily from the following detailed description of the invention, when taken in conjunction with the accompanying drawings.

[0025] **FIG. 1** is a block diagram of an illustrative overall computer-assisted surveillance ("CAS") system utilizing one aspect of the invention.

[0026] **FIG. 2** is a high-level block diagram of an illustrative CAS computer according to one embodiment of the invention.

[0027] **FIG. 3** is block diagram of a video analysis system according to one embodiment of the invention.

[0028] **FIG. 4** is a flow chart that depicts an illustrative tracking methodology according to one embodiment of the invention.

[0029] **FIG. 5** is an illustrative track graph according to one embodiment of the invention.

[0030] **FIGS. 6A and 6B** are schematic depictions of a monitored environment.

[0031] **FIG. 7A** includes schematic depictions of two series of video frames.

[0032] **FIG. 7B** includes two illustrative transition probability tables according to one embodiment of the invention.

[0033] **FIG. 8** is a series of schematic depictions of partial track graphs according to one embodiment of the invention.

[0034] **FIG. 9** is a flow chart of a method of determining node matches according to one embodiment of the invention.

[0035] **FIG. 10** includes two illustrative data association matrices according to one embodiment of the invention.

[0036] **FIG. 11** is a flow chart of a method for counting objects in a monitored environment according to one embodiment of the invention.

[0037] **FIG. 12** is a flow chart of a method of determining a tracking solution according to one embodiment of the invention.

[0038] **FIG. 13** is a flow chart of another method of determining a tracking solution according to one embodiment of the invention.

[0039] **FIG. 14** is a more detailed version of a portion of the general video analysis system depicted in **FIG. 3**.

[0040] **FIG. 15** is an illustrative finite state machine implementing a regular expression according to one embodiment of the invention.

[0041] **FIG. 16** is an illustrative data structure corresponding to a monitored object according to one embodiment of the invention.

DETAILED DESCRIPTION

[0042] In a surveillance system, cameras capture image data that depicts the interaction of people and things in a monitored environment. Types of cameras include analog video cameras, digital video cameras, or any device that can generate image data. The word "camera," is used as a generic term that encompasses any sensor that can output image data. In one embodiment, the CAS system observes a monitored environment through a number of input sensors although its primary sources of information are cameras. The majority of CCTV installations use common visible-light video cameras. In such installations, the CAS system employs advanced video analysis algorithms for the extraction of information from analog NTSC or PAL video. These algorithms, however, are not limited to the visible light spectrum; they can also be applied to infrared video or even imagery from radar or sonar installations if available.

[0043] **FIG. 1** shows an illustrative computer-assisted surveillance ("CAS") system **100**. A plurality of cameras or other image input devices **102** provide image inputs to a computer **104** programmed to provide image analysis. CAS computer **104** can include a display **106** providing a graphical user interface for setup, control and display. CAS computer **104** can also include one or more user input devices (not shown) such as keyboards, mice, etc. to allow users to input control signals.

[0044] CAS computer **104** performs advanced image processing including image feature extraction and tracking. CAS computer **104** can automatically detect objects and activity and can generate warning and other information that can be transmitted over a digital communications network or other interface **108**. CAS computer **104** also uses interface **108** to retrieve data, such as previously recorded video stored on recorder **112** or information stored on other computers. CAS computer **104** provides the outputs of the various cameras **102** to a multiplexer **110** for recording, typically continuous or stop-frame, by recorder **112** and for display on one or more displays **114** via a switcher **116**. An additional user interface (e.g., provided by another computer **118** and user input including, for example, a joystick **120**) can be used to allow an operator to control switcher **116** to select images to view and to control other parts of system **100** including CAS computer **104**. Mutiplexer **110** and/or switcher **116** can respond to external alarms that occur when certain types of activity have been automatically detected (e.g., an alarm generated by a motion sensor) and record or display video appropriately. These alarms can also be generated by CAS computer **104** based on detected activities in the video streams.

[0045] The illustrative CAS Computer **104** system integrates seamlessly into any existing security infrastructure. The illustrative embodiment CAS system **100** is compatible

with, for example, legacy analog video sources, in addition to newer digital video sources such as USB, FireWire, or IP cameras on wired or wireless networks. The CAS computer **104** acts as a passive repeater of its input signals, so that in the unlikely event of a CAS computer **104** failure, the remainder of the security infrastructure continues to function without the CAS computer **104**.

[**0046**] While video cameras **102** are the typical primary sensors for the CAS system **100**, the system can also accommodate other commonly-used sensors, such as motion detectors, smoke detectors, spill detectors, microphones, point-of-sale (POS) recordings, electronic article surveillance (EAS) systems, and access control systems. The illustrative CAS system **100** combines information from these sensors with the video analysis results to provide an even richer description of activities in the world. For example, POS information may be used with video images to verify that a customer purchased a particular product.

[**0047**] **FIG. 2** shows a high-level block diagram of an illustrative CAS computer **104**. For illustrative purposes, the computer components are grouped into two main classes: single-view processing blocks **202** (SVPs) and multi-view processing blocks **204** (MVPs). Each image input source is attached to a SVP **202**. Image input sources include cameras **102** as well as a variety of storage devices including, for example, computer disks, VHS tapes, and digital videotapes. For purposes of data analysis, image data outputted by a video storage device is the equivalent of image data generated by a camera. Each SVP **202** typically performs video processing tasks that require only a single video stream. The outputs of the SVP **202** are connected to a MVP **204** that processes multiple video streams at once. Depending on the embodiment, a processing module includes a MVP **204**, or a combination of one or more SVPs **202** and one or more MVPs **204**. The CAS computer also includes memory modules (not shown) for receiving and storing incoming image data. The memory modules can be a part of the processing module, or they can be separate from the processing module.

[**0048**] The single-view processing components **202** and the multi-view processing components **204** typically analyze data as a series of video frames depicting a scene. In one embodiment, image data is analyzed directly from a camera. In another embodiment, the analyzed image data can originate from a storage device. Some cameras and video storage devices create and store image data on a frame-by-frame basis. Other storage systems may only store video frame updates, i.e. detected changes to the scene. To carry out analysis of image data, the CAS computer **104** constructs a video frame (e.g., with a frame grabber) from stored image data that may be stored in a variety of devices and formats.

[**0049**] **FIG. 3** is a block diagram of an illustrative video analysis system according to one embodiment of the invention. In this embodiment, the video analysis system **300** may include a receving module **302**, a tracking module (also referred to as a "tracker") **304**, a classifier **306**, and a rules engine **308**.

[**0050**] In one embodiment, the receving module receives a plurality of series of video frames from a plurality of cameras **310** (e.g., cameras **102** of **FIG. 1**). In the case that the video analysis system **300** is implemented on the CAS computer **104**, described above, each series of video frames is forwarded to a respective SVP **202**. In one embodiment, a central receiving module receives a plurality of series of video frames and distributes the series to a plurality of SVPs **202**. In another embodiment, each SVP **202** has its own receiving module for a single series of video frames generated by a single camera **310**. A receiving module **302** can include a data input port, such as a parallel port, a serial port, a firewire port, an ethernet adapter, a coaxial cable input, an RCA jack, an S-video jack, composite video jacks, a VGA adaptor or any other form of port for receiving video data.

