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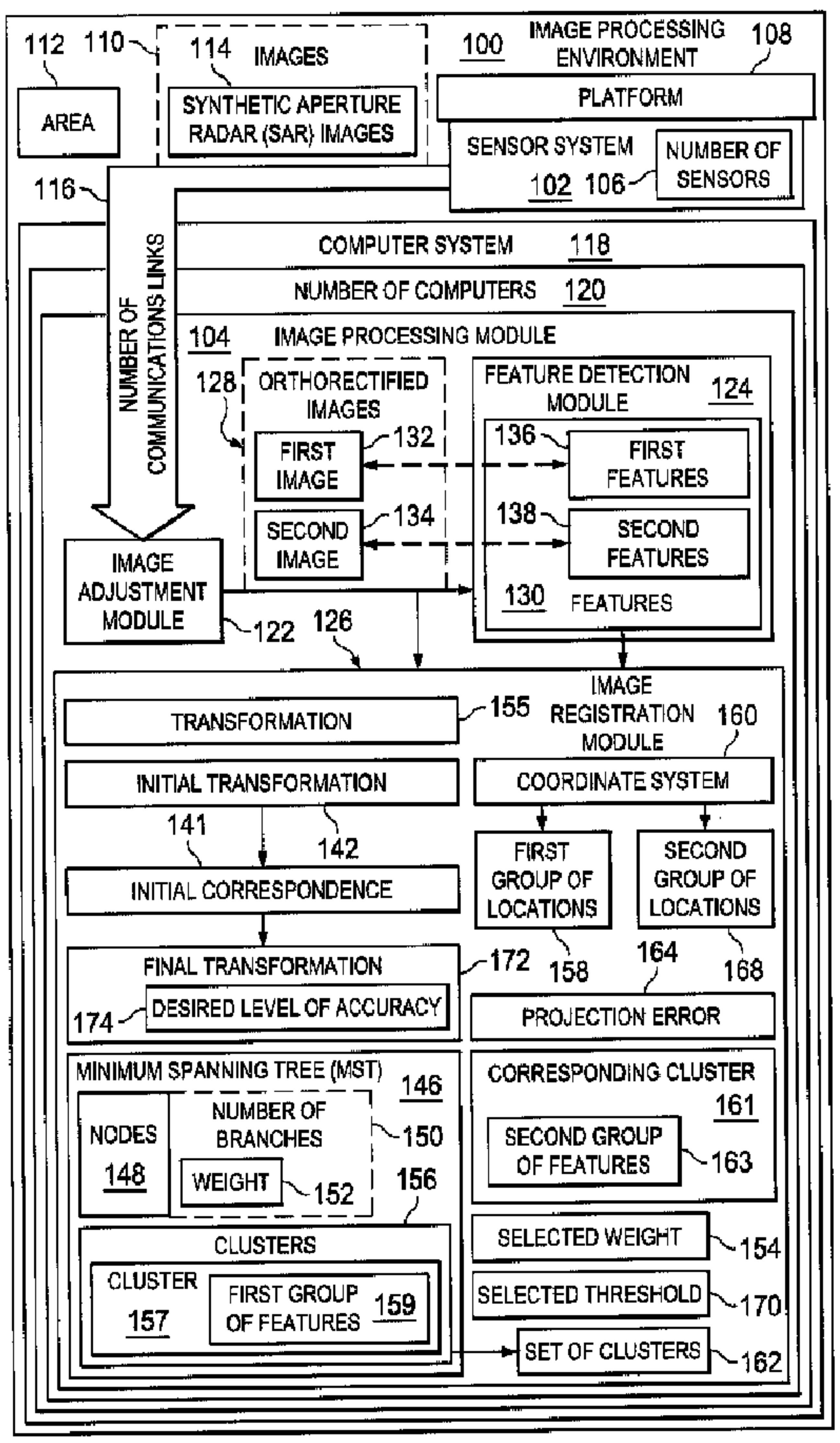


(57) **Abrégé/Abstract:**

A method and apparatus for processing images (110). Clusters (156) of first features (136) identified in a first image (132) are identified. Each cluster in the clusters comprises a first group of features (159) from the first features (136). A transformation (155)

(57) **Abrégé(suite)/Abstract(continued):**
for registering each cluster in the clusters with a corresponding cluster (161) comprising a second group of features (163) from second features (138) identified in a second image (134) is identified using an initial correspondence between the first features in the first image and the second features in the second image. A set of clusters (162) from the clusters of the first features is identified using the transformation identified for each cluster. A final transformation (172) for registering the first image with the second image is identified using the set of clusters.

ABSTRACT

A method and apparatus for processing images (**110**). Clusters (**156**) of first features (**136**) identified in a first image (**132**) are identified. Each cluster in the clusters comprises a first group of features (**159**) from the first features (**136**). A transformation (**155**) for registering each cluster in the clusters with a corresponding cluster (**161**) comprising a second group of features (**163**) from second features (**138**) identified in a second image (**134**) is identified using an initial correspondence between the first features in the first image and the second features in the second image. A set of clusters (**162**) from the clusters of the first features is identified using the transformation identified for each cluster. A final transformation (**172**) for registering the first image with the second image is identified using the set of clusters.

IMAGE REGISTRATION

BACKGROUND INFORMATION

Field

The present disclosure relates generally to processing images and, in particular, to registering synthetic aperture radar (SAR) images. Still more particularly, the present disclosure relates to a method and apparatus for registering synthetic aperture radar images that have been orthorectified.

Background

Images are used in performing various types of operations. These operations may include, for example, without limitation, object recognition, object tracking, and/or other suitable types of operations. Oftentimes, image registration is performed prior to performing these operations. Image registration is the alignment of images of a same scene generated at different times, from different viewpoints, and/or by different sensors.

Feature-based image registration is an example of one type of image registration. Feature-based registration transforms a first image of a scene such that features in the first image align with the same features in a second image of the same scene. The second image may also be referred to as a reference image or a source image.

With feature-based image registration, different types of transformation models may be used to transform the first image to align the first image with the reference image. One type of transformation model is a linear transformation. A linear transformation may include, for example, without limitation, translation, rotation, scaling, and/or other suitable types of affine transformations. An affine transformation is any transformation that preserves collinearity between points and ratios of distances between points on a line.

Feature-based image registration may be used with different types of images. These different types of images may include, for example, without limitation, visible spectrum images, optical images, infrared images, radar images, synthetic aperture radar (SAR) images, and other suitable types of images.

Typically, synthetic aperture radar images are orthographically rectified prior to performing image registration. This process may also be referred to as orthorectification. Orthorectification is the removal of geometric distortions from an image such that the scale of the image is substantially uniform. These geometric distortions may be caused by tilt of the sensor that generated the image, terrain relief, lens distortion, and/or other suitable sources of distortion. Images that have been orthographically rectified may be referred to as orthorectified images.

Feature-based image registration of orthorectified images may include using an orthographic transformation that translates and/or rotates an orthorectified image to align with a reference image. The reference image is also orthorectified. Currently-available methods for performing feature-based image registration of synthetic aperture radar images may not be as accurate as currently-available methods for feature-based image registration of visible spectrum images.

For example, a greater amount of noise may be present in synthetic aperture radar images as compared to visible spectrum images. This greater amount of noise may make the identification of features in synthetic aperture radar images less accurate as compared to the identification of features in visible spectrum images, using currently-available methods for identifying features in images. As a result, currently-available methods for feature-based image registration of synthetic aperture radar images may be less accurate than desired.

SUMMARY

In one embodiment, a method for processing images is provided. Clusters of first features identified in a first image are identified. Each cluster in the clusters comprises a first group of features from the first features. A transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from second features identified in a second image is identified using an initial correspondence between the first features in the first image and the second features in the second image. A set of clusters from the clusters of the first features is identified using the transformation identified for each cluster. A final transformation for registering the first image with the second image is identified using the set of clusters.

In another embodiment, a method for registering images is provided. First features in a first image in the images and second features in a second image in the images are identified. An initial transformation is identified for registering the first image with the second image using the first features and the second features.

An initial correspondence between the first features in the first image and the second features in the second image is identified using the initial transformation for registering the first image with the second image. Clusters of the first features in the first image are identified using a minimum spanning tree formed using the first features. Each cluster in the clusters comprises a first group of features from the first features. A transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from the second features identified in the second image is identified using the initial correspondence. A cluster in the clusters is added to a set of clusters when a projection error for the transformation identified for the cluster is less than a selected threshold. A final transformation for registering the first

image with the second image is identified using features in the set of clusters and a random sample consensus algorithm. The first image is registered with the second image using the final transformation.

In yet another embodiment, an apparatus comprises an image processing module. The image processing module is configured to identify clusters of first features identified in a first image. Each cluster in the clusters comprises a first group of features from the first features.

The image processing module is further configured to identify a transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from second features identified in a second image using an initial correspondence between the first features in the first image and the second features in the second image. The image processing module is further configured to identify a set of clusters from the clusters of the first features using the transformation identified for each cluster. The image processing module is further configured to identify a final transformation for registering the first image with the second image using the set of clusters.

Another embodiment has a method comprising:

identifying a first number of closed contours in the first image and a second number of closed contours in the second image; and

identifying an initial transformation for registering the first image with the second image using the first number of closed contours, the second number of closed contours, and a matching algorithm.

In accordance with one aspect of the invention there is provided a method for processing images. The method involves identifying clusters of first features identified in a first image, each cluster in the clusters including a first group of features from the first features. The method also involves identifying a transformation for registering each cluster in the clusters with a corresponding cluster includes a second group of features from second features identified in a second image using an initial correspondence between the first features in the first image and the second features in the second image, and identifying a set of clusters from the clusters of the first features using the transformation identified for each cluster. The method further involves adding a cluster in the clusters to the set of clusters when a projection error for the transformation identified for the cluster is less than a selected threshold, and identifying a final transformation for registering the first image with the second image using the set of clusters.

The method may involve identifying the initial correspondence between the first features in the first image and the second features in the second image using an initial transformation for registering the first image with the second image.

The method may involve identifying the initial transformation for registering the first image with the second image using the first features identified in the first image, the second features identified in the second image, and a random sample consensus algorithm.

The method may involve identifying a first number of closed contours in the first image and a second number of closed contours in the second image, and identifying an initial transformation for registering the first image with the second image using the first number of closed contours, the second number of closed contours, and a matching algorithm.

The step of identifying the clusters of the first features identified in the first image may involve forming a minimum spanning tree using the first features, where the minimum spanning tree may include nodes and a number of branches in which each node in the nodes is a feature in the first features and each branch in the number of branches has a weight, and removing any branch in the number of branches from the minimum spanning tree when the weight of the any branch is greater than a selected weight to form the clusters of the first features, where each cluster in the clusters may involve the first group of features from the first features.

The step of identifying the transformation for registering each cluster in the clusters with the corresponding cluster may involve the second group of features from the second features being identified in the second image using the initial correspondence between the first features in the first image and the second features in the second image may involve identifying features from the second features identified in the second image that correspond to the first group of features in a cluster in the clusters as the second group of features using the initial correspondence, where the second group of features form the corresponding cluster, and identifying the transformation for registering the cluster with the corresponding cluster using a least squares algorithm, where the transformation projects the first group of features in the cluster onto the second image to align the first group of features in the cluster with the second group of features in the corresponding cluster.

The step of identifying the set of clusters from the clusters using the transformation identified for each cluster may involve identifying a first group of locations in the second image onto which the first group of features are projected using the transformation, identifying a projection error using distances between the first group of locations for the first group of features and a second group of locations in the second image for the second group of features, and.

The step of identifying the final transformation for registering the first image with the second image using the set of clusters may involve identifying the final transformation for registering the first image with the second image using features in the set of clusters and a random sample consensus algorithm.

The method may involve identifying the first features in the first image and the second features in the second image.

Identifying the first features in the first image and the second features in the second image may involve identifying first lines in the first image and second lines in the second image using a line detection algorithm, and identifying intersections of lines in the first lines as the first features and intersections of lines in the second lines as the second features.

The step of identifying the first features in the first image and the second features in the second image may be performed using a feature detection module in which the feature detection module uses at least one of a Steger algorithm, a Canny line detection algorithm, an edge detection algorithm, a Hough transform, a scale-invariant feature transform, a speeded up robust features detector, and a Kanade-Lucas-Tomasi transform to identify the first features and the second features.

The method may involve registering the first image with the second image using the final transformation to align the first image with the second image with a desired level of accuracy, where the first image and the second image may be synthetic aperture radar images that are orthorectified.

In accordance with another aspect of the invention there is provided a method for registering images. The method involves using a processing module in a computer system for identifying first features in a first image in the images and second features in a second image in the images, identifying an initial transformation for registering the first image with the second image using the first features and the second features, and identifying an initial correspondence between the first features in the first image and the second features in the second image using the initial transformation for registering the first image with the second image. The method also involves identifying clusters of the first features in the first image using a minimum spanning tree formed using the first features, each cluster in the clusters including a first group of features from the first features. The method further involves identifying a transformation for registering each cluster in the clusters with a corresponding cluster including a second group of features from the second features identified in the second image using the initial correspondence. The method also involves adding a cluster in the clusters to a set of clusters when a projection error for the transformation identified for the cluster is less than a selected threshold, identifying a final transformation for registering the first image with the second image using features in the set of clusters and a random sample consensus algorithm, and registering the first image with the second image using the final transformation.