[**0051**] The tracking module **304** is a logical construct that receives video data from a receiving module **302**, and, in some embodiments, may concurrently track a pluarlity of objects both within a single camera **310** field-of-view and among multiple camera **310** fields-of-view. In some embodiments, the tracking module functionality is distributed among a plurality of processing elements. For example, in one embodiment implemented on the CAS computer **104**, the functionality is distributed between the SVPs **202** and the MVP **204**. In other embodiments, the functionality of the tracking module **304** is aggregated into a single processing element. The functionality of the tracking module **304**, regardless of how it is distributed, can be implemented in either software or in hardware. The output of the tacking module **304** may be stored as tracking metadata in, for instance, a database (not shown).

[**0052**] In some embodiments, the system **300** may also include a classifier **306**. The classifier can be an independent processing module, or its functionality can be combined within the tracking module **304** or rules engine **308**. The information created by the classifier **306** may also be stored in a database. In some embodiments, the classifier **306** may perform two different types of classification, static classification and dynamic classification.

[**0053**] Static classification refers to a classification procedure that operates on a group of pixels from a single instant in time (i.e., from a single frame of video). This type of classification may include assigning instantaneous properties of the pixel group to the pixel group. These properties may include, for example, size, color, texture, or shape to determine if the group of pixels is interesting or not. It should be understood that the particular properties and threshold used to classify may vary depending on the specific environment in which the system is operating. This is also true for dynamic classification.

[**0054**] Dynamic classification refers to classification rules that examine a pixel group over a period of time to make a classification. Examples of dynamic classification properties include velocity, acceleration, change in size, change in area, change in color, lack of motion, or any property that includes some time dependence. These properties, and others, may be considered predetermined characteristics that may be evaluated by the rules engine **308**.

[**0055**] Any classifier may be used in the present invention. A particularly useful classifier may operate as described below. The classifier **306** may include a first pass classifier that is used to remove noisy pixels and other artifacts or external variables. A second pass classifier is used in correlation with the output of the tracking module **304**. This interaction includes but is not limited to any combination of spatial, temporal, image feature, and motion output from a tracking system. This classification of objects may be

applied on a per frame basis. In more detail, the first pass classifier is used to filter out any pixel groups in an image which are visibly noise or remnants and determines, therefore that those pixel groups are not interesting. This basically is similar to a more conventional noise classifier approach. The classifier **306** may then rely on the tracking module to create a matching between every remaining pixel group and a certain object for each video frame. The second pass classifier then looks at the data from the tracking module **304** and compares it with data from other frames. Characteristics of followed objects are analyzed along with a state history of that particular object. In some embodiments, the classifier may keep an active memory of how a given object (now correlated to pixel group) was created. If that particular object has been seen on this or another camera in the past, all of its history is remembered. If an object is new, very little is known about it so any decisions the classifier makes will have a lower probability of correctness than an object that has been tracked for several frames. In some embodiments, various predetermined characteristics of the pixel group may help in the classification process. This example may include, for example: Motion information (has the object moved and, if so, how fast?); Grouping information; and Appearance/Signature information.

[**0056**] The system **300** may also include a rules engine **308**. This optional rules engine is described in greater detail below. In general, however, the rules engine **308** evaluates tracking metadata to determine whether specific conditions have been met and may also allow users to search for specific information created by the tracking module **304** that, in some instances, may also been processed by the classifier **306**.

[**0057**] **FIG. 4** is a flow chart that depicts an illustrative tracking methodology **400** employed by the tracking module **304** according to one embodiment of the invention. In brief overview, in one embodiment of the invention, tracking **400** includes two steps, constructing a track graph representing the movement of "blobs" through a monitored environment, and solving the track graph to correspond the blobs to specific objects. A blob is a plurality of substantially contiguous pixels that are determined not to be part of the background of a video frame. To create a track graph, the tracking module **304** determines new nodes (step **402**), determines possible edges connecting candidate nodes to the new nodes (step **404**), determines the strength of the possible edges (step **406**), and matches the new nodes to the candidate nodes (step **408**). The tracking module **304** then determines a tracking solution (step **410**). These steps will be decribed in greater detail with reference to **FIGS. 5-13**.

[**0058**] **FIG. 5** shows an illustrative data structure referred to as "track graph"**500**, that may be used by the tracking module **304** in carrying out its tracking functionality **400**. Of course, other data structures or methods of tracking may be used. In general, a track graph **500** records observations of blobs from multiple image sensors for a substantially long period of time. In some embodiments, the track graph **500** records blob observations for the entire time the tracking module **304** monitors a monitored environment. Since blob data is stored for a substantially long period of time, a tracking algorithm operating on a track graph **500** can use information far in the past rather than, for example, just from the previous frame. In one embodiment, at least some information in the track graph **500** never changes, only the interpretation does (e.g., as new information is added). In this way, decisions made by the tracking module **304** using the track graph **500** can be "undone" or changed without losing information. As discussed above, information created by the tacking module may be stored in a database as metadata.

[**0059**] Specifically, the track graph **500** consists of nodes **502** and edges **504**. Nodes **502** represent the appearance of an object or group of objects in an image sensor. Each node **502** corresponds to the state of a blob at an instant in time (e.g., in a single video frame) or over a period of time (e.g., a sequence of video frames). A blob could represent one or more objects, and, conversely, a single object may correspond to one or more blobs. For example, if a number of persons are standing closely together, blob extraction may only detect a single continuous blob that includes all of the persons. Similarly, if a monitored person stands behind an obstruction, such as a railing, that only partially obstructs a camera's view of the person, the person might appear to a CAS camera as two blobs on either side of the obstruction. Edges **504** connect together nodes **502** and represent possible trajectories that objects may have taken through the monitored environment. Edges **504** are directed and point from older nodes **502** to newer nodes **502**. In one embodiment, older nodes **502** are nodes that appear above newer nodes in a track graph **500**. For example, in track graph **500** nodes at time t are older than nodes at time t+**2**.

[**0060**] In the example track graph **500**, each node **502** and edge **504** is annotated with a number. In the case of nodes **502**, the number represents the number of objects at that node **502** (the "node count"). In the case of edges **504**, the number represents the number of objects "moving" along that edge **504** to the next node **502** (the "edge **504** count"). For a track graph **500** to be consistent, these numbers may need to satisfy certain properties. First, the number of objects entering the most recently detected nodes **502** may need to equal the number of objects leaving previously existing nodes **502**. Second, for a newly detected node, the number of objects at a node **502** may need to equal the sum of the number of objects entering the node **502**. In some embodiments, the number of objects entering the most recently detected nodes **502** must equal the number of objects leaving previously existing nodes and the number of objects at a node **502** equals the sum of the number of objects entering the node. When annotated in this way, the track graph **500** has many of the properties of a "flow graph," which is a commonly studied graph in computer science. In one embodiment, multiple connected consecutive nodes which each only have single edges leaving the nodes can be combined into one node with an associated duration equal to the number of nodes combined.

[**0061**] The track graph **500** can also includes at least one source node **506** and at least one sink node **508**. Source nodes **506** are nodes **502** that have no incoming edges **504**, and sink nodes **510** are nodes **502** that have no outgoing edges **504**. Source and sink nodes **506** and **508** generally correspond to the beginning or end of the track graph **500**, or the beginning and end of an object in the track graph **500**, such as an entrance or exit of a monitored environment.