The first image may be a first synthetic aperture radar image and the second image is a second synthetic aperture radar image in which the first synthetic aperture radar image and the second synthetic aperture radar image are orthorectified and the step of registering the first image with the second image using the final transformation may involve performing at least one of a translation and a rotation of the first image using the final transformation to align the first image with the second image with a desired level of accuracy.

In accordance with another aspect of the invention there is provided an apparatus including an image processing module configured to identify clusters of first features identified in a first image. Each cluster in the clusters includes a first group of features from first features. The image processing module is also configured to identify a transformation for registering each cluster in the clusters with a corresponding cluster includes a second group of features from second features identified in a second image using an initial correspondence between the first features in the first image and the second features in the second image. The image processing module is further configured to identify a set of clusters from the clusters of the first features using the transformation identified for each cluster, and to add a cluster in the clusters to the set of clusters when a projection error for the transformation identified for the cluster is less than a selected threshold. The image processing module is also configured to identify a final transformation for registering the first image with the second image using the set of clusters.

The image processing module may be configured to identify the clusters of the first features identified in the first image by forming a minimum spanning tree using the first features, the minimum spanning tree including nodes and a number of branches in which each node in the nodes is a feature in the first features and each branch in the number of branches has a weight, and removing any branch in the number of branches from the minimum spanning tree when the weight of the any branch is greater than a selected weight to form the clusters of the first features, where each cluster in the clusters may include the first group of features from the first features.

The image processing module may further include a feature detection module in the image processing module, the feature detection module being configured to identify the first features in the first image and the second features in the second image.

The image processing module may further include a sensor system in communication with the image processing module, the sensor system being configured to generate the first image and the second image.

The features, functions, and advantages can be achieved independently in various embodiments of the present disclosure or may be combined in yet other embodiments in which further details can be seen with reference to the following description and drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

The novel features believed characteristic of the advantageous embodiments are set forth in the appended claims. The advantageous embodiments, however, as well as a preferred mode of use, further objectives, and advantages thereof, will best be understood by reference to the following detailed description of an advantageous embodiment of the present disclosure when read in conjunction with the accompanying drawings, wherein:

Figure 1 is an illustration of an image processing environment in the form of a block diagram in accordance with an advantageous embodiment;

Figure 2 is an illustration of features identified in orthorectified images in accordance with an advantageous embodiment;

Figure 3 is an illustration of features identified from a first image and a second image in accordance with an advantageous embodiment;

Figure 4 is an illustration of a first image registered with a second image in accordance with an advantageous embodiment;

Figure 5 is an illustration of features identified in images in accordance with an advantageous embodiment;

Figure 6 is an illustration of a feature identified in an image in accordance with an advantageous embodiment;

Figure 7 is an illustration of a flowchart of a process for registering images in accordance with an advantageous embodiment;

Figure 8 is an illustration of a flowchart of a process for identifying features in an image in accordance with an advantageous embodiment;

Figure 9 is an illustration of a flowchart of a process for identifying an initial transformation for registering a first image with a second image in accordance with an advantageous embodiment;

Figure 10 is an illustration of a flowchart of a process for identifying an initial correspondence between first features in a first image and second features in a second image in accordance with an advantageous embodiment;

Figure 11 is an illustration of a flowchart of a process for identifying clusters of first features identified in a first image in accordance with an advantageous embodiment;

Figure 12 is an illustration of a flowchart of a process for identifying a set of clusters from clusters of first features in a first image in accordance with an advantageous embodiment; and

Figure 13 is an illustration of a data processing system in accordance with an advantageous embodiment.

DETAILED DESCRIPTION

The different advantageous embodiments recognize and take into account a number of different considerations. For example, the different advantageous embodiments recognize and take into account that synthetic aperture radar (SAR) images may have more noise than desired. Synthetic aperture radar imaging systems send pulses of electromagnetic radiation. These pulses are also referred to as electromagnetic signals. These electromagnetic signals are directed at an area, such as, for example, an area of terrain, a neighborhood, a section of a forest, a portion of a city, a plant, or some other suitable type of area.

The different advantageous embodiments recognize and take into account that at least a portion of the electromagnetic signals is reflected off of a surface of the area when these electromagnetic signals encounter the surface. The electromagnetic waves that are reflected off the surface may be referred to as backscatter, scattered electromagnetic waves, scattered electromagnetic signals, echo waves, or echoes.

Synthetic aperture radar imaging systems are configured to detect these scattered electromagnetic signals and generate synthetic aperture radar images. This detection is referred to as coherent detection. This type of detection is performed on the scattered electromagnetic signals and is a type of detection that allows both amplitude information and phase information to be captured for the signals. The different advantageous embodiments recognize and take into account that using coherent detection produces an undesired level of non-Gaussian noise in the synthetic aperture radar images that are generated.

Additionally, the different advantageous embodiments recognize and take into account that the reflectivity of electromagnetic signals off of surfaces may depend on the angles at which the electromagnetic signals are directed towards the surface. In this manner, synthetic aperture radar images are often anisotropic. In other words, the appearance of a scene in synthetic aperture radar images may vary, depending on the angles at which the electromagnetic signals are sent towards the area by the synthetic aperture radar imaging systems.

The different advantageous embodiments recognize and take into account that the non-Gaussian noise present in synthetic aperture radar images and the anisotropism of these types of images may make processing synthetic aperture radar images more difficult as compared to processing visible spectrum images. In particular, image registration of synthetic aperture radar images may be more difficult as compared to image registration of visible spectrum images.

For example, currently available methods for image registration of synthetic aperture radar images typically use a feature detection algorithm and an algorithm for estimating a transformation model for registering the synthetic aperture radar images. The transformation model is estimated based on the detection of a feature in the synthetic aperture radar images.

However, the different advantageous embodiments recognize and take into account that these currently-available methods for image registration of synthetic aperture radar images may not have a desired level of accuracy. In particular, the amount of noise present in synthetic aperture radar images may make the detection of features in these images using currently-available feature detection algorithms less accurate and less reliable than desired. As a result, image registration of these synthetic aperture radar images may be less accurate than desired.

The different advantageous embodiments recognize and take into account that accurate image registration of synthetic aperture radar images may be desirable when performing object recognition. For example, the different advantageous embodiments also recognize and take into account that when these types of images are registered with an accuracy less than a desired level of accuracy, a number of false identifications of objects may be increased and/or a number of identifications of objects that are not objects of interest may be increased.

As one illustrative example, without a desired level of accuracy for registering synthetic aperture radar images, shadows may be more often falsely identified as objects of interest. Further, the different advantageous embodiments recognize and take into account that a less than desired level of accuracy for registering synthetic aperture radar images may make it more difficult than desired to track objects in these images over time.

Additionally, the different advantageous embodiments recognize and take into account that using synthetic aperture radar images of various portions of a scene to form a larger image of the scene may not be possible when the level of accuracy for registering these types of images is less than desired.

Thus, the different advantageous embodiments provide a method and apparatus for registering images. In one advantageous embodiment, a method for processing images is provided. Clusters of first features identified in a first image are identified. Each cluster in the clusters comprises a first group of features from the first features. A transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from second features identified in a second image is identified using an initial correspondence between the first features in the first image and the second features in the second image. A set of clusters from the clusters of the first features is identified using the transformation identified for each cluster. A final transformation for registering the first image with the second image is identified using the set of clusters.

With reference now to **Figure 1**, an illustration of an image processing environment in the form of a block diagram is depicted in accordance with an advantageous embodiment. Image processing environment **100** includes sensor system **102** and image processing module **104**.

In these illustrative examples, sensor system **102** may comprise number of sensors **106**. As used herein, "a number of items" means one or more items. For example, "a number of sensors" means one or more sensors. Number of sensors **106** may include, for example, without limitation, at least one of an optical camera, an infrared camera, a radar imaging system, a synthetic aperture radar imaging system, and other suitable types of sensors.

As used herein, the phrase "at least one of", when used with a list of items, means that different combinations of one or more of the listed items may be used and only one of each item in the list may be needed. For example, "at least one of item A, item B, and item C" may include, for example, without limitation, item A, or item A and item B. This example also may include item A, item B, and item C, or item B and item C. In other examples, "at least one of" may be, for example, without limitation, two of item A, one of item B, and **10** of item C; four of item B and seven of item C; and other suitable combinations.

As depicted, sensor system **102** is associated with platform **108**. A first component, such as sensor system **102**, may be considered to be associated with a second component, such as platform **108**, by being secured to the second component, bonded to the second component, welded to the second component, fastened to the second component, and/or connected to the second component in some other suitable manner. The first component also may be connected to the second component using a third component. The first component may also be considered to be associated with the second component by being formed as part of and/or an extension of the second component.

In these illustrative examples, platform **108** may be selected from one of a mobile platform, a stationary platform, a land-based structure, an aquatic-based structure, a space-based structure, an aerial vehicle, an aircraft, an unmanned aerial vehicle, a surface ship, a tank, a personnel carrier, a train, a spacecraft, a space station, a satellite, a submarine, an automobile, a power plant, a bridge, a dam, a manufacturing facility, and a building.

As depicted, sensor system **102** is configured to generate images **110** of area **112**. In these illustrative examples, area **112** may be an area under platform **108**. Further, in these illustrative examples, images **110** take the form of synthetic aperture radar (SAR) images **114**.

Sensor system **102** is configured to send images **110** to image processing module **104** over number of communications links **116**. Number of communications links **116** may include at least one of a wireless communications link, a wired communications link, an optical communications link, and some other suitable type of communications link.

In these depicted examples, image processing module **104** may be implemented using hardware, software, or a combination of the two. As one illustrative example, image processing module **104** may be implemented in computer system **118**. Computer system **118** comprises number of computers **120**. When more than one computer is present in computer system **118**, these computers may be in communication with each other.

Number of computers **120** may be in locations on platform **108** and/or remote to platform **108**. In one illustrative example, all of number of computers **120** may be located on platform **108**. In another illustrative example, a portion of number of computers **120** may be located on platform **108**, while another portion of number of computers **120** may be located at a ground station remote to platform **108**.

In these illustrative examples, image processing module **104** may comprise image adjustment module **122**, feature detection module **124**, and image registration module **126**. Image adjustment module **122** is configured to orthographically rectify images **110** received from sensor system **102** to form orthorectified images **128**.

Orthographically rectifying images **110** includes removing geometric distortions from images **110** such that the scale for each image in images **110** is substantially uniform. The geometric distortions present in an image in images **110** may be caused by a tilt of the sensor in number of sensors **106** that generated the image, terrain relief in area **112**, lens distortion of the sensor, and/or other suitable sources of distortion.

As depicted, image adjustment module **122** sends orthorectified images **128** to feature detection module **124**. Feature detection module **124** is configured to identify features **130** in orthorectified images **128**. Feature detection module **124** may identify features **130** using at least one of a Steger algorithm, a Canny line detection algorithm, an edge detection algorithm, a Hough transform, a scale-invariant feature transform (SIFT), a speeded up robust features detector (SURF detector), a Kanade-Lucas-Tomasi tracker (KLT), a line detection algorithm, and other suitable types of algorithms.

As one illustrative example, orthorectified images **128** include first image **132** and second image **134**. First image **132** and second image **134** may have been generated by sensor system **102** at different times, by different sensors within number of sensors **106**, and/or from different viewpoints.

First image **132** and second image **134** are examples of two images that are to be registered using image registration module **126**. In particular, first image **132** is to be registered with second image **134** based on first features **136** and second features **138**. Second image **134** may also be referred to as a reference image or a source image.

First features **136** in first image **132** and second features **138** in second image **134** are identified using feature detection module **124**. The features in first features **136** and second features **138** may be selected from at least one of lines, shapes, and other suitable types of features.

Feature detection module **124** sends features **130** identified in orthorectified images **128** to image registration module **126**. Image registration module **126** also receives orthorectified images **128** from image adjustment module **122**.

Image registration module **126** registers first image **132** with second image **134** to align first image **132** with second image **134**. In particular, registering first image **132** with second image **134** aligns first features **136** in first image **132** with second features **138** in second image **134**. This alignment may not be a substantially perfect alignment.

In other words, when first image **132** is registered with second image **134**, portions of first features **136** may substantially overlap with second features **138.** Other portions of first features **136,** however, may not overlap with second features **138** or may have less overlap than the portions of first features **136** that substantially overlap with second features **138**. The amount of overlap between first features **136** and second features **138** may be used in determining a level of accuracy for registering first image **132** with second image **134**.

In these illustrative examples, image registration module **126** is configured to identify initial correspondence **141** between first features **136** and second features **138.** Initial correspondence **141** is a one-to-one correspondence in these depicted examples.

In other words, each feature in first features **136** in first image **132** has a corresponding feature in second features **138** in second image **134**. Further, each feature in second features **138** corresponds to a feature in first features **136.** In some illustrative examples, initial correspondence **141** may only be identified between a portion of first features **136** and a portion of second features **138**.

Initial correspondence **141** is identified using initial transformation **142** for registering first image **132** with second image **134**. In one illustrative example, image registration module **126** may identify initial transformation **142** using first features **136**, second features **138**, and a random sample consensus (RANSAC) algorithm.

Initial transformation **142** may be an orthographic transformation in these depicted examples. In other words, registering first image **132** with second image **134** using initial transformation **142** translates and/or rotates first image **132** to align first features **136** in first image **132** with second features **138** in second image **134**.

As one illustrative example, image registration module **126** uses initial transformation **142**, first image **132**, second image **134**, and an algorithm for matching first features **136** with second features **138** to identify initial correspondence **141**. In this illustrative example, the algorithm may be, for example, a k-dimensional tree algorithm, a nearest neighbor matching algorithm, or some other suitable type of algorithm.