[**0062**] Some edges, referred to as alias edges **510**, are used to connect two nodes **502** that represent the same physical object. Alias edges **510** connect nodes **502** corresponding to

objects concurrently included in the fields-of-view of multiple cameras and nodes in a single video frame if the nodes **502** correspond to the same object (e.g., an object divided by a pole). Nodes **502** connected by alias edges **510** essentially become a single node **502** (referred to as a "supernode"**514**). The edges **504** into and out of a supernode **514** are the union of the edges **504** into and out of the constituent nodes **502**. In some embodiments, alias edges **510** do not enter into any calculations (such as flow calculations), and flow constraints apply to the supernode **514** as a whole rather than the individual nodes **502**.

[**0063**] In general, it is useful to store various data at the nodes **502** and edges **504** of the track graph **500**, for example, the edge and node counts, described above. In addition, in some embodiments, an "edge **504** strength" is stored in association with an edge **504**. An edge strength is a real number that represents the likelihood of an edge **504** being correct. In one embodiment, the strength is constrained to be between 0 and 1, and represents the probability that a blob transitioned from an older node **502** to a newer node **502**. In other embodiments, the track graph **500** stores the log of such a transition likelihood.

[**0064**] With respect to nodes **502**, in addtion to the node count, in one embodiment, the tracking module **304** stores a variety of information about the blob and/or object(s) to which the node **502** corresponds. The node **502** stores the duration (e.g., seconds or number of frames) that the node **502** has existed, an identification of the camera that generated the video frame(s) that includes the blob that corresponds with the node **502**, and the location(s) of the corresponding blobs in the video frames. In other embodiments, nodes **502** also contain additional properties about the blob/object(s) included in the node **502**, such as the size, color histogram, velocity, acceleration, classification information (e.g., human vs. car), etc. of the object(s). The stored properties, taken together, are referred to as the signature of the blob, and can be used to make decisions during the tracking process.

[**0065**] **FIG. 6A-6B** are schematic depictions of a monitored environment **600** at times t and t+**1**, respectively. The monitored environment includes two cameras **602** and **604**. Each camera has its own field-of-view **606** and **608**. The fields-of-view **608** and **610** overlap in one overlapping area **610** of the monitored environment **600**. The monitored environment **600** also includes four objects, **612**, which are moving through the monitored environment **600** from time t to time t+**1**.

[**0066**] **FIG. 7A** includes schematic depictions of the two series of video frames **702***a-b* and **704***a-b* generated by the cameras **602** and **604**, respectively, in the monitored environment **600**, at times t and t+**1**. The first video frames **702***a* and **704***a* were generated at time t, and the second video frames **702***b* and **704***b* were generated at time t+**1**. Video frame **702***a* is empty. Video frame **704***a* includes three blobs **706***a*$_1$-a$_3$. Video frame **702***a* includes two blobs **706***b*$_1$ and **706***b*$_2$. Video frame **704***b* also includes three blobs **706***b*$_3$-b$_5$.

[**0067**] **FIG. 8** includes illustrative partial track graph updates **800**, **802**, **804** and **806** demonstrating the construction of the track graph **808** that that is created by the tracking module **304** as it applies the tracking methodology **400** to the series of video frames **702** and **704**, according to one embodiment of the invention. The partial track graph **800** depicts the lowest level of the track graph at time t. The partial track graph **800** includes three nodes **810***a*$_1$-a$_3$, i.e., one node for each blob **706***a*$_1$-a$_3$ included in video frames **702***a* and **704***a*. For illustrative purposes, it will be assumed that the node counts for the nodes **810***a*$_1$-a$_3$ are all equal to one.

[**0068**] Upon receiving video frames **702***b* and **704***b*, the tracking module **304** adds new nodes **812***b* to the track graph **800** (step **504**). The tracking module **304** analyzes the video frames **702***b* and **704***b* to detect blobs. The tracking module **304** adds new nodes **812** (e.g., new nodes **812***b*$_1$-b$_5$) to the track graph **800** to correspond to the detected blobs **706***b*$_1$-b$_5$, resulting in partial track graph **802**. Nodes **810***a*$_1$-a$_3$, no longer being the newest nodes, are now considered candidate nodes.

[**0069**] The tracking module **304** finds potential edges **814***e*$_1$-e$_{15}$ that could connect the new nodes **812***b*$_1$-b$_5$ to candidate nodes **810***a*$_1$-a$_3$ (step **504**), as depicted in partial track graph **804**. After the possible edges **814***e*$_1$-e$_{15}$ are added to the track graph (step **504**), the tracking module **304** determines the edge strengths for the possible edges **814***e*$_1$-e$_{15}$ between the candidate nodes **810***a*$_1$-a$_3$ and the new nodes **812***b*$_1$-b$_5$ (step **506**). In one embodiment, the tracking module **304** determines the strength of edges that connect candidate nodes from one camera's field-of-view to new nodes from that same camera's field-of-view (e.g., edge e$_5$) by using predictive tracking techniques known in the art, such as applying a Kalman filter. To take into account the possibility that the new blobs in a camera's field-of-view may correspond to a candidate node in a second camera's field-of-view, the tracking module **304** determines the strength of edges connecting nodes from different camera fields-of-view (e.g., edge e$_1$), refferred to as trans-camera edge strengths.

[**0070**] In one embodiment, the tracking module **304** determines trans-camera edge strengths using a dynamic field-of-view relationship determination technique as described in U.S. patent application Ser. No. 10/660,955 (referred to hereafter as the "'955 application"), entitled "Computerized Method and Apparatus for Determing Field-of-View Relationships Among Multiple Image Sensors," filed on Sep. 11, 2003. Among other things, the '955 application describes determining a pluarlity of probabilities and statistical values relating to observations of object appearances in video frames generated by a pluarlity of cameras. The probabilities include, for example, the probability that an object is seen in a first location i, p$_i$, the probability that an object is seen in a second locationj, p$_j$, and the probability that an object is seen in location i followed by an object being seen in locationj after a period of time Δt, p$_{ij}$(Δt). The statistical values include the lift and correlation coefficients between image regions of video frames generated by the same or different cameras over various time periods Δt.

[**0071**] Trans-camera scores can be based on the lift values, the correlation coefficients described in the '955 application, or on a transition probability calculated based on the probabilities described therein. In one embodiment, the transition probability is defined as:

$$p_{trans(i,j)}(\Delta t) = \frac{-(1 - p_i - p_j) + \sqrt{(1 - p_i - p_j)^2 - 4(p_i p_j - p_{ij}(\Delta t))}}{2} \quad (1)$$

[0072] **FIG. 7B** includes illustrative transition probability tables determined for a subset of the image regions included in video frames **702** and **704**. The first table **708** includes the transition probabilities between pairs of image regions at Δt=**0**, i.e., the probability that blobs concurrently seen in the two image regions correspond to the same object. For example, the transition probability between image regions A**2** and B**2** at Δt=**0** is 1 indicating that those image regions correspond to the overlapping area **610**. Nodes corresponding to blobs in such image regions are joined with an alias edge **510** to form a super node **514**. The second table **710** includes the transition probabilities between pairs of image at Δt=**1**, i.e., the probability that a blob corresponding to an object in a first frame will correspond to a blob in a second frame one time instant later. For example, the transition probability between A**1** and B**1** at Δt=**1** is 0.8, indicating, for example that objects are highly likely to move from image region B**1** to image region A**1** one time instant later. In one embodiment, the trans-camera edge strength is equal to the transition probability at Δt=**1**. In other embodiments, the transition probability is one factor used in calculating the trans-camera edge strength.