Further, image registration module **126** is configured to form minimum spanning tree (MST) **146** using first features **136**. Minimum spanning tree **146** has nodes **148** and number of branches **150**.

Each node in nodes **148** is a feature in first features **136**. In this manner, all of first features **136** are represented in minimum spanning tree **146** in these illustrative examples. Each branch in number of branches **150** connects two nodes in nodes **148**. Further, each branch in number of branches **150** has weight **152**. In these illustrative examples, weight **152** for each branch is a distance in pixels between the two nodes in nodes **148** connected by the branch.

Image registration module **126** is configured to remove any branch in number of branches **150** having weight **152** greater than selected weight **154** from minimum spanning tree **146**. When all branches having weight **152** greater than selected weight **154** are removed from minimum spanning tree **146**, clusters **156** of first features **136** are formed in minimum spanning tree **146**.

In these illustrative examples, image registration module **126** identifies transformation **155** for each cluster in clusters **156**. Transformation **155** is an orthographic transformation for registering each cluster in clusters **156** for first image **132** with a corresponding cluster for second image **134**. Transformation **155** may be identified using a least squares algorithm in these depicted examples.

Cluster **157** is an example of one of clusters **156**. Cluster **157** comprises first group of features **159.** "A group of items", as used herein, means one or more items. For example, "a group of features" is one or more features.

Image registration module **126** identifies corresponding cluster **161** for cluster **157**. In particular, image registration module **126** identifies second group of features **163** from second features **138** that correspond to first group of features **159** based on initial correspondence **141**. Second group of features **163** forms corresponding cluster **161**. With initial correspondence being a one-to-one correspondence, the total number of features in first group of features **159** is the same as the total number of features in second group of features **163**.

Image registration module **126** uses transformation **155** identified for cluster **157** to project first group of features **159** onto second image **134.** In particular, first group of features **159** is projected onto second image **134** to align first group of features **159** with second group of features **163** in second image **134**. First group of features **159** is projected onto coordinate system **160** for second image **134** in these illustrative examples.

Image registration module **126** then identifies first group of locations **158** in second image **134** onto which first group of features **159** is projected. First group of locations **158** is defined using coordinate system **160**. Further, second group of features **163** has second group of locations **168** in second image **134** that is also defined using coordinate system **160**.

In these depicted examples, image registration module **126** forms set of clusters **162** from clusters **156**. "A set of items", as used herein, means zero or more items. "A set of items" may be, for example, a null or empty set.

A cluster in clusters **156,** such as cluster **157**, is added to set of clusters **162** when projection error **164** is less than selected threshold **170.** Projection error **164** is an error for aligning first group of features **159** with second group of features **163** in second image **134**. Projection error **164** may be measured in a number of different ways.

For example, projection error **164** may be the sum of the distances between first group of locations **158** for first group of features **159** in cluster **157** and second group of locations **168** for second group of features **163** in corresponding cluster **161**. In some illustrative examples, projection error **164** may be the sum of the distances between first group of locations **158** and second group of locations **168** divided by the total number of features in first group of features **159**.

Image registration module **126** uses set of clusters **162** to identify final transformation **172** for registering first image **132** with second image **134.** In particular, image registration module **126** uses the features included in set of clusters **162** and a random sample consensus (RANSAC) algorithm to identify final transformation **172** for registering first image **132** with second image **134**.

In these illustrative examples, image registration module **126** registers first image **132** with second image **134** using final transformation **172**. Final transformation **172** is an orthographic transformation in these examples. In other words, final transformation **172** aligns first image **132** with second image **134** using only translation and/or rotation.

Final transformation **172** is a refined transformation as compared to initial transformation **142** in these examples. In other words, registration of first image **132** with second image **134** using final transformation **172** may be performed with desired level of accuracy **174**. Desired level of accuracy **174** may be greater than a level of accuracy for registering first image **132** with second image **134** using initial transformation **142**.

In this manner, image processing module **104** provides a system for registering images **110** generated by sensor system **102** with desired level of accuracy **174**. Desired level of accuracy **174** may be greater than the level of accuracy for currently-available methods for registering images.

The illustration of image processing environment **100** in **Figure 1** is not meant to imply physical or architectural limitations to the manner in which an advantageous embodiment may be implemented. Other components in addition to and/or in place of the ones illustrated may be used. Some components may be unnecessary. Also, the blocks are presented to illustrate some functional components. One or more of these blocks may be combined and/or divided into different blocks when implemented in an advantageous embodiment.

For example, in some illustrative examples, feature detection module **124** may be part of image registration module **126**. In other illustrative examples, first image **132** may be registered with a reference image generated by a sensor system other than sensor system **102**. For example, a second sensor system associated with a second platform may be present in image processing environment **100**. Images **110** generated by sensor system **102** may be aligned with a reference image generated using the sensor system.

In still other illustrative examples, initial transformation **142** may be identified using an algorithm other than a random sample consensus algorithm. For example, initial transformation **142** may be identified by matching Fourier contour descriptors for a first number of closed contours identified in first image **132** and a second number of closed contours identified in second image **134**.

With reference now to **Figure 2**, an illustration of features identified in orthorectified images is depicted in accordance with an advantageous embodiment. In this illustrative example, images **200** are examples of orthorectified images **128** in **Figure 1**.

Images **200** include first image **202** and second image **204**. First image **202** is an example of one implementation for first image **132** in **Figure 1**. Second image **204** is an example of one implementation for second image **134** in **Figure 1**. As depicted, first features **206** have been identified in first image **202**. Further, second features **208** have been identified in second image **204**.

With reference now to **Figure 3**, an illustration of features identified from first image **202** and second image **204** in **Figure 2** is depicted in accordance with an advantageous embodiment. In this illustrative example, first features **206** identified from first image **202** in **Figure 2** are superimposed over second features **208** identified from second image **204** in **Figure 2**.

First features **206** are superimposed over second features **208** with respect to a coordinate system for second image **204**. In particular, first features **206** are in locations **300** with respect to a coordinate system for second image **204** prior to first image **202** being registered with second image **204**. Further, second features **208** are in locations **302** with respect to the coordinate system for second image **204**.

In this illustrative example, projected features **304** are the projections of first features **206** onto the coordinate system for second image **204** performed using, for example, final transformation **172** in **Figure 1**. In other words, projected features **304** are first features **206** after first features **206** have been aligned with second features **208** using final transformation **172**.

Projected features **304** are in locations **306**. As depicted, the portion of projected features **304** that are in locations **306** that are within a selected distance from locations **302** for the corresponding portion of second features **208** are considered inliers. A level of accuracy for the alignment of first features **206** with second features **208** may be determined based on the percentage of projected features **304** that are inliers.

With reference now to **Figure 4**, an illustration of first image **202** registered with second image **204** from **Figure 2** is depicted in accordance with an advantageous embodiment. In this illustrative example, first image

202 has been registered with second image **204** from **Figure 2** using final transformation **172** in **Figure 1**. In this illustrative example, first image **202** is translated, rotated, and then overlaid on second image **204**. As depicted, after first image **202** is registered with second image **204**, first image **202** and second image **204** share coordinate system **400**.

Turning now to **Figure 5**, an illustration of features identified in images is depicted in accordance with an advantageous embodiment. In this illustrative example, features **502** are identified for a first image, such as first image **132** in **Figure 1**. Features **504** are identified for a second image, such as second image **134** in **Figure 1**.

Additionally, in this depicted example, projected features **506** are the projections of features **502** performed using final transformation **172** in **Figure 1**. As depicted in this illustrative example, a portion of projected features **506** are inliers **508**.

With reference now to **Figure 6**, an illustration of a graph formed using closed contours identified for an image is depicted in accordance with an advantageous embodiment. In this illustrative example, image **600** is an example of one implementation for first image **132** in **Figure 1**.

As depicted in this example, graph **601** is formed using closed contours **602** identified in image **600**. Closed contours **602** are identified for objects in image **600**. For example, closed contour **604** is identified for tree **606** in image **600**.

Further, in this illustrative example, centroids **608** have been identified for closed contours **602**. Graph **601** is formed by connecting centroids **608** to each other using branches **610**. Centroids **608** form the nodes for graph **601**.

In this illustrative example, the lengths for branches **610** may be sorted to identify the longest branches in branches **610**. In particular, the two longest branches in branches **610** are identified. As depicted, branch **612** and branch **614** are the two longest branches. Branch **612** connects centroid **616** for closed contour **604** to centroid **618** for closed contour **620**. Branch **614** connects centroid **616** for closed contour **604** with centroid **622** for closed contour **624**.

Closed contours **604, 618** and **624** at the ends of branch **612** and branch **614** and/or branch **612** and branch **614** may be selected for comparison with closed contours identified in a second image. This comparison may be used to identify an initial transformation for aligning image **600** with the second image.

With reference now to **Figure 7**, an illustration of a flowchart of a process for registering images is depicted in accordance with an advantageous embodiment. The process illustrated in **Figure 7** may be implemented using image processing module **104** in **Figure 1**.

The process begins by identifying first features in a first image and second features in a second image (operation **700**). In this illustrative example, the first image and the second image are orthorectified images. These orthorectified images may be generated by, for example, image adjustment module **122** in **Figure 1,** using images received from a sensor system, such as sensor system **102** in **Figure 1**. The images received from the sensor system are synthetic aperture radar images in this illustrative example.

The process then identifies an initial transformation for registering the first image with the second image (operation **702**). In this illustrative example, operation **702** may be performed using the first features identified in the first image, the second features identified in the second image, and a random sample consensus algorithm. The initial transformation may be used to register the first image with the second image by translating and/or rotating the first image to align with the second image. The initial transformation model has an accuracy for aligning the first image with the second image that is less than a desired level of accuracy.

Next, the process identifies an initial correspondence between the first features in the first image and the second features in the second image using the initial transformation (operation **704**). The process then identifies clusters of the first features in the first image using a minimum spanning tree formed using the first features (operation **706**). Each cluster in the clusters identified comprises a first group of features from the first features.

Thereafter, the process identifies a transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from the second features in the second image using the initial correspondence (operation **708**). In operation **708**, the second group of features that form the corresponding cluster may be identified based on the initial correspondence.

Further, in operation **708,** the transformation projects the first group of features in a cluster onto the second image to align the first group of features in the cluster with the second group of features in the corresponding cluster in the second image. Operation **708** may be performed using a least squares algorithm to identify the best transformation for aligning the first group of features with the second group of features in the second image.

The process adds a cluster in the clusters to a set of clusters when a projection error for the transformation identified for the cluster is less than a selected threshold (operation **710**). In this manner, in performing operation **710**, a set of clusters is identified from the clusters of the first features in the first image. In operation **710,** the projection error identifies the error in aligning the first group of features with the second group of features in the second image when the first group of features is projected onto the second image using the transformation identified for the cluster comprising the first group of features.

Thereafter, the process identifies a final transformation for registering the first image with the second image using features in the set of clusters and a random sample consensus algorithm (operation **712**). The process then registers the first image with the second image using the final transformation (operation **714**), with the process terminating thereafter.

With reference now to **Figure 8**, an illustration of a flowchart of a process for identifying features in an image is depicted in accordance with an advantageous embodiment. The process illustrated in **Figure 8** may be used to implement operation **700** in **Figure 7**.

The process begins by identifying Steger edges in the first image and Steger edges in the second image (operation **800**). Steger edges are edges identified using the Steger algorithm. The process then identifies infinite lines in the first image and infinite lines in the second image using a Hough transform (operation **802**).

Thereafter, the process selects a portion of the infinite lines in the first image to form first lines for the first image using the Steger edges in the first image (operation **804**). The process selects a portion of the infinite lines in the second image to form second lines for the second image using the Steger edges in the second image (operation **806**).

In operation **804** and operation **806**, the selection of the portion of the infinite lines in the first image and the infinite lines in the second image may be performed in a similar manner. In particular, an infinite line is selected when a desired amount of alignment between the infinite line and a Steger edge is present.

Next, the process identifies intersections of lines in the first lines for the first image to form first features for the first image and intersections of lines in the second lines for the second image to form second features for the second image (operation **808**), with the process terminating thereafter. The first features and the second features may be referred to as point features in this illustrative example.

With reference now to **Figure 9**, an illustration of a flowchart of a process for identifying an initial transformation for registering a first image with a second image is depicted in accordance with an advantageous embodiment. The process illustrated in **Figure 9** may be used in implementing operation **702** in **Figure 7**.

The process begins by identifying first closed contours in the first image and second closed contours in the second image (operation **900**). The first closed contours and the second closed contours are identified for objects that are present in the first image and the second image, respectively.

Operation **900** may be performed using currently-available methods for identifying closed contours, such as, for example, a linking algorithm for forming a chain of connected pixels. In these illustrative examples, a closed contour is a continuous closed curve. In other illustrative examples, a closed contour may be a discontinuous closed curve. In other words, gaps may be present in the closed curve.

Next, the process identifies first centroids for the first closed contours and second centroids for the second closed contours (operation **902**). The process then connects the first centroids to each other using first branches to form a first graph (operation **904**). The process connects the second centroids to each other using second branches to form a second graph (operation **906**).

Thereafter, the process identifies and sorts lengths of the first branches and lengths of the second branches (operation **908**). The process then selects a number of the first branches having the longest lengths of the first branches to form first selected branches (operation **910**).

In operation **910**, the two branches having the longest lengths may be selected. In some illustrative examples, the three branches having the longest lengths may be selected. Of course, any number of the first branches having the longest lengths may be selected.

The process then selects each branch in the second branches having a length greater than a selected length to form second selected branches (operation **912**). The selected length is shorter than the length of the shortest branch in the first selected branches in this illustrative example. In this manner, the number of branches in the second selected branches may be greater than the number of branches in the first selected branches.

Next, the process identifies a number of combinations of the second selected branches (operation **914**). In operation **914**, each combination of the second selected branches has a number of branches equal to the number of branches in the first selected branches. The process selects a particular combination of branches in the number of combinations for processing (operation **916**).

The process then compares a first number of properties for the first selected branches with a second number of properties for the particular combination of branches selected to identify a matching score (operation **918**). The first number of properties and the second number of properties may include at least one of, for example, without limitation, a length of the branches, a number of angles between branches, Fourier contour descriptors for the closed contours at the ends of the branches, and other suitable types of properties.

Fourier contour descriptors comprise numbers that describe a shape of a closed contour and do not vary substantially when the shape is translated and/or rotated. Further, these descriptors do not vary substantially with respect to scale.

In operation **918**, the comparison between these properties may be performed using a matching algorithm that calculates the matching score. The matching score measures how closely the first number of properties and the second number of properties match. In other words, the matching score measures how similar the first number of properties for the first selected branches is to the second number of properties for the particular combination of branches selected.

The matching algorithm for calculating the matching score may comprise the following equations:

$$D = E + \sum S_i \text{, and}$$

$$E = \sum p_j,$$

where D is the matching score; E is a sum of the distances between locations of the first centroids for the first closed contours at the ends of the first selected branches and the locations of the corresponding second centroids for the second closed contours at the ends of the branches in the particular combination of branches selected; S_i is a difference score between the Fourier contour descriptors for the first closed contours at the ends of the first selected branches and the Fourier contour descriptors for the second closed contours at the ends of the branches in the particular combination of branches selected; and p is a distance between a location for the jth first centroid in the first image and a location for the corresponding second centroid in the second image.

The process then determines whether the matching score is greater than a selected threshold (operation **920**). If the matching score is greater than the selected threshold, the process identifies a transformation for aligning the first closed contours at the ends of the first selected branches with the second closed contours at the ends of the branches in the particular combination of branches selected (operation **922**), with the process terminating thereafter. This transformation is the initial transformation for registering the first image with the second image identified in operation **702** in **Figure 7**.

With reference again to operation **920**, if the matching score is less than the selected threshold, the process determines whether any additional unprocessed combinations in the number of combinations identified are present (operation **924**). If no additional unprocessed combinations are present, the process terminates. Otherwise, the process returns to operation **916** as described above.

With reference now to **Figure 10**, an illustration of a flowchart of a process for identifying an initial correspondence between first features in a first image and second features in a second image is depicted in accordance with an advantageous embodiment. The process illustrated in **Figure 10** may be used to implement operation **704** in **Figure 7**.

The process begins by projecting the first features identified in the first image onto the second image using the initial transformation (operation **1000**). The process then selects a feature from the first features identified in the first image as a first selected feature (operation **1002**).

Next, the process identifies a feature from the second features in the second image as a second selected feature (operation **1004**). In operation **1004**, the feature identified from the second features as the second selected feature is the feature having a location in the second image that is closer to a location of the selected feature projected onto the second image than any of the locations of the other features in the second features.

The process then determines whether a difference between a value for the first selected feature in the second image and a value for the second selected feature in the second image features is less than a selected threshold (operation **1006**). When the first selected feature and the second selected feature are point features, the values for these features may be the values of the pixels at the locations of these features.

If the difference is less than the selected threshold, the process identifies a correspondence between the first selected feature and the selected feature for forming an initial correspondence between the first features in the first image and the second features in the second image (operation **1008**).

The process then determines whether any additional unprocessed features from the first features are present (operation **1010**). If no additional unprocessed features are present, the process terminates. Otherwise, the process returns to operation **1002** as described above.

With reference again to operation **1006**, if the difference is not less than the selected threshold, the process removes the first selected feature from consideration in forming the initial correspondence (operation **1012**). In this manner, not all of the first features identified in the first image may be identified as having a corresponding feature in the second features in the second image. Thereafter, the process proceeds to operation **1010** as described above.

With reference now to **Figure 11**, an illustration of a flowchart of a process for identifying clusters of first features identified in a first image is depicted in accordance with an advantageous embodiment. The process illustrated in **Figure 11** may be used to implement operation **706** in **Figure 7**.

The process begins by forming a minimum spanning tree using the first features identified in the first image (operation **1100**). The minimum spanning tree comprises nodes and a number of branches. Each node in the nodes is a feature in the first features, and each branch in the number of branches has a weight. The process then removes all branches in the number of branches having a weight greater than a selected weight from the minimum spanning tree to form the clusters of the first features (operation **1102**), with the process terminating thereafter.

With reference now to **Figure 12**, an illustration of a flowchart of a process for identifying a set of clusters from clusters of first features in a first image is depicted in accordance with an advantageous embodiment. The process illustrated in **Figure 12** may be used to implement operation **710** in **Figure 7**.

The process begins by selecting a cluster from the clusters for processing (operation **1200**). The process then projects the first group of features in the cluster onto the second image using the transformation identified for the selected cluster (operation **1202**). The process identifies a first group of locations in the second image onto which the first group of features are projected (operation **1204**). The first group of locations is defined with respect to a coordinate system for the second image.

The process identifies a second group of locations for the second group of features in the second image corresponding to the first group of features (operation **1206**). The process then identifies a projection error based on distances between locations in the first group of locations and corresponding locations in the second group of locations (operation **1208**).

Next, the process determines whether the projection error is less than a selected threshold (operation **1210**). If the projection error is less than selected threshold, the process adds the selected cluster to a set of clusters (operation **1212**). The process then determines whether any additional unprocessed clusters are present (operation **1214**). If no additional unprocessed clusters are present, the process terminates. Otherwise, the process returns to operation **1200** as described above.

With reference again to operation **1210**, if the projection error is not less than the selected threshold, the process proceeds to operation **1214** as described above.

The flowcharts and block diagrams in the different depicted embodiments illustrate the architecture, functionality, and operation of some possible implementations of apparatuses and methods in an advantageous embodiment. In this regard, each block in the flowcharts or block diagrams may represent a module, segment, function, and/or a portion of an operation or step. For example, one or more of the blocks may be implemented as program code, in hardware, or a combination of the program code and hardware. When implemented in hardware, the hardware may, for example, take the form of integrated circuits that are manufactured or configured to perform one or more operations in the flowcharts or block diagrams.

In some alternative implementations of an advantageous embodiment, the function or functions noted in the block may occur out of the order noted in the figures. For example, in some cases, two blocks shown in succession may be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. Also, other blocks may be added in addition to the illustrated blocks in a flowchart or block diagram.

Turning now to **Figure 13**, an illustration of a data processing system is depicted in accordance with an advantageous embodiment. In this illustrative example, data processing system **1300** may be used to implement one or more of number of computers **120** in computer system **118** in **Figure 1**.

As depicted, data processing system **1300** includes communications fabric **1302**, which provides communications between processor unit **1304**, memory **1306**, persistent storage **1308**, communications unit **1310**, input/output (I/O) unit **1312**, and display **1314**.

Processor unit **1304** serves to execute instructions for software that may be loaded into memory **1306**. Processor unit **1304** may be a number of processors, a multi-processor core, or some other type of processor, depending on the particular implementation. A number, as used herein with reference to an item, means one or more items. Further, processor unit **1304** may be implemented using a number of heterogeneous processor systems in which a main processor is present with secondary processors on a single chip. As another illustrative example, processor unit **1304** may be a symmetric multi-processor system containing multiple processors of the same type.

Memory **1306** and persistent storage **1308** are examples of storage devices **1316**. A storage device is any piece of hardware that is capable of storing information, such as, for example, without limitation, data, program code in functional form, and/or other suitable information either on a temporary basis and/or a permanent basis. Storage devices **1316** may also be referred to as computer readable storage devices in these examples. Memory **1306**, in these examples, may be, for example, a random access memory or any other suitable volatile or non-volatile storage device. Persistent storage **1308** may take various forms, depending on the particular implementation.

For example, persistent storage **1308** may contain one or more components or devices. For example, persistent storage **1308** may be a hard drive, a flash memory, a rewritable optical disk, a rewritable magnetic tape, or some combination of the above. The media used by persistent storage **1308** also may be removable. For example, a removable hard drive may be used for persistent storage **1308**.

Communications unit **1310**, in these examples, provides for communications with other data processing systems or devices. In these examples, communications unit **1310** is a network interface card. Communications unit **1310** may provide communications through the use of either or both physical and wireless communications links.

Input/output unit **1312** allows for input and output of data with other devices that may be connected to data processing system **1300**. For example, input/output unit **1312** may provide a connection for user input through a keyboard, a mouse, and/or some other suitable input device. Further, input/output unit **1312** may send output to a printer. Display **1314** provides a mechanism to display information to a user.

Instructions for the operating system, applications, and/or programs may be located in storage devices **1316**, which are in communication with processor unit **1304** through communications fabric **1302**. In these illustrative examples, the instructions are in a functional form on persistent storage **1308**. These instructions may be loaded into memory **1306** for execution by processor unit **1304**. The processes of the different embodiments may be performed by processor unit **1304** using computer-implemented instructions, which may be located in a memory, such as memory **1306**.

These instructions are referred to as program code, computer usable program code, or computer readable program code that may be read and executed by a processor in processor unit **1304**. The program code in the different embodiments may be embodied on different physical or computer readable storage media, such as memory **1306** or persistent storage **1308**.

Program code **1318** is located in a functional form on computer readable media **1320** that is selectively removable and may be loaded onto or transferred to data processing system **1300** for execution by processor unit **1304**. Program code **1318** and computer readable media **1320** form computer program product **1322** in these examples. In one example, computer readable media **1320** may be computer readable storage media **1324** or computer readable signal media **1326**.

Computer readable storage media **1324** may include, for example, an optical or magnetic disk that is inserted or placed into a drive or other device that is part of persistent storage **1308** for transfer onto a storage device, such as a hard drive, that is part of persistent storage **1308**. Computer readable storage media **1324** also may take the form of a persistent storage, such as a hard drive, a thumb drive, or a flash memory, that is connected to data processing system **1300**. In some instances, computer readable storage media **1324** may not be removable from data processing system **1300**.

In these examples, computer readable storage media **1324** is a physical or tangible storage device used to store program code **1318** rather than a medium that propagates or transmits program code **1318**. Computer readable storage media **1324** is also referred to as a computer readable tangible storage device or a computer readable physical storage device. In other words, computer readable storage media **1324** is media that can be touched by a person.

Alternatively, program code **1318** may be transferred to data processing system **1300** using computer readable signal media **1326**. Computer readable signal media **1326** may be, for example, a propagated data signal containing program code **1318**. For example, computer readable signal media **1326** may be an electromagnetic signal, an optical signal, and/or any other suitable type of signal. These signals may be transmitted over communications links, such as wireless communications links, optical fiber cable, coaxial cable, a wire, and/or any other suitable type of communications link. In other words, the communications link and/or the connection may be physical or wireless in the illustrative examples.

In some advantageous embodiments, program code **1318** may be downloaded over a network to persistent storage **1308** from another device or data processing system through computer readable signal media **1326** for use within data processing system **1300**. For instance, program code stored in a computer readable storage medium in a server data processing system may be downloaded over a network from the server to data processing system **1300**. The data processing system providing program code **1318** may be a server computer, a client computer, or some other device capable of storing and transmitting program code **1318**.

The different components illustrated for data processing system **1300** are not meant to provide architectural limitations to the manner in which different embodiments may be implemented. The different advantageous embodiments may be implemented in a data processing system including components in addition to or in place of those illustrated for data processing system **1300**. Other components shown in **Figure 13** can be varied from the illustrative examples shown. The different embodiments may be implemented using any hardware device or system capable of running program code. As one example, the data processing system may include organic components integrated with inorganic components and/or may be comprised entirely of organic components excluding a human being. For example, a storage device may be comprised of an organic semiconductor.

In another illustrative example, processor unit **1304** may take the form of a hardware unit that has circuits that are manufactured or configured for a particular use. This type of hardware may perform operations without needing program code to be loaded into a memory from a storage device to be configured to perform the operations.

For example, when processor unit **1304** takes the form of a hardware unit, processor unit **1304** may be a circuit system, an application specific integrated circuit (ASIC), a programmable logic device, or some other suitable type of hardware configured to perform a number of operations. With a programmable logic device, the device is configured to perform the number of operations. The device may be reconfigured at a later time or may be permanently configured to perform the number of operations. Examples of programmable logic devices include, for example, a programmable logic array, a programmable array logic, a field programmable logic array, a field programmable gate array, and other suitable hardware devices. With this type of implementation, program code **1318** may be omitted, because the processes for the different embodiments are implemented in a hardware unit.

In still another illustrative example, processor unit **1304** may be implemented using a combination of processors found in computers and hardware units. Processor unit **1304** may have a number of hardware units and a number of processors that are configured to run program code **1318**.

With this depicted example, some of the processes may be implemented in the number of hardware units, while other processes may be implemented in the number of processors.

In another example, a bus system may be used to implement communications fabric **1302** and may be comprised of one or more buses, such as a system bus or an input/output bus. Of course, the bus system may be implemented using any suitable type of architecture that provides for a transfer of data between different components or devices attached to the bus system.