[0073] The above described trans-camera edge strength determination techniques are based on the analysis of appearances of objects within video frames over time, and not on the calibration of the cameras, or on a fused or calibrated scene. Therefore, the tracking module can determine trans-camera edge strengths independent of camera or environment calibration. If the cameras or the scene are calibrated, however, such information can be used. However, calibration data is unnecessary to provide satisfactory tracking results. Because calibration is unnecessary (but could be included), a tracking module operating as described above may be referred to as "calibration-independent."

[0074] In the illustrative embodiment, if the edge strength for a give edge is below a threshold (e.g., <0.1), the tracking module **304** immediately removes the edge from the track graph. Partial track graph **806** illustrates the state of the track graph after the edge strengths have been calculated (step **406**) and highly unlikely edges are removed.

[0075] Based on the edge strengths, the tracking module **304** matches the new nodes **810** with the candidate nodes **812** (step **408**). The matching process is similar to the standard abstract data association problem. In the standard abstract data association problem, two sets, A and B, contain objects to be matched. Each object in A is allowed to map to one object in B and vice versa. Each potential match (a,b) has a score associated with it, and some potential matches may be disallowed. The task is to find a set of matches that satisfies these constraints and has a maximum (or minimum) score. The problem is commonly visualized as a matrix, with the elements of A corresponding to columns and the elements of B corresponding to rows. X's denote disallowed matches. A valid matching (denoted with circles) includes only one element from each row and column. This standard data association problem is well-known, and it can be solved efficiently.

[0076] Standard data association problem solutions, however, cannot readily be applied in the video surveillance context. In the video surveillance context, the objects to be matched are blobs (represented by nodes). Single nodes from one set can, and often do, correspond to multiple nodes in a second **810** set, and visa versa. For example, considering **FIGS. 6A, 6B**, 7A, and 7B, blob **706***a*$_3$ node a_3 in video frame **704***a* corresponds to two objects, a man and a woman. At time t+**1**, the two objects have separated and the tracking module **304** detects two blobs **706**, instead of one. As a result the track graph updated for time t+**1** includes two nodes **812***b*$_4$ and **812***b*$_5$ that that the tracking module **304** should determine to correspond to candidate node a_3. In general, a group of individuals, considered by the tracking module as a single node, may split, resulting in several nodes. Similarly individuals can converge into group, resulting in a single new node corresponding to several candidate nodes. The video surveillance data association problem should handle one-to-many, many-to-one, and many-to-many correspondences.

[0077] **FIG. 9** is a flow chart of one illustrative method of solving the video surveillance data association problem, i.e., determining node matches (step **408**), according to one embodiment of the invention. At the beginning of the association problem, no new nodes **812** have been matched with candidate nodes **810** (step **902**). Unmatched candidate nodes **810** are then matched with new nodes **812** (step **904**) using a standard data association solution, where the edge strengths are used as matching scores. If any new nodes **812** are still unmatched after initial attempts to match the new nodes **812** to candidates nodes **810** (step **905**), the tracking module **304** executes the data association algorithm on a smaller set of data that only includes edge strengths between the unmatched new nodes **812** and all the candidate nodes **810** (step **804**). If any candidate nodes **810** or new nodes **812** remain unmatched (step **907**), the tracking module **304** returns to step **802** and runs the data association algorithm only taking consideration of the unmatched candidate nodes **810**. The process continues untill all candidate nodes and new nodes have been matched. If a new node cannot be matched to a corresponding candidate node **810**, the tracking module **304** links the new node **812** to a source node **506** or to another new mode through an alias edge. Similarly, if a match cannot be found for a candidate node **810**, in one embodiment, the candidate node is linked to a sink node **508**. In another embodiment, the tracking module attempts to match the unmatched candidate node **810** to new nodes **812** received over a predetermined number of subsequent time instants before the candidate node **810** is linked to the sink node **508**. In one embodiment, after all nodes are matched, edges **814** that correspond to unselected matching pairs are removed from the track graph **806**.

[0078] **FIG. 10A** is a matrix **1000** that depicts an initial solution to matching the new nodes **812***b*$_1$-*b*$_5$ with the candidate nodes **810***a*$_1$-*a*$_3$ according to step **904**. Cell values in the matrix **1000** correspond to the strength of edges **814***e*$_1$-*e*$_6$ connecting the nodes. Note that new nodes **812***b*$_3$ and *b*$_4$ are matched to candidate nodes **810***a*$_2$ and *a*$_3$, respectively, even though the edge strength between **810***a*$_2$ and **812***b*$_4$ is larger than the selected edge strengths. The selection, however, leads to a higher total score, i.e., 2.1, for the set than if **810***a*$_2$ were matched **812***b*$_4$ and **810***a*$_3$ were matched with **812***b*$_5$ (the next highest edge score after

812b_4), i.e., 2.0. The data association solution depicted in matrix **1000** has left new nodes **812**b_2 or **812**b_5 without matching candidate nodes.

[**0079**] No edges connect to new node **812**b_2, indicating that it either represents a new object, originating from a source node, or that it corresponds to a node in an overlapping image region from another camera. As mentioned above, the transition probability between image region A**2** and image region B**2** at Δt=**0** is 1, indicating overlap. As a result, an alias edge is added to the track graph **808** to connect new nodes **812**b_2 and **812***b***3** (a node located in that overlapping image image region).

[**0080**] **FIG. 10B** is a matrix **1002** that depicts a solution to the secondary node matching step (step **906**) that matches unmatched new nodes to candidate nodes. Node **812**b_5 is the only unmatched new node **812**, and the tracking module **304** matches node **812**b_5 to candidate node **810**a_3. After all candidate nodes **810** and new nodes **812** are matched, unselected edges **814**e_1-e_{15} are removed from the track graph **806**, yielding the updated track graph **808**.

[**0081**] Referring back to **FIG. 4** and **FIG. 5**, based on a track graph **500**, the tracking module **304** determines a tracking solution (step **410**). The track graph **500** includes nodes **502** and possible links between the nodes over a period of time (i.e., edges **504**). The track graph **500** does not track specific objects. For example, as objects converge and diverge as they move through a monitored environment, so too do the nodes **502** that correspond to those objects. In terms of a track graph **500**, an object is a path through the track graph **500**. In one embodiment, paths start at a source node **506** (where objects are "created" or enter) and end at a sink node **508** (where objects are "destroyed" or exit). If the track graph **500** is incomplete (e.g., it is being constructed from live video), then the partial paths may not end in sink nodes **508**.

[**0082**] A solution to the track graph **500** is a set of paths that satisfy the flow properties of the track graph **500** described above. Each path in the solution represents a different object that has been observed. In one embodiment, to reduce the size of the solution space, a number of constraints are applied. First, the size of the solution (in terms of the number of objects) is required to be minimum. That is, the number of paths is limited to the minimum number required to explain all edges **504** with greater than a certain edge weight (e.g., 0.1). Second, the solution is required to be "optimal." Each path in the solution can be assigned a score that measures its likelihood (or, equivalently, a cost that measures its unlikelihood). In one embodiment, an optimal solution maximizes (minimizes) the sum of the scores (costs) over all paths. In another embodiment, an optimal solution maximizes (minimizes) the average of the scores (costs) over all paths. Even with these constraints, more than one minimal, optimal solution may exist. In these cases, simply finding one solution is sufficient. Any errors in the chosen solution can be corrected later by the user if needed.