Additionally, a communications unit may include a number of devices that transmit data, receive data, or transmit and receive data. A communications unit may be, for example, a modem or a network adapter, two network adapters, or some combination thereof. Further, a memory may be, for example, memory **1306**, or a cache, such as found in an interface and memory controller hub that may be present in communications fabric **1302**.

Thus, the different advantageous embodiments provide a method and apparatus for registering images. In one advantageous embodiment, a method for processing images is provided. Clusters of first features identified in a first image are identified. Each cluster in the clusters comprises a first group of features from the first features. A transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from second features identified in a second image is identified using an initial correspondence between the first features in the first image and the second features in the second image. A set of clusters from the clusters of the first features is identified using the transformation identified for each cluster. A final transformation for registering the first image with the second image is identified using the set of clusters.

The different advantageous embodiments provide a system for registering images with a desired level of accuracy. This desired level of accuracy is provided even in the presence of non-Gaussian noise in the images.

The description of the different advantageous embodiments has been presented for purposes of illustration and description and is not intended to be exhaustive or limited to the embodiments in the form disclosed. Many modifications and variations will be apparent to those of ordinary skill in the art. Further, different advantageous embodiments may provide different advantages as compared to other advantageous embodiments. The embodiment or embodiments selected are chosen and described in order to best explain the principles of the embodiments, the practical application, and to enable others of ordinary skill in the art to understand the disclosure for various embodiments with various modifications as are suited to the particular use contemplated.

THE EMBODIMENTS OF THE INVENTION IN WHICH AN EXCLUSIVE PROPERTY OR PRIVILEGE IS CLAIMED ARE DEFINED AS FOLLOWS:

1. A method for processing images, the method comprising:

identifying clusters of first features identified in a first image, wherein each cluster in the clusters comprises a first group of features from the first features;

identifying a transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from second features identified in a second image using an initial correspondence between the first features in the first image and the second features in the second image;

identifying a set of clusters from the clusters of the first features using the transformation identified for each cluster;

adding a cluster in the clusters to the set of clusters when a projection error for the transformation identified for the cluster is less than a selected threshold; and

identifying a final transformation for registering the first image with the second image using the set of clusters.

2. The method of claim **1** further comprising:

identifying the initial correspondence between the first features in the first image and the second features in the second image using an initial transformation for registering the first image with the second image.

3. The method of claim **2** further comprising:

identifying the initial transformation for registering the first image with the second image using the first features identified in the first image, the second features identified in the second image, and a random sample consensus algorithm.

4. The method of claim **2** further comprising:

identifying a first number of closed contours in the first image and a second number of closed contours in the second image; and

identifying an initial transformation for registering the first image with the second image using the first number of closed contours, the second number of closed contours, and a matching algorithm.

5. The method of any of claims **1** – **4**, wherein the step of identifying the clusters of the first features identified in the first image comprises:

forming a minimum spanning tree using the first features, wherein the minimum spanning tree comprises nodes and a number of branches in which each node in the nodes is a feature in the first features and each branch in the number of branches has a weight; and removing any branch in the number of branches from the minimum spanning tree when the weight of the any branch is greater than a selected weight to form the clusters of the first features, wherein each cluster in the clusters comprises the first group of features from the first features.

6. The method of any of claims **1** – **5**, wherein the step of identifying the transformation for registering each cluster in the clusters with the corresponding cluster comprising the second group of features from the second features identified in the second image using the initial correspondence between the first features in the first image and the second features in the second image comprises:

identifying features from the second features identified in the second image that correspond to the first group of features in a cluster in the clusters as the second group of features using the initial correspondence, wherein the second group of features form the corresponding cluster; and

identifying the transformation for registering the cluster with the corresponding cluster using a least squares algorithm, wherein the transformation projects the first group of features in the cluster onto the second image to align the first group of features in the cluster with the second group of features in the corresponding cluster.

7. The method of claim **6**, wherein the step of identifying the set of clusters from the clusters using the transformation identified for each cluster comprises:

identifying a first group of locations in the second image onto which the first group of features is projected using the transformation;

identifying a projection error using distances between the first group of locations for the first group of features and a second group of locations in the second image for the second group of features; and.

8. The method of any of claims **1** – **7**, wherein the step of identifying the final transformation for registering the first image with the second image using the set of clusters comprises:

identifying the final transformation for registering the first image with the second image using features in the set of clusters and a random sample consensus algorithm.

9. The method of any of claims **1** – **8** further comprising:

identifying the first features in the first image and the second features in the second image.

10. The method of claim **9** whereinidentifying the first features in the first image and the second features in the second image comprises:

identifying first lines in the first image and second lines in the second image using a line detection algorithm; and identifying intersections of lines in the first lines as the first features and intersections of lines in the second lines as the second features.

11. The method of any of claims **1 – 10**, wherein the step of identifying the first features in the first image and the second features in the second image is performed using a feature detection module in which the feature detection module uses at least one of a Steger algorithm, a Canny line detection algorithm, an edge detection algorithm, a Hough transform, a scale-invariant feature transform, a speeded up robust features detector, and a Kanade-Lucas-Tomasi transform to identify the first features and the second features.

12. The method of any of claims **1 – 11** further comprising:

registering the first image with the second image using the final transformation to align the first image with the second image with a desired level of accuracy, wherein the first image and the second image are synthetic aperture radar images that are orthorectified.

13. A method for registering images, the method comprising using a processing module in a computer system for:

identifying first features in a first image in the images and second features in a second image in the images;

identifying an initial transformation for registering the first image with the second image using the first features and the second features;

identifying an initial correspondence between the first features in the first image and the second features in the second image using the initial transformation for registering the first image with the second image;

identifying clusters of the first features in the first image using a minimum spanning tree formed using the first features, wherein each cluster in the clusters comprises a first group of features from the first features;

identifying a transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from the second features identified in the second image using the initial correspondence;

adding a cluster in the clusters to a set of clusters when a projection error for the transformation identified for the cluster is less than a selected threshold;

identifying a final transformation for registering the first image with the second image using features in the set of clusters and a random sample consensus algorithm; and

registering the first image with the second image using the final transformation.

14. The method of claim **13**, wherein the first image is a first synthetic aperture radar image and the second image is a second synthetic aperture radar image in which the first synthetic aperture radar image and the second synthetic aperture radar image are orthorectified and wherein the step of registering the first image with the second image using the final transformation comprises:

performing at least one of a translation and a rotation of the first image using the final transformation to align the first image with the second image with a desired level of accuracy.

15. An apparatus comprising an image processing module configured to:

identify clusters of first features identified in a first image, wherein each cluster in the clusters comprises a first group of features from first features;

identify a transformation for registering each cluster in the clusters with a corresponding cluster comprising a second group of features from second features identified in a second image using an initial correspondence between the first features in the first image and the second features in the second image;

identify a set of clusters from the clusters of the first features using the transformation identified for each cluster;

add a cluster in the clusters to the set of clusters when a projection error for the transformation identified for the cluster is less than a selected threshold; and identify a final transformation for registering the first image with the second image using the set of clusters.

16. The apparatus of claim **15** wherein the image processing module is configured to identify the clusters of the first features identified in the first image by:

forming a minimum spanning tree using the first features, wherein the minimum spanning tree comprises nodes and a number of branches in which each node in the nodes is a feature in the first features and each branch in the number of branches has a weight; and

removing any branch in the number of branches from the minimum spanning tree when the weight of the any branch is greater than a selected weight to form the clusters of the first features, wherein each cluster in the clusters comprises the first group of features from the first features.

17. The apparatus of claim **15**, wherein the image processing module further comprises:

a feature detection module in the image processing module, wherein the feature detection module is configured to identify the first features in the first image and the second features in the second image.

18. The apparatus of claim **15**, wherein the image processing module further comprises:

a sensor system in communication with the image processing module, wherein the sensor system is configured to generate the first image and the second image.

Application number / numéro de demande: 2776129

Figures:

Pages: 2/12, 3/12, 4/12, 5/12, 6/12

Unscannable items
received with this application
(Request original documents in File Prep. Section on the 10th floor)

Documents reçu avec cette demande ne pouvant être balayés
(Commander les documents originaux dans la section de préparation des dossiers au
10ème étage)

FIG. 1

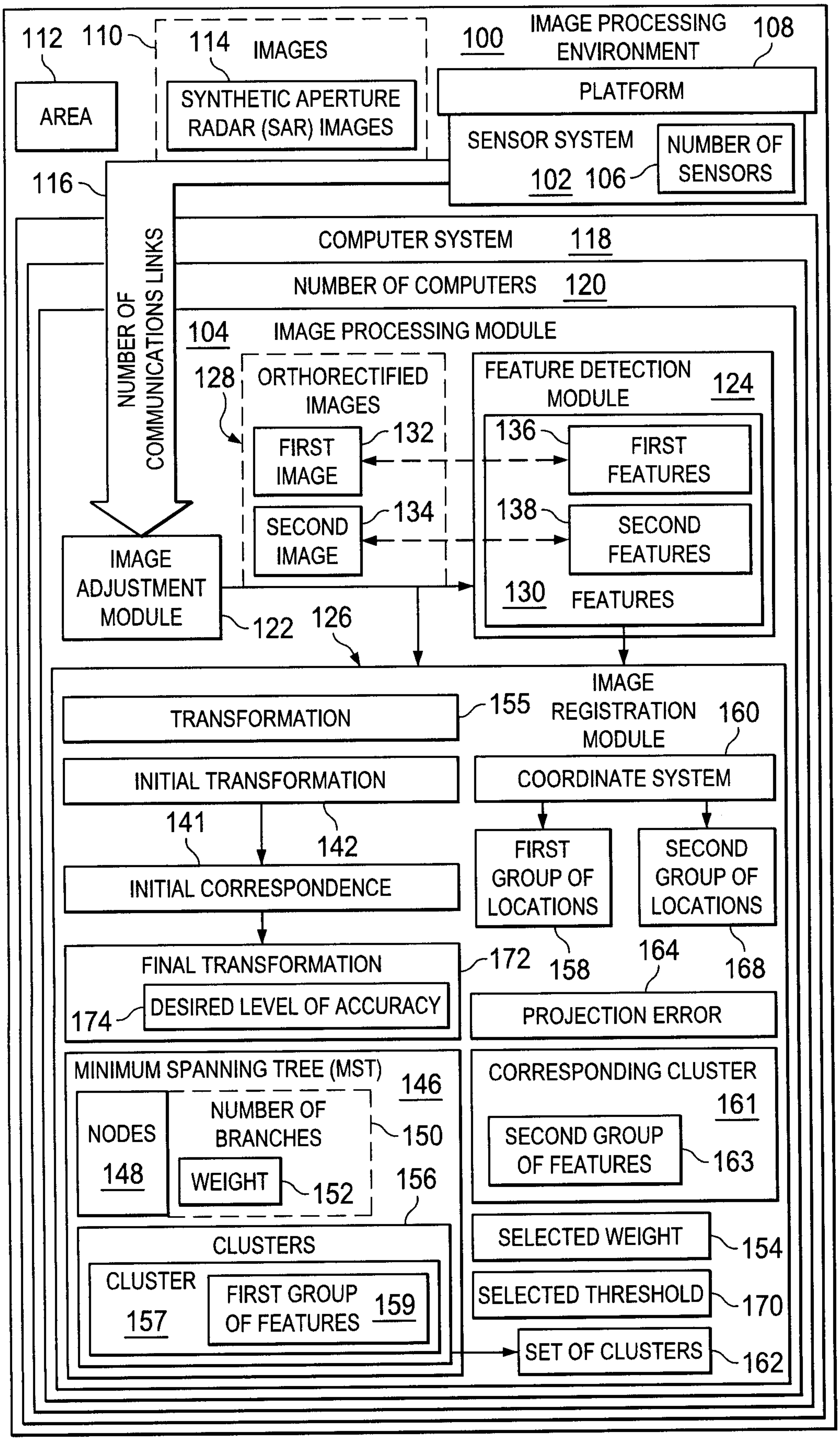


IMAGE PROCESSING ENVIRONMENT
100
AREA
112
110
IMAGES
114
SYNTHETIC APERTURE RADAR (SAR) IMAGES
108
PLATFORM
SENSOR SYSTEM
102
NUMBER OF SENSORS
106
116
NUMBER OF COMMUNICATIONS LINKS
COMPUTER SYSTEM
118
NUMBER OF COMPUTERS
120
IMAGE PROCESSING MODULE
104
ORTHORECTIFIED IMAGES
128
FIRST IMAGE
132
SECOND IMAGE
134
FEATURE DETECTION MODULE
124
136
FIRST FEATURES
138
SECOND FEATURES
130
FEATURES
IMAGE ADJUSTMENT MODULE
122
126
TRANSFORMATION
155
IMAGE REGISTRATION MODULE
160
INITIAL TRANSFORMATION
COORDINATE SYSTEM
141
142
INITIAL CORRESPONDENCE
FIRST GROUP OF LOCATIONS
SECOND GROUP OF LOCATIONS
158
168
164
FINAL TRANSFORMATION
172
DESIRED LEVEL OF ACCURACY
174
PROJECTION ERROR
MINIMUM SPANNING TREE (MST)
146
NODES
148
NUMBER OF BRANCHES
150
WEIGHT
152
156
CORRESPONDING CLUSTER
161
SECOND GROUP OF FEATURES
163
SELECTED WEIGHT
154
CLUSTERS
CLUSTER
157
FIRST GROUP OF FEATURES
159
SELECTED THRESHOLD
170
SET OF CLUSTERS
162

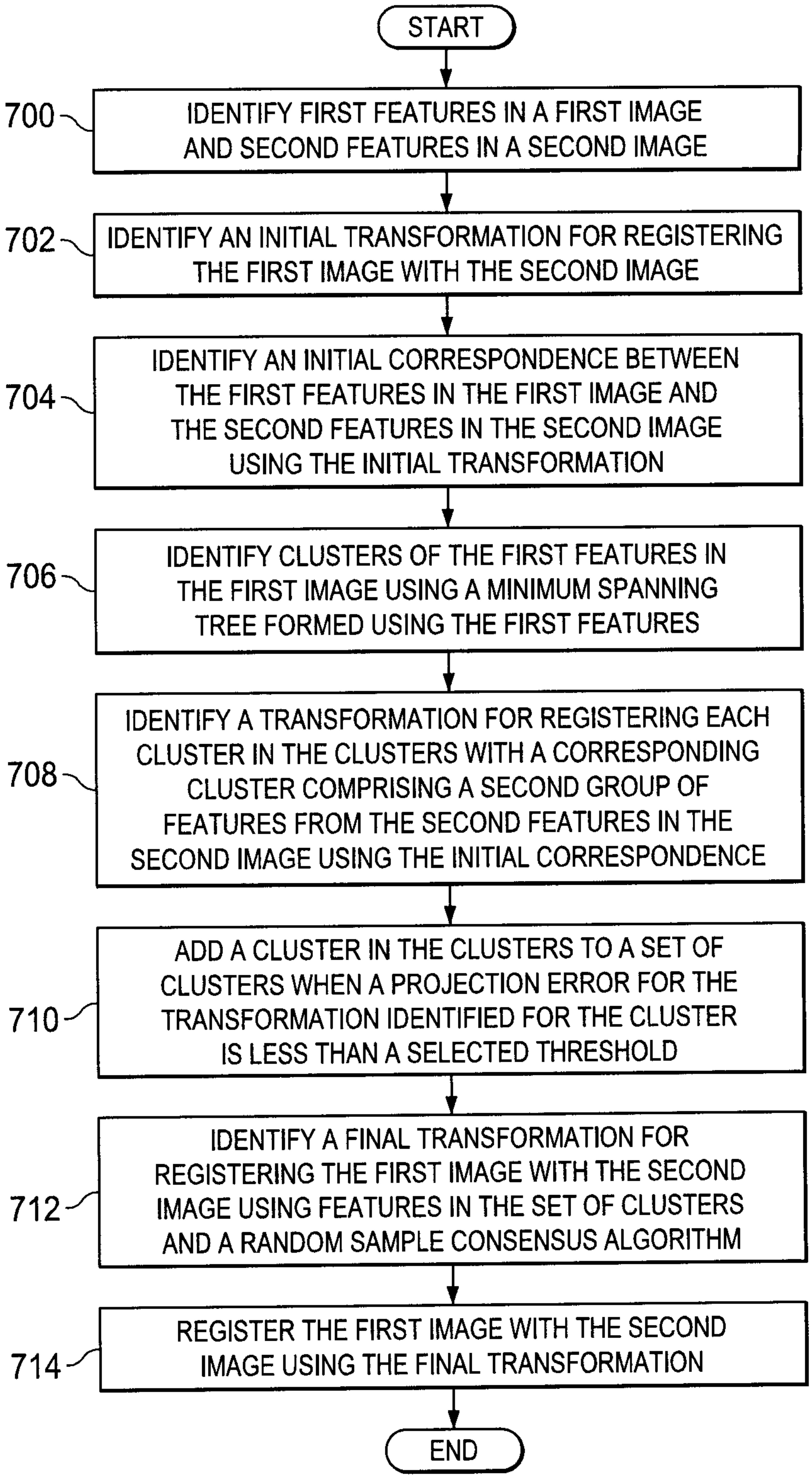

START
700
IDENTIFY FIRST FEATURES IN A FIRST IMAGE AND SECOND FEATURES IN A SECOND IMAGE
702
IDENTIFY AN INITIAL TRANSFORMATION FOR REGISTERING THE FIRST IMAGE WITH THE SECOND IMAGE
704
IDENTIFY AN INITIAL CORRESPONDENCE BETWEEN THE FIRST FEATURES IN THE FIRST IMAGE AND THE SECOND FEATURES IN THE SECOND IMAGE USING THE INITIAL TRANSFORMATION
706
IDENTIFY CLUSTERS OF THE FIRST FEATURES IN THE FIRST IMAGE USING A MINIMUM SPANNING TREE FORMED USING THE FIRST FEATURES
708
IDENTIFY A TRANSFORMATION FOR REGISTERING EACH CLUSTER IN THE CLUSTERS WITH A CORRESPONDING CLUSTER COMPRISING A SECOND GROUP OF FEATURES FROM THE SECOND FEATURES IN THE SECOND IMAGE USING THE INITIAL CORRESPONDENCE
710
ADD A CLUSTER IN THE CLUSTERS TO A SET OF CLUSTERS WHEN A PROJECTION ERROR FOR THE TRANSFORMATION IDENTIFIED FOR THE CLUSTER IS LESS THAN A SELECTED THRESHOLD
712
IDENTIFY A FINAL TRANSFORMATION FOR REGISTERING THE FIRST IMAGE WITH THE SECOND IMAGE USING FEATURES IN THE SET OF CLUSTERS AND A RANDOM SAMPLE CONSENSUS ALGORITHM
714
REGISTER THE FIRST IMAGE WITH THE SECOND IMAGE USING THE FINAL TRANSFORMATION
END

FIG. 7

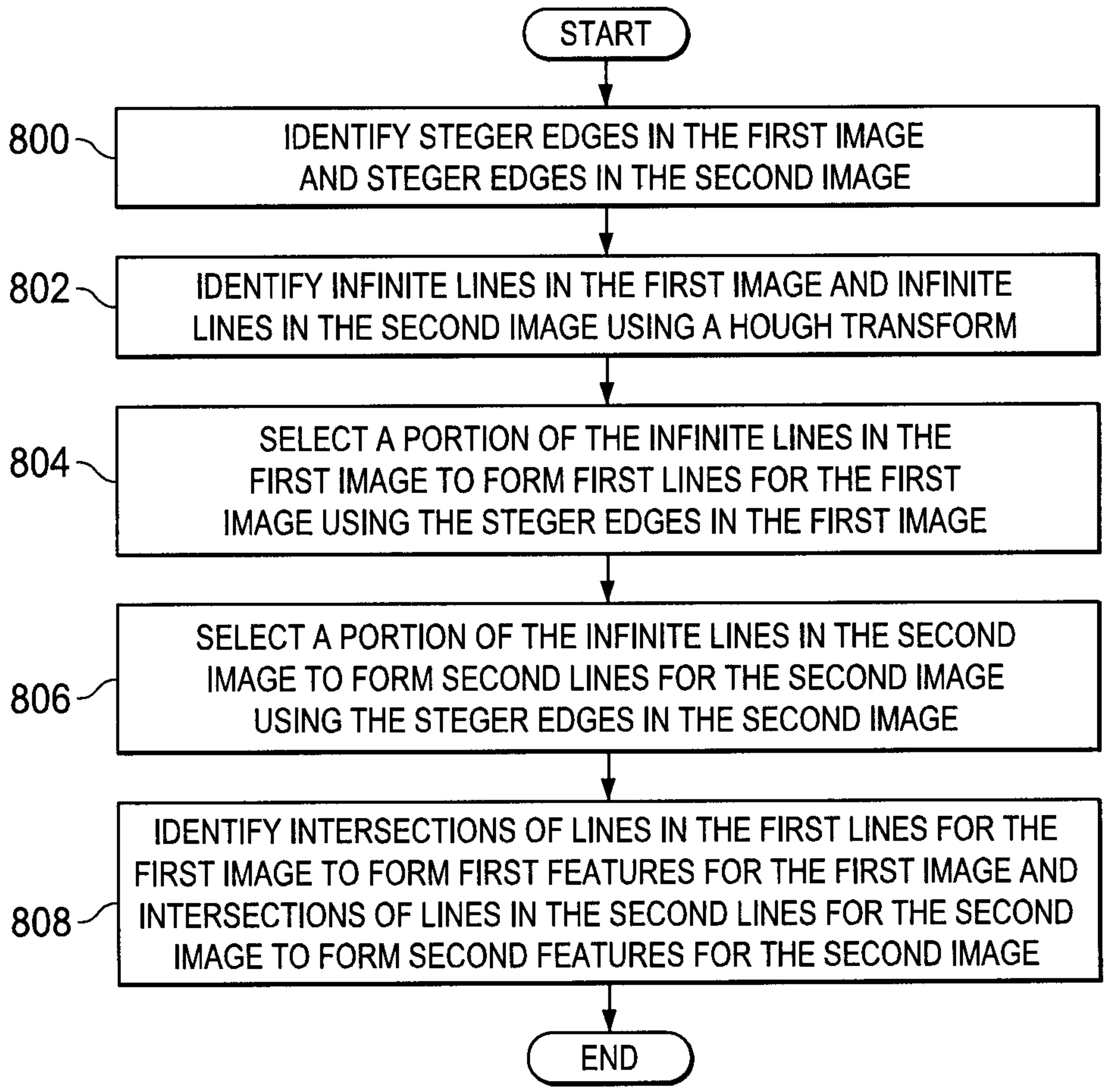

START
800
IDENTIFY STEGER EDGES IN THE FIRST IMAGE AND STEGER EDGES IN THE SECOND IMAGE
802
IDENTIFY INFINITE LINES IN THE FIRST IMAGE AND INFINITE LINES IN THE SECOND IMAGE USING A HOUGH TRANSFORM
804
SELECT A PORTION OF THE INFINITE LINES IN THE FIRST IMAGE TO FORM FIRST LINES FOR THE FIRST IMAGE USING THE STEGER EDGES IN THE FIRST IMAGE
806
SELECT A PORTION OF THE INFINITE LINES IN THE SECOND IMAGE TO FORM SECOND LINES FOR THE SECOND IMAGE USING THE STEGER EDGES IN THE SECOND IMAGE
808
IDENTIFY INTERSECTIONS OF LINES IN THE FIRST LINES FOR THE FIRST IMAGE TO FORM FIRST FEATURES FOR THE FIRST IMAGE AND INTERSECTIONS OF LINES IN THE SECOND LINES FOR THE SECOND IMAGE TO FORM SECOND FEATURES FOR THE SECOND IMAGE
END

FIG. 8

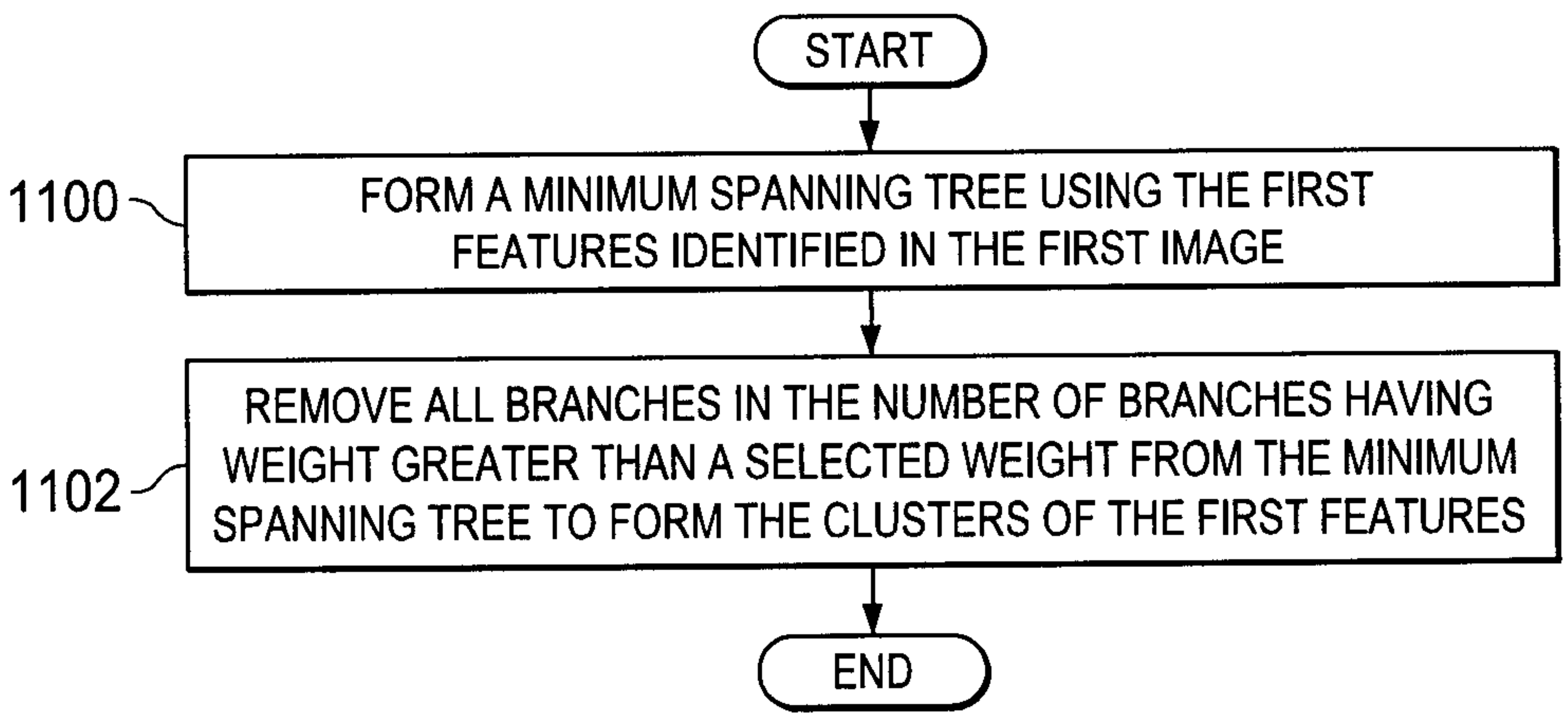

START
1100
FORM A MINIMUM SPANNING TREE USING THE FIRST FEATURES IDENTIFIED IN THE FIRST IMAGE
1102
REMOVE ALL BRANCHES IN THE NUMBER OF BRANCHES HAVING WEIGHT GREATER THAN A SELECTED WEIGHT FROM THE MINIMUM SPANNING TREE TO FORM THE CLUSTERS OF THE FIRST FEATURES
END