[**0083**] The tracking module **304** can operate in real-time, or in a forensic mode. In forensic operation, the tracking module analyzes previously recorded video (e.g., from a video cassette or a digital video recorder, etc.) of a monitored environment. If the tracking module **304** is tracking objects in real-time, the tracking module can update the tracking solution after the track graph construction process (steps **402-408**) is completed for each time instant analyzed, or the tracking module **304** can update the the track graph **500** periodically (e.g., every 2, 5,10, etc. time instants). For forensic tracking, the tracking module **304** can build the entire track graph **500** before determining a tracking solution.

[**0084**] As finding the true optimal solution for all but the smallest track graphs is an intractable problem, the tracking module **304** utilizes heuristic algorithms for approximating optimal solutions Although computing the optimal solution is intractable, computing the size of the optimal solution (i.e., the number of paths) can be done efficiently. This algorithm is described in the next paragraph, followed by two algorithms for approximating optimal solutions.

[**0085**] The algorithm for counting objects relies on a property of minimal solutions: each path in a minimal solution must contain at least one edge that is not shared with any other path. That is, each path in the minimal solution must contain at least one edge with an edge count of 1. If a minimal solution did contain a path that violated this property, then one could remove a copy of this path from the solution (reducing the edge counts along the path by 1), resulting in a smaller solution. Thus, the original solution was not minimal.

[**0086**] **FIG. 11** is a flow chart of a method **1100** of counting the number of objects in a track graph **500**. The tracking module **304** initializes the edge counts of the track graph **500** to 0 (step **1102**). The tracking module **304** then adds paths to track graph **500** until all edge counts are greater than or equal to 1 (step **1104**). The tracking module **304** then removes paths that do not contain at least one edge with an edge count equal to 1 until it is no longer possible to do so (step **1106**), that is, until all paths include at least one edge with an edge count equal to 1. At this point, the paths satisfy the minimal solution property, and the number of paths is the desired answer (the size of the minimal solution) (step **1108**). In one embodiment the number of paths, if not known explicitly, can be found by summing the number of paths leaving each source node **506** in the track graph **500**.

[**0087**] **FIG. 12** is a flow chart of an illustrative method of tracking an object based on a track graph **1200**. The method **1200** is similar to the above described counting algorithm. The basic approach is the same: add paths to the solution until all edges **504** have an edge count greater than 1. Then paths are removed until the minimal criterion is achieved. The difference is in deciding which paths are added and removed. In the counting algorithm, any valid path could be added or removed. However, in the case of trying to find an "optimal" solution, the decision of which paths should be added or removed is based on path costs.

[**0088**] In one embodiment, the cost of a path is defined in terms of the signatures in its constituent nodes. As described above, data related to several properties of blobs are stored in the nodes corresponding to those blobs. The properties can include, color, size, velocity, acceleration, etc. A low-cost path contains nodes whose signatures are similar. A high-cost path contains nodes whose signatures are dissimilar.

[**0089**] Measuring the similarity/dissimilarity of a pair of signatures depends on the particular representation of the

signature. In one embodiment, blob properties are treated as feature vectors (i.e., arrays of numbers). A single feature might be described with multiple numbers (e.g., the average color may be represented with three numbers: red, green, and blue). Similarity can be measured by the distance (often Euclidean distance or Mahalanobis distance) between the feature vectors in high-dimensional space (e.g., 3-dimensional in the case of RGB colors, 4-dimensional if size is considered, as well, etc.). A small distance implies similarity and a large distance otherwise. In another embodiment, for signatures with multiple features, the distances between vectors representing each feature are combined (e.g., added or averaged) to arrive at a single distance. Similarity can also be measured by the dot-product of the feature vectors. A larger dot-product corresponds to a greater similarity. In one embodiment, to improve the robustness of the signature comparison of signatures including many features, some features that have large distances are ignored. For example, if a signature has 15 different features, then the 2 "worst" matching features could be ignored in a comparison.

[**0090**] The cost of a path can be measured by combining (e.g., adding or averaging) the costs of all pairs of signatures in the path. This procedure could become computationally prohibitive for long paths, so a simpler approach is to average the costs of pairs of adjacent nodes in the path. Alternatively, one could average the costs of nearby adjacent nodes in the graph.

[**0091**] Given a way of scoring paths, the algorithm proceeds as follows. The tracking module **304** initializes the track graph's **500** edge counts to 0 (Step **1202**). The tracking module **304** creates a new path by selecting a starting edge. In the illustrative embodiment, the tracking module selects a starting edge with an edge count equal to 0 (step **1204**). The starting edge and the nodes that the starting edge connects form an initial path. The tracking module **304** adds to the path using a greedy decision rule. That is, when adding edges to the path, the lowest cost edges are added first. Paths are "grown" from the starting edge by adding nodes **502** that result in the lowest cost path. Nodes **502** are added incrementally to the beginning (step **1206**) and end of the path (step **1208**). At any point at which there is a decision to make (i.e., more than one edge leave or enter a node **502**), the tracking module **304** computes the cost of adding each node **502**, and the tracking module **304** selects the node **502** that adds the minimun cost to the path. The tracking module **304** adds nodes **502** in this way until the path reaches a source and a sink. In one embodiment, multiple nodes **503** are added at a time. In this case, the algorithm considers the cost of adding all of the nodes **502** as a whole. Adding multiple nodes **502** has the advantage that a single poorly matching node **502** cannot cause the path to divert to even poorer matching nodes **502**. After a given path is completed, the tracking module **304** determines whether any edges **504** remain with edge counts less than one (step **1209**). If there are any such edges **504**, the traker **304** repeates the process (steps **1204-1208**) until all edge counts are greater than 0.

[**0092**] Once all edge counts are greater than zero, excess paths may need to be removed. Each path has a cost, and the paths can be sorted in order of decreasing cost. Redundant paths (i.e., those having no edge counts equal to 1) are removed in order of decreasing cost until no redundant paths remain (step **1210**). After all redundant paths are removed, each remaining path corresponds to an object that was included in the monitored environment at some point in time. After a solution set is determined, the track graph **500** is updated to include the appropriate edge and node counts.

[**0093**] **FIG. 13** is a flow chart of another method **1300** of determining a tracking solution. In the method **1300**, the tracking module **304** derives a tracking solution incrementally, using a data association solution algorithm similar to the one described above with respect to matching new nodes **812** to candidate nodes **810**. For illustrative purposes, referring back to **FIGS. 4 and 8**, upon completion of the track graph **808** for video frames received at time t+**1** (steps **402-408**) (step **1302**), the tracking module **304** solves the newly updated track graph **808** (step **410**/steps **1304-1310**). The tracking module **304** determines the currently known number of paths, N, in the track graph **808** (i.e., the sum of the node counts at time t) (step **1304**). The tracking module **304** then determines the number of new nodes **812**, M, which have been connected to the track graph **808** (step **1306**). The tracking module **304** calculates the incremental path costs associated with adding each node **812** m to each path n that m is connected to by an edge (step **1308**). The tracking solution problem can be set up as an N×M data association problem and solved (step **1310**) in the manner discussed previously (see method **900**); however, instead of using edge scores and candidate nodes to solve the data association problem, the tracking module **304** uses the calculated incremental path costs and paths n_r.

[**0094**] After solving the data association problem, it is possible that a single path matches to more than one new node **812**. For example, referring back to **FIG. 8**, the node counts for nodes **810**a_1, a_2, and a_3 were all 1 at time t, indicating the existence of only three paths. At time t+**1**, however, the path passing through node a_3 matches to nodes **812**b_4 and b_5. In such cases, a new object needs to be created for each additional node detected, as a single object cannot be in multiple places at once. A new object is assigned a path corresponding to the old object's path plus the new node **812** that matched it. The prior node counts and edge counts are updated to indicate the additional object traversing the path. The case in which multiple paths match with a single node **812** simply means that those objects coincide at that point in time and no special treatment is necessary other than assigning the single node a node count equal to the number of paths matching the node.