FIG. 11

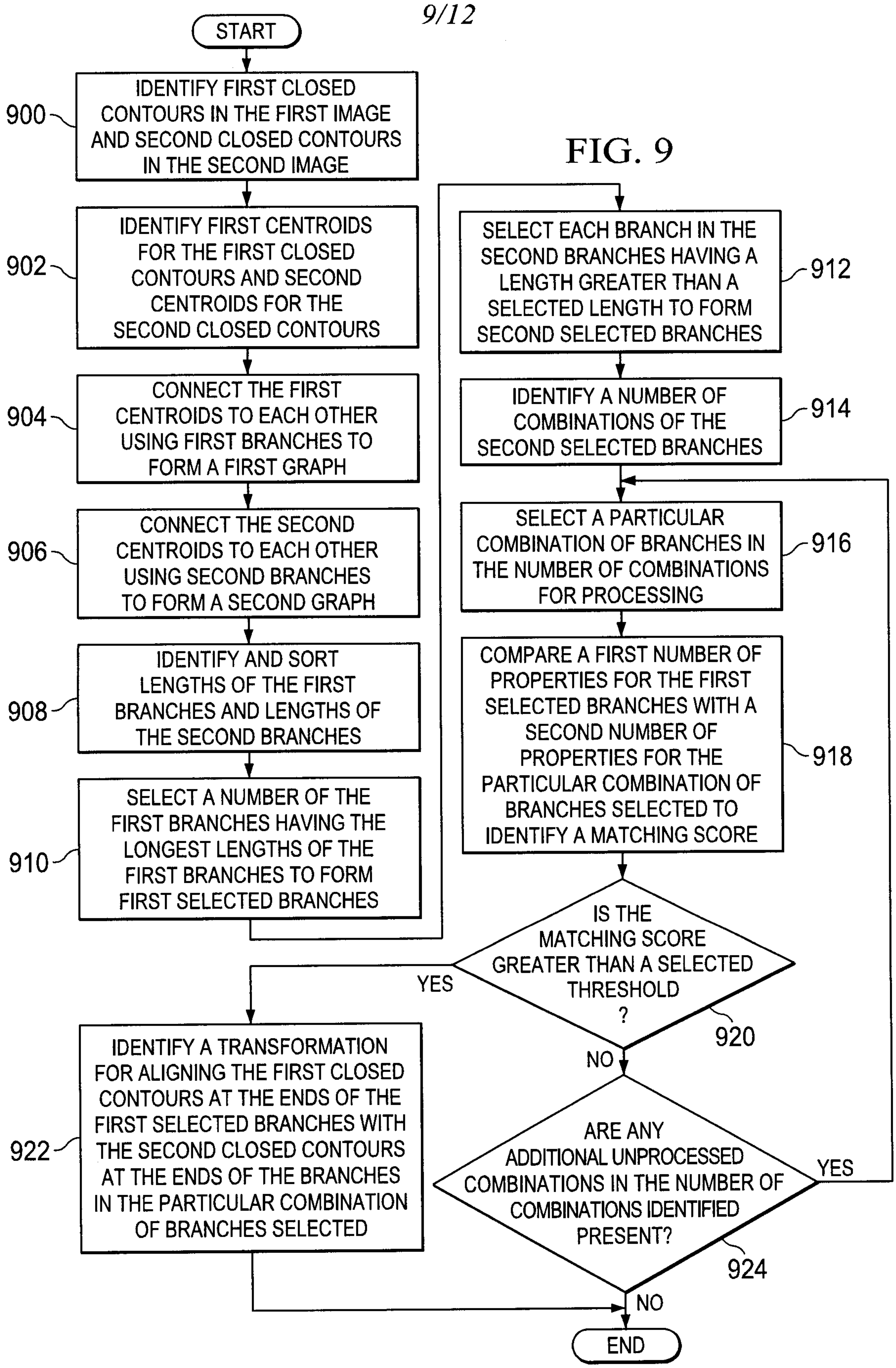

START
IDENTIFY FIRST CLOSED CONTOURS IN THE FIRST IMAGE AND SECOND CLOSED CONTOURS IN THE SECOND IMAGE
900
IDENTIFY FIRST CENTROIDS FOR THE FIRST CLOSED CONTOURS AND SECOND CENTROIDS FOR THE SECOND CLOSED CONTOURS
902
CONNECT THE FIRST CENTROIDS TO EACH OTHER USING FIRST BRANCHES TO FORM A FIRST GRAPH
904
CONNECT THE SECOND CENTROIDS TO EACH OTHER USING SECOND BRANCHES TO FORM A SECOND GRAPH
906
IDENTIFY AND SORT LENGTHS OF THE FIRST BRANCHES AND LENGTHS OF THE SECOND BRANCHES
908
SELECT A NUMBER OF THE FIRST BRANCHES HAVING THE LONGEST LENGTHS OF THE FIRST BRANCHES TO FORM FIRST SELECTED BRANCHES
910
SELECT EACH BRANCH IN THE SECOND BRANCHES HAVING A LENGTH GREATER THAN A SELECTED LENGTH TO FORM SECOND SELECTED BRANCHES
912
IDENTIFY A NUMBER OF COMBINATIONS OF THE SECOND SELECTED BRANCHES
914
SELECT A PARTICULAR COMBINATION OF BRANCHES IN THE NUMBER OF COMBINATIONS FOR PROCESSING
916
COMPARE A FIRST NUMBER OF PROPERTIES FOR THE FIRST SELECTED BRANCHES WITH A SECOND NUMBER OF PROPERTIES FOR THE PARTICULAR COMBINATION OF BRANCHES SELECTED TO IDENTIFY A MATCHING SCORE
918
IS THE MATCHING SCORE GREATER THAN A SELECTED THRESHOLD ?
920
YES
NO
IDENTIFY A TRANSFORMATION FOR ALIGNING THE FIRST CLOSED CONTOURS AT THE ENDS OF THE FIRST SELECTED BRANCHES WITH THE SECOND CLOSED CONTOURS AT THE ENDS OF THE BRANCHES IN THE PARTICULAR COMBINATION OF BRANCHES SELECTED
922
ARE ANY ADDITIONAL UNPROCESSED COMBINATIONS IN THE NUMBER OF COMBINATIONS IDENTIFIED PRESENT?
924
YES
NO
END

FIG. 9

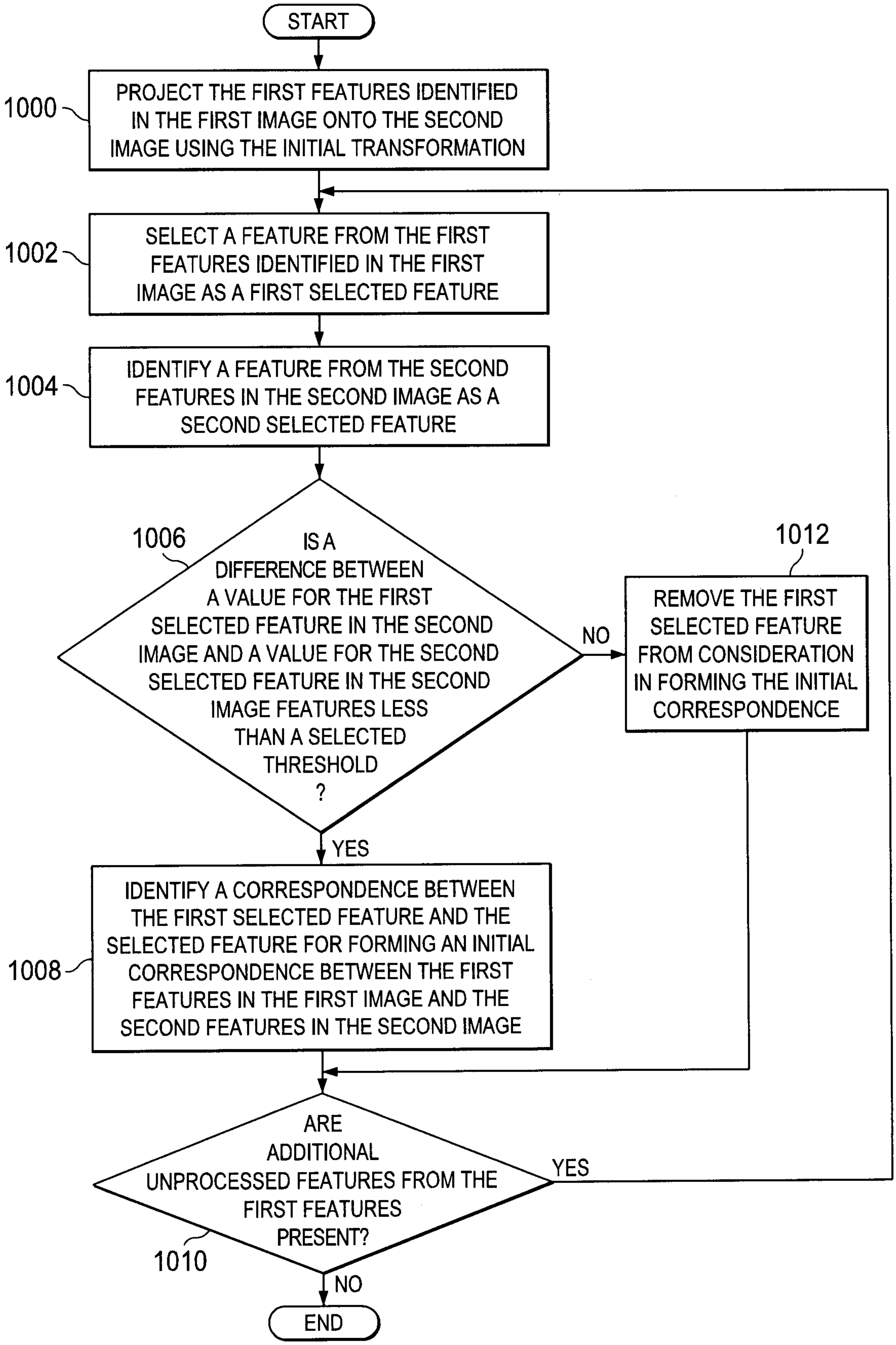

START
PROJECT THE FIRST FEATURES IDENTIFIED IN THE FIRST IMAGE ONTO THE SECOND IMAGE USING THE INITIAL TRANSFORMATION
1000
SELECT A FEATURE FROM THE FIRST FEATURES IDENTIFIED IN THE FIRST IMAGE AS A FIRST SELECTED FEATURE
1002
IDENTIFY A FEATURE FROM THE SECOND FEATURES IN THE SECOND IMAGE AS A SECOND SELECTED FEATURE
1004
IS A DIFFERENCE BETWEEN A VALUE FOR THE FIRST SELECTED FEATURE IN THE SECOND IMAGE AND A VALUE FOR THE SECOND SELECTED FEATURE IN THE SECOND IMAGE FEATURES LESS THAN A SELECTED THRESHOLD ?
1006
NO
REMOVE THE FIRST SELECTED FEATURE FROM CONSIDERATION IN FORMING THE INITIAL CORRESPONDENCE
1012
YES
IDENTIFY A CORRESPONDENCE BETWEEN THE FIRST SELECTED FEATURE AND THE SELECTED FEATURE FOR FORMING AN INITIAL CORRESPONDENCE BETWEEN THE FIRST FEATURES IN THE FIRST IMAGE AND THE SECOND FEATURES IN THE SECOND IMAGE
1008
ARE ADDITIONAL UNPROCESSED FEATURES FROM THE FIRST FEATURES PRESENT?
1010
YES
NO
END