[**0095**] In another embodiment, it is possible to consider more than one new time instant, (i.e., multiple levels of nodes) in determining a solution. In such embodiments, all possible sub-paths (chains of new nodes connected by edges) must be enumerated. The subpaths are then input to the data association problem instead of the single nodes. The matching algorithm, then proceeds as previously described above. Considering small sub-paths, as opposed to single nodes, is more resilient to anomalous nodes that would otherwise cause an incorrect decision to be made.

[**0096**] In another embodiment, the tracking module calculates matches using sub-paths, but the tracking module only adds a portion of a matched sub-path to a given known path. In the next iteration of the algorithm (i.e., when new nodes are available for matching), new sub-paths are formed from the new nodes and the previous nodes that were not added to the object paths. This approach provides the algorithm with some "look ahead" capability but does not

commit to large increases in the paths prematurely. In another embodiment, a user can select both the size of the sub-path to be analyzed and the number of nodes from the analyzed sub-paths to add to the already known paths (e.g., look ahead 3 time instants, add one node). It is possible to use these look ahead approachs in the greedy path determination method **1200**, as well.

[**0097**] In one embodiment, a separate data structure, referred to as an object store, stores tracking metadata corresponding to each object within the monitored environment, including the path the object follows through the track graph. The object store maintains one entry for each object or path tracked by the tracking module **304**. Other tracking metadata may include, without limitation, the size, color, velocity, and acceleration of the object over time. Further tracking metadata may include classifications assigned by the classifier. The tracking module **304** can output any or all of the tracking metadata to a classifier or to a rules engine for further analysis.

[**0098**] The previous description related generally to a CAS system and was directed primarily to the operation of the tracking module. The following description relates to ways in which the tracking metadata produced by the tracking module and the classifier may be used to provide real-world functionality. To that end, in one embodiment, the CAS system described herein may include the capability to search metadata created by the tracking module by use of a rules engine.

[**0099**] **FIG. 14** shows a more detailed version of a portion of the general system shown in **FIG. 3** and includes further dataflow connections. In particular, **FIG. 14** includes the tracking module, classifier and rules engine shown in **FIG. 3**. In this example, the classifier is part of the tracking module but, of course, the classifier could be a stand alone module.

[**0100**] The portion of the CAS system **1400** shown in **FIG. 14** includes a tracking module **1402**, a rule engine **1404**, and a tracking metadata database **1406**. The tracking metadata may be produced, for example, by the tracking module that is described above and further classified by the classifier **1410**. Of course, other tracking modules or classifiers could be used as will be readily understood by one of skill in the art.

[**0101**] Regardless of the tracking module used, the output thereof may be archived in a meta database **1406** and, in some embodiments, may also be directly analyzed by the rule engine **1404**. In general, the rule engine **1404** evaluates rules against the tracking metadata and generates events if a rule matches some pattern in the metadata. These events may be archived in the database and, thus, also be made available to a user for review as indicated by the event data flow line **1412**.

[**0102**] In general, the system shown in **FIG. 14** may provide two types of searches: queries and alerts. A query is a one-time search that is evaluated on (possibly subsets of) all of the metadata in the metadata database **1402**. A query may return many search results, which may, for example, be ranked and presented to the user. Executing a query is typically a user-interactive experience with many potential matches that may be reduced with further queries. To this end, the rules engine **1404** may be provided with access to the metadata database as indicated by data line **1414**.

[**0103**] Alerts are searches that the system continually performs. Whenever the metadata database **1406** receives new metadata from the tracking module **1402**, the new metadata is checked by the rule engine **1404** to see if it satisfies any of the pending alert criteria. The rule engine **1404** may perform this analysis on data that is in the metadata database **1406** or directly on the metadata as it is received from the tracking module **1402**.

[**0104**] In either case, alerts are used to search for exceptional conditions in the tracking metadata that may be of interest to a human user. In some embodiments, executing an alert is not interactive but, rather, is based on previously specified alert criteria. When an alert fires (i.e., some data is found that meets the search criteria), the system may generate some sort of alert notification, such as a page, an email, a flashing screen, a sound, etc.

[**0105**] While used in different ways, queries and alerts may be implemented similarly. Each is a search that is executed on the tracking metadata stored in the metadata database **1406**. The two merely differ in the frequency with which the search is executed and how the search results are presented to the user. As such, they will collectively be referred to as "searches" below.

[**0106**] As discussed above, searches may be conducted in tracking metadata stored in the metadata database **1406** and which was received from the tracking module **1402**. At the highest level, the metadata in the metadata database **1406** may contain information about the contents of each video frame. For example, the metadata might record whether objects are in the frame or not, it might record the average color of the scene (e.g., for detecting lighting changes), or it might record the state of an object in the scene. In general, the tracking metadata records the properties of scene objects, background or foreground, considered independently or as a whole. However, because it is tracking metadata (i.e., received from the tracking module), it can contain dynamic properties as well as static properties. These dynamic properties may include, for example, motion characteristics such as velocity, acceleration and direction of an object.

[**0107**] The tracking module **1402** may produce properties for any object in the scene (or for the whole video frame itself). In general, the properties can be organized on a per-object basis (e.g., the entire video frame can be considered an object for sake of generality). Thus, when discussing a property, it can be assumed that the property is associated with some object that is being tracked by the system.

[**0108**] It is often the case that tracking engines, such as tracking module **1402**, produce metadata for moving objects in the scene. Some interesting properties of these objects might include velocity, acceleration, direction, size, average color, gait, centroid, position, area, or other properties directly calculable from pixel intensities.

[**0109**] Tracking engines often include various classification algorithms, the output of which can also be included as object properties in the tracking metadata. Such classification properties might be one of car, human, animate, inanimate, employee, customer, criminal, victim, animal, child, adult, shopping cart, box, liquid, indeterminate, etc. A single object may be assigned many different classifications. For example, a young boy might be classified as human, animate, customer, child. A shopping cart might be inanimate, shopping cart.

[0110] The classification might also determine gender, ethnicity, age, etc. Other classification systems might deduce the state of the object, such as loitering, running, falling, walking, hiding, crashing, moving backwards, appeared, disappeared, etc. These designations can also be stored in the metadata.

[0111] Some tracking systems might be location-aware, in which case location information can be stored in the metadata. For example, each object may have a property that describes in which aisle or which department it is currently located.

[0112] The tracking system can also annotate an object with a list of other objects that are in close proximity to the first object. For example, an object might be close to a doorway, which could be recorded as a property (it could also be interpreted as a location, since doorways do not move). Also, an object might be close to another moving object; both objects could be annotated with the other's identifier. Sometimes objects might be nearby one another very often. It is possible that these objects are somehow associated (e.g., girlfriend and boyfriend, shopper and shopping cart, etc.) Associated objects can also be stored in metadata.

[0113] Often the properties of objects may change over time. For example, the classification may change from walking to running, or the location may change as the object moves through the environment. Because of this, the tracking metadata must also include timing information to accurately encode the series of the properties associated with each object. In many cases, a single property is not important, but a particular sequence of properties is interesting.

[0114] Searching the metadata database **1406** by the rule engine **1404** may entail finding objects that have certain properties or combinations of properties. These combinations of properties are expressed as "rules." For example, the rule "size=BIG and color=RED" will find all big, red objects that have been tracked. Another rule might be "objectID=**1432**," which retrieves the object that is labeled with ID #**1432** in the metadata database. In this way, the metadata database **1406** is treated like a conventional database, and searches (queries, alerts, or rules-all the same) can be structured in similar ways. In this document, the terms "search" and "rule" are largely interchangeable, and "query" and "alert" have the distinctions described previously.

[0115] It is also useful to search the metadata for sequences of properties. For example, the search "state=RUNNING then FALLING" will find all objects that fell after running. It might be desired to find property transitions that are not consecutive but whose relative order is still preserved. For example, the search "location=HOUSEWARES followed by CHECKOUT" will find all people (and objects) that moved from the location identified as "housewares" to the location identified as "checkout," regardless of the locations visited in between the two specified locations.

[0116] Example Scenarios

[0117] Some searches are fairly generic (e.g., searching by objectID), but other searches are useful in specific scenarios. The following paragraphs describe a series of scenarios and some of the searches that are useful in those cases.

[0118] Detecting Theft Activities

[0119] Many theft activities in retail environments follow familiar patterns. Criminals may move through stores in well-known ways or do things that are out-of-the-ordinary. Careful specification of search criteria can often identify a retail theft before it finishes or allow a detective to find such activities during an investigation. Examples of such searches might be:

[0120] location=RETAIL_FLOOR followed by RETURNS_DESK

[0121] (location=ENTRANCE followed by (not POINT-OF-SALE) then EXIT) and (location

[0122] =EXIT and associated_object.classification=SHOPPING_CART)

[0123] (location=EXIT and associated_object.classification=SHOPPING_CART and duration>3 min)

[0124] Improving Parking Lot Security

[0125] Parking lots present a huge liability problem to the businesses that own and maintain them. Visitors and customers may be mugged or raped while in the parking lot, or cars and property may be stolen. Often, these criminal activities are preceded by suspicious behaviors of one or more individuals. For example, a mugger might be seen loitering in a parking lot before he attacks a victim. Automated searching of tracking metadata can be used to identify these behaviors before a crime is committed. For example:

[0126] classification=HUMAN and duration>5 minutes

[0127] classification=HUMAN and nearby_object-.classification=HUMAN and nearby_object.state=RUNNING

[0128] (classification=CAR) and (state=MOVING then STOPPED) and (nearby_object.classification=CAR) and (nearby_object.state=MOVING then STOPPED)

[0129] (classification=HUMAN) and (state=MOVING then STOPPED then MOVING then STOPPED then MOVING then STOPPED) and (nearby_object-.classification=CAR)

[0130] classification=CAR and state=MOVING and speed>25 mph

[0131] Improving Child Safety

[0132] Protecting the safety of children is one of the top priorities of security professionals, especially in retail and entertainment venues. Metadata searches can be used to find lost children, children that are being kidnapped, or children that are near dangerous equipment. Some searches for protecting children are as follows:

[0133] classification=CHILD and location=DANGEROUS_AREA

[0134] classification=CHILD and nearby_object=NONE

[0135] classification=CHILD and nearby_object not_equal associated_object and nearby_object.classification=HUMAN,ADULT

[0136] classification=CHILD and nearby_object not_equal associated_object and nearby_object.classification=HUMAN,ADULT and location=EXIT

[0137] Improving Public Safety

[0138] Protecting the safety of people in general is also a primary concern. People can fall down in public places (e.g., slip-and-fall events), walk too close to dangerous areas (e.g., platform edge in a subway), or go the wrong way through an exit or on an escalator. These events are useful to flag as sources of injury to people and source of liability to businesses. Some example searches follow.

[0139] classification=HUMAN and location=DANGEROUS_AREA

[0140] classification=INANIMATE and location=WALKWAY and state=APPEARED

[0141] classification=HUMAN and ((location=OUTSIDE_EXIT followed by INSIDE_EXIT) or (location=INSIDE_ENTRANCE followed by OUTSIDE_ENTRANCE))

[0142] classification=HUMAN and state=FALLING

[0143] Operations and Merchandising

[0144] Often a business not only wants to ensure the security of its customers and products, but it also wants to know how those customers behave and react inside the business' environment. The statistics of how customers move throughout a store is very important for marketing and advertising purposes. Searching through tracking metadata is a very useful tool for acquiring those statistics. In this scenario, the specific search results are not particularly interesting, but the numbers of them are. So, a 'count' operator is introduced that simply counts the number of returned search results. By counting many different searches, interesting and useful statistics can be generated. Other useful operators can include 'SUM' and 'AVG' yielding the sum or the average, respectively, of returned search results. Here are a few examples:

[0145] count(location=ENTRANCE and state=APPEARED)

[0146] count(location=ENTRANCE then AISLE1)

[0147] count(location=ADVERTISING_DISPLAY and state=STOPPED and duration>30 s and duration <=1 min)

[0148] count(location=CHECKOUT_LINE and state=WAITING and duration>1 min)

[0149] Implementation

[0150] Many of the queries described above are easily implemented in standard database query languages. However, some of the "sequential" queries (e.g., then and followed by) do not have a direct correspondence with traditional database searches. Fortunately, as long as the tracking metadata is encoded in an appropriate format, these sequential queries can be implemented using a well-known computer science search technique known as "regular expressions."

[0151] Regular expressions are traditionally used for matching strings. A string is simply a sequence of characters (or tokens) taken from some finite alphabet. For example, ABCBCA is a string from the alphabet of capital letters. A regular expression is just a shorthand for describing large sets of strings with a single small expression. A regular expression is said to match a string if that string is a member of the set of strings that the regular expression describes.

[0152] As an example, consider the regular expression A(BC)*[AD] over the alphabet of capital letters. In words, this expression says "match any string that starts with an 'A' followed by any number of 'BC' segments and then ends in an 'A' or a 'D.'" In regular expression syntax, the parentheses group B and C into a single unit, the brackets mean "A or D," and the asterisk denotes "zero or more of the preceding unit." Thus, this expression matches AA, ABCD, and ABCBCA, but it does not match ABA, ABCBA, or AAA.

[0153] Regular expressions can be evaluated very simply using finite state machines (FSMs). A finite state machine consists of a set of states and a transition rule that describes how to transition from one state to another given some input. Some of the states are designated as "accepting" states. If, at the end of the input, the FSM state is an accepting state, then the FSM is said to accept (or match) the input.

[0154] When matching strings, the input to the FSM is the string. For each token in the string, the FSM transitions to a state. At the end of the string, the state of the FSM (accepting or not) determines is the string is matched or not.

[0155] For example, an FSM **1500** that implements the previously describe regular expression is shown in **FIG. 15**. FSM's for use in the system of the present invention may be implemented in software, hardware, firmware or combinations thereof as will be readily apparent to one of skill in the art. Each edge is annotated with the input that causes that transition to be taken from that state. Accepting states are shown with double lines.