FIG. 10

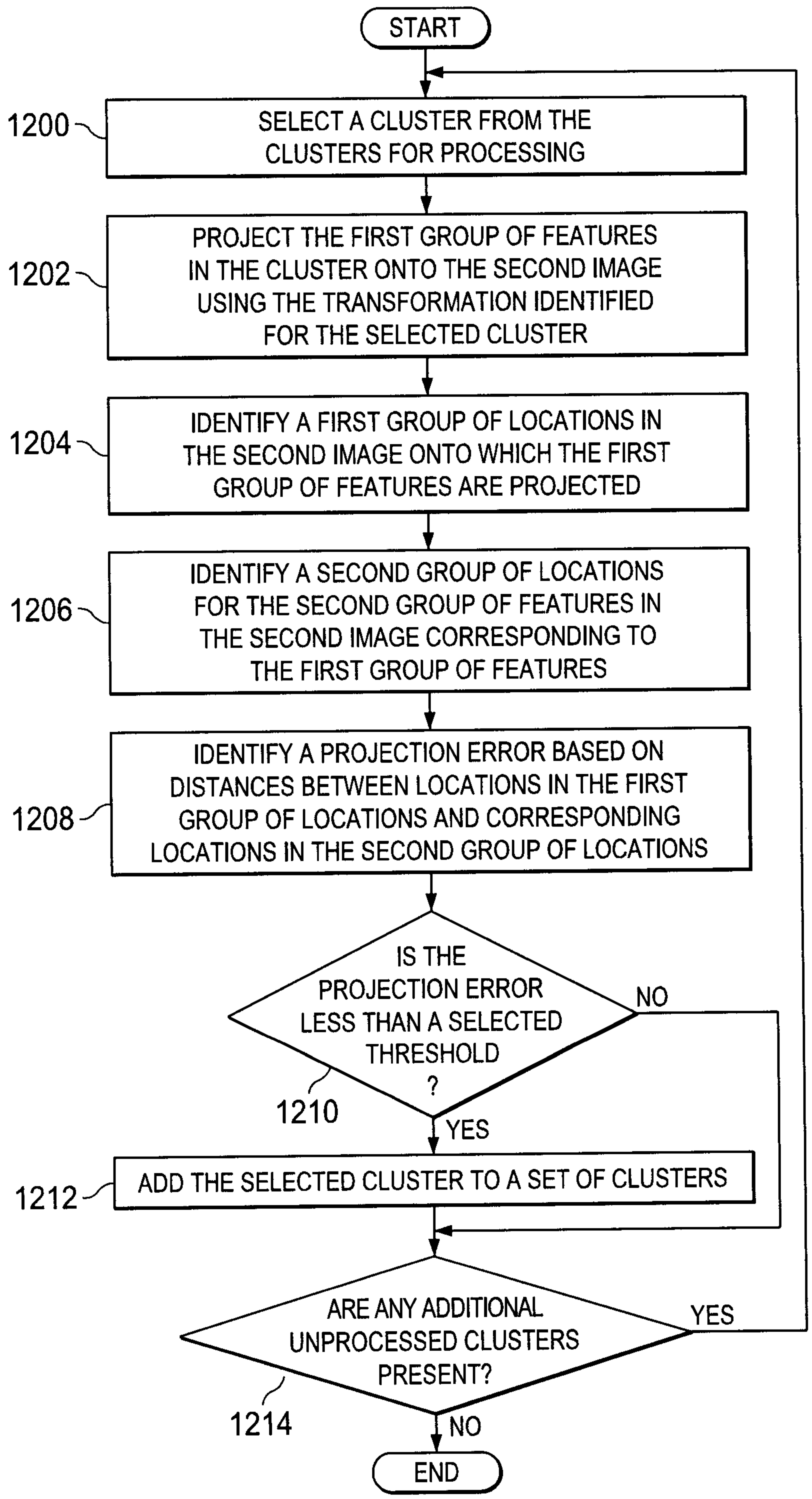
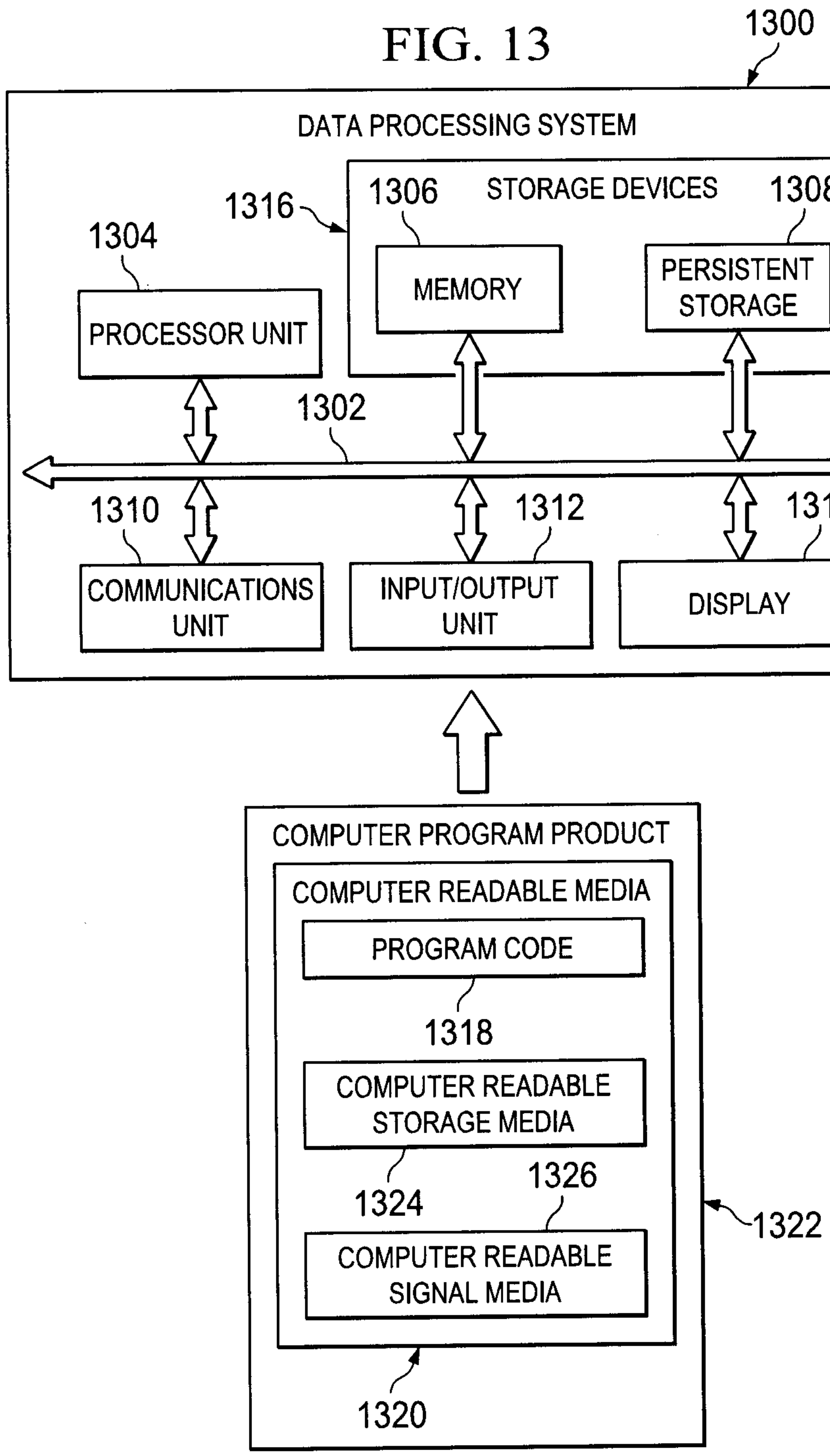
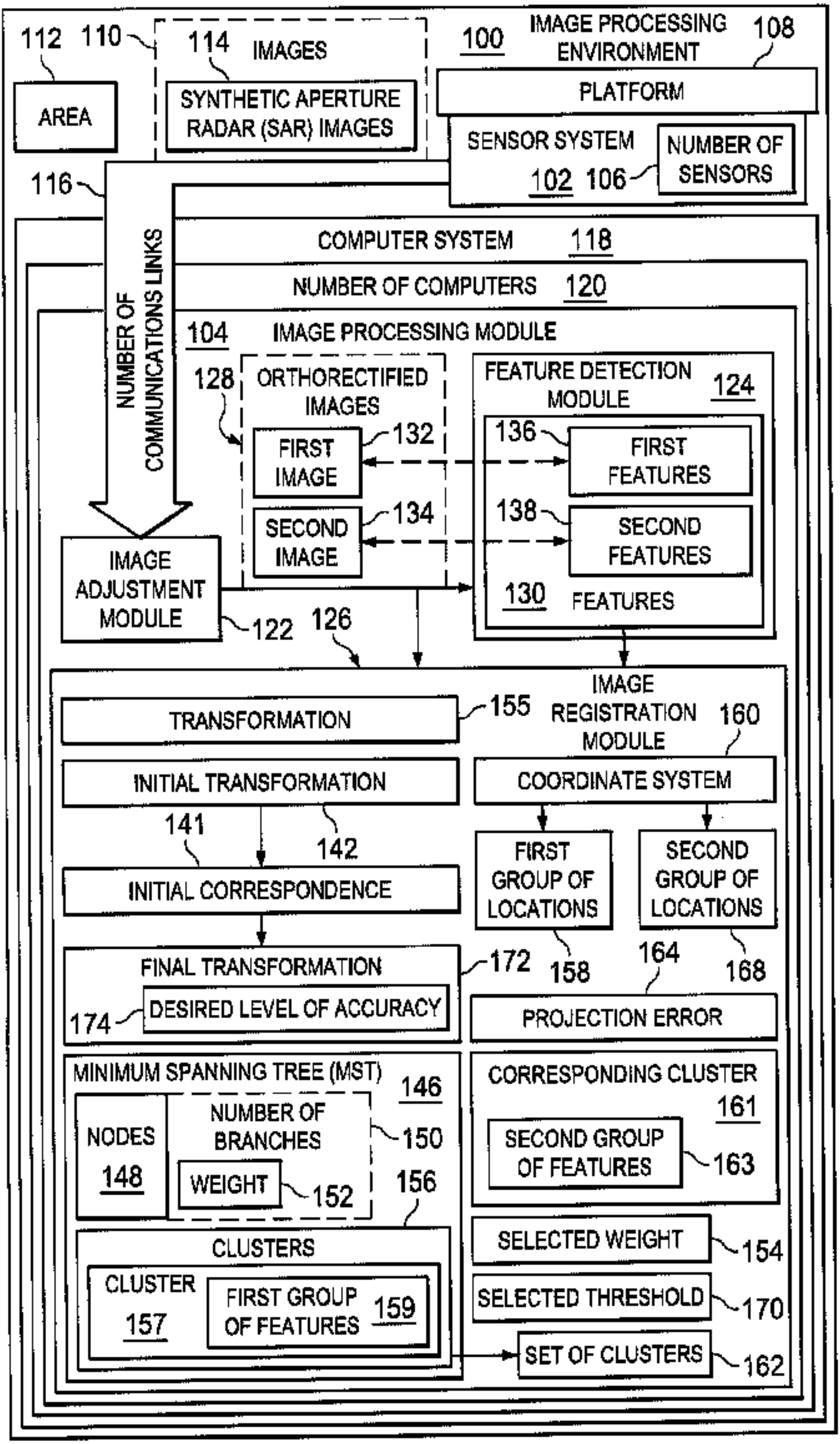

START
1200
SELECT A CLUSTER FROM THE CLUSTERS FOR PROCESSING
1202
PROJECT THE FIRST GROUP OF FEATURES IN THE CLUSTER ONTO THE SECOND IMAGE USING THE TRANSFORMATION IDENTIFIED FOR THE SELECTED CLUSTER
1204
IDENTIFY A FIRST GROUP OF LOCATIONS IN THE SECOND IMAGE ONTO WHICH THE FIRST GROUP OF FEATURES ARE PROJECTED
1206
IDENTIFY A SECOND GROUP OF LOCATIONS FOR THE SECOND GROUP OF FEATURES IN THE SECOND IMAGE CORRESPONDING TO THE FIRST GROUP OF FEATURES
1208
IDENTIFY A PROJECTION ERROR BASED ON DISTANCES BETWEEN LOCATIONS IN THE FIRST GROUP OF LOCATIONS AND CORRESPONDING LOCATIONS IN THE SECOND GROUP OF LOCATIONS
IS THE PROJECTION ERROR LESS THAN A SELECTED THRESHOLD ?
NO
1210
YES
1212
ADD THE SELECTED CLUSTER TO A SET OF CLUSTERS
ARE ANY ADDITIONAL UNPROCESSED CLUSTERS PRESENT?
YES
1214
NO
END

FIG. 12

FIG. 13


1300
DATA PROCESSING SYSTEM
1316
1306
STORAGE DEVICES
1308
1304
MEMORY
PERSISTENT STORAGE
PROCESSOR UNIT
1302
1310
1312
1314
COMMUNICATIONS UNIT
INPUT/OUTPUT UNIT
DISPLAY
COMPUTER PROGRAM PRODUCT
COMPUTER READABLE MEDIA
PROGRAM CODE
1318
COMPUTER READABLE STORAGE MEDIA
1324
1326
1322
COMPUTER READABLE SIGNAL MEDIA
1320


112
110
114
IMAGES
100
IMAGE PROCESSING ENVIRONMENT
108
AREA
SYNTHETIC APERTURE RADAR (SAR) IMAGES
PLATFORM
SENSOR SYSTEM
102
106
NUMBER OF SENSORS
116
NUMBER OF COMMUNICATIONS LINKS
COMPUTER SYSTEM
118
NUMBER OF COMPUTERS
120
104
IMAGE PROCESSING MODULE
128
ORTHORECTIFIED IMAGES
FEATURE DETECTION MODULE
124
FIRST IMAGE
132
136
FIRST FEATURES
SECOND IMAGE
134
138
SECOND FEATURES
IMAGE ADJUSTMENT MODULE
130
FEATURES
122
126
IMAGE REGISTRATION MODULE
TRANSFORMATION
155
160
INITIAL TRANSFORMATION
COORDINATE SYSTEM
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INITIAL CORRESPONDENCE
FIRST GROUP OF LOCATIONS
SECOND GROUP OF LOCATIONS
FINAL TRANSFORMATION
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SECOND GROUP OF FEATURES
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WEIGHT
152
156
CLUSTERS
SELECTED WEIGHT
154
CLUSTER
157
FIRST GROUP OF FEATURES
159
SELECTED THRESHOLD
170
SET OF CLUSTERS
162