[0156] In particular, different states are shown as nodes **1502**, **1504**, **1506** and **1508**, and the transition rule is illustrated with edges, **1510**, **1512**, **1514**, **1516**, **1518**, **1520**, and **1522** between the nodes. In this example, node **1502** represents the start state. If, while in the start state of node **1502** the rule engine detects the appearance of an A, the FSM **1500** moves to node **1504** as indicated by edge **1512**. If an A is not detected (i.e., ~A) the FSM **1500** remains at node **1502** as indicated by edge **1510**. From node **1504** the FSM **1400** will move to the accepting state **1506** if it receives either an A or a D as indicated by edge **1514**. The FSM will remain at node **1504** unless it receives an input that is not an A, a B or a D at which point it returns to start node **1502** as indicated by edge **1516** or it will transition to node **1408** if it receives a B as indicated by edge **1520**. From state **1508** the FSM will return to the start node **1502** if it receives anything other than a C (as indicated by edge **1524**) or will transition to state **1504** if it receives a C. In all cases, if the FSM **1500** reaches node **1506** the criteria is met, an alarm or other notification may be presented to a user and the FSM **1500** returns to start state **1502**. The fact that an alarm was created may also be stored in the metadata database for further searching if desired.

[0157] In order to use regular expressions to search tracking metadata, the metadata may need to be encoded as strings. This encoding can be accomplished as follows. Each object property can be assigned a value from a finite set of

values (i.e., the alphabet). Then, the time-ordered sequence of property values (i.e., tokens) for each object can be considered a string over the alphabet of property values. Certain sequences of property values can then be matched efficiently using regular expressions and FSMs.

[0158] For example, consider the object illustrated in **FIG. 16**. The object has three properties, location (row **1602**), state (row **1604**), and duration (row **1606**) and each property can take on a different value at each time step. As shown in **FIG. 16**, each row **1608**, **1610**, **1614** and **1616** represents a different time period. The sequences of properties result in three strings that describe the evolution of the object properties as it is tracked by the tracking module. These strings can be searched for patterns of properties using regular expressions and finite state machines.

[0159] For example, consider the query location=ENTRANCE followed by (not POINT-OF-SALE) then EXIT.

[0160] Written as a regular expression, this query is ENTRANCE(~POS)*EXIT. In this case, ~is a negation operator that means "any token except POS." The FSM implementing this regular expression is shown in **FIG. 17**.

[0161] Sometimes, it is useful search for property sequences that involve combinations of properties (e.g., location=ENTRANCE, state=WALKING followed by location=DANGEROUS_AREA, state=FALLING). Cases like this can be accommodated by combining the two property strings in a single combined property string. In the combined string, each token consists of two sub-tokens from each individual string. The alphabet of the combined string is the cross-product of the two individual alphabets (i.e., it consists of all unique pairs (a,b) of tokens, where a is from the first alphabet and b is from the second alphabet). This technique can be extended to three or more properties as needed.

[0162] For example, the combining the first two properties of the object in **FIG. 16** for all time references (e.g., rows **1608-1616** respectively) results in the string <ENTRANCE, WALKING> <AISLE2,WALKING> <DVD's,STOPPED> <RETURNS,WAITING> <EXIT,RUNNING>. One might be interested in regular expressions containing the token <EXIT,RUNNING> to determine if a person recently stole a DVD from a store and ran out of the store.

[0163] One skilled in the art will realize the invention may be embodied in other specific forms without departing from the spirit or essential characteristics thereof. The foregoing embodiments are therefore to be considered in all respects illustrative rather than limiting of the invention. The scope of the invention is not limited to just the foregoing description.

What is claimed is:

1. A computerized method of video analysis comprising:

receiving a plurality of series of video frames generated by a plurality of image sensors, each having a field-of-view, which monitor portions of a monitored environment; and

concurrently tracking, independent of calibration (i) a plurality of objects within the monitored environment as the objects move between fields-of-view, at least two of which overlap, and ii) a plurality of objects within one field-of-view based on the plurality of received series of video frames.

2. The method of claim 1 wherein the image sensors are cameras.

3. The method of claim 1 further comprising tracking objects based on a probability that an object included in one video frame generated by a first image sensor at a first point in time will be included in a video frame generated by a second image sensor a second point in time.

4. The method of claim 1 further comprising:

storing a plurality of blob states over time, each state including a number of objects included in the blob and a blob signature; and

storing a plurality of transition likelihood values representing the probability that objects within one blob at one instant in time correspond to objects within other blobs at other instants in time.

5. The method of claim 4 further comprising altering the stored transition probabilities upon analysis of additional video frames.

6. The method of claim 4 further comprising storing object data indicating correspondences between objects and blob states.

7. The method of claim 4 generating a tracking solution based on the blob states and transition probabilities.

8. The method of claim 1 generating tracking metadata including at least one of object track data, tracking solutions, object feature data and field-of-view data.

9. The method of claim 8 further comprising:

selecting a rule set to analyze generated tracking metadata; and

evaluating, using a rules engine, the tracking metadata-based on the rule set.

10. The method of claim 9 further comprising selecting the rule set to monitor parking lot security.

11. The method of claim 9 further comprising selecting the rule set to detect property theft.

12. The method of claim 9 further comprising selecting the rule set to detect hazards to children.

13. The method of claim 9 further comprising selecting the rule set to monitor public safety.

14. The method of claim 9 further comprising selecting the rule set to determine merchandizing and operations statistics.

15. A computerized system for video analysis comprising:

a receiving module configured to receive a plurality of series of video frames, the series of video frames generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view; and

a calibration-independent tracking module in communication with the receiving module and configured to i) concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view at least two of which overlap and ii) concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames, the tracking module outputting tracking metadata.

16. The system of claim 15 further comprising a rules engine in communication with the tracking module and receiving the tracking metadata.

17. A system for monitoring parking lot security comprising:

a receiving module configured to receive a plurality of series of video frames, the series of video frames generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view;

a calibration-independent tracking module in communication with the receiving module and configured to i) concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view at least two of which overlap and ii) concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames, the tracking module outputting tracking metadata; and

a rules engine utilizing a parking lot security rule set configured to receive and evaluate the tracking metadata.

18. A system for property theft detection comprising:

a receiving module configured to receive a plurality of series of video frames, the series of video frames generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view;

a calibration-independent tracking module in communication with the receiving module and configured to i) concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view at least two of which overlap and ii) concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames, the tracking module outputting tracking metadata; and

a rules engine utilizing a theft detection rule set configured to receive and evaluate the tracking metadata.

19. A system for child hazard detection comprising:

a receiving module configured to receive a plurality of series of video frames, the series of video frames generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view;

a calibration-independent tracking module in communication with the receiving module and configured to i) concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view at least two of which overlap and ii) concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames, the tracking module outputting tracking metadata; and

a rules engine utilizing a child safety rule set configured to receive and evaluate the tracking metadata.

20. A system for property theft detection comprising:

a receiving module configured to receive a plurality of series of video frames, the series of video frames generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view;

a calibration-independent tracking module in communication with the receiving module and configured to i) concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view at least two of which overlap and ii) concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames, the tracking module outputting tracking metadata; and

a rules engine utilizing a public safety monitoring rule set configured to receive and evaluate the tracking metadata.

21. A system for merchandizing and operations statistical analysis comprising:

a receiving module configured to receive a plurality of series of video frames, the series of video frames generated by a plurality of image sensors which monitor portions of a monitored environment and have a field-of-view;

a calibration-independent tracking module in communication with the receiving module and configured to i) concurrently track a plurality of objects within the monitored environment as the objects move between fields-of-view at least two of which overlap and ii) concurrently track a plurality of objects within one field-of-view based on the plurality of received series of video frames, the tracking module outputting tracking metadata; and

a rules engine utilizing a merchandizing and operations statistical rule set configured to receive and evaluate the tracking metadata.

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