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(71) Applicant: MDA SYSTEMS LTD. [CA/CA]; 13800 Commerce Parkway, Richmond, British Columbia V6V 2J3 (CA).

(72) Inventor: CHEN, Ji; c/o MDA Systems Ltd., 13800 Commerce Parkway, Richmond, British Columbia V6V 2J3 (CA).

(74) Agent: HOWE, Kent C.; Own Innovation, 210-137 Glasgow Street, Office 214, Kitchener, Ontario N2G 4X8 (CA).

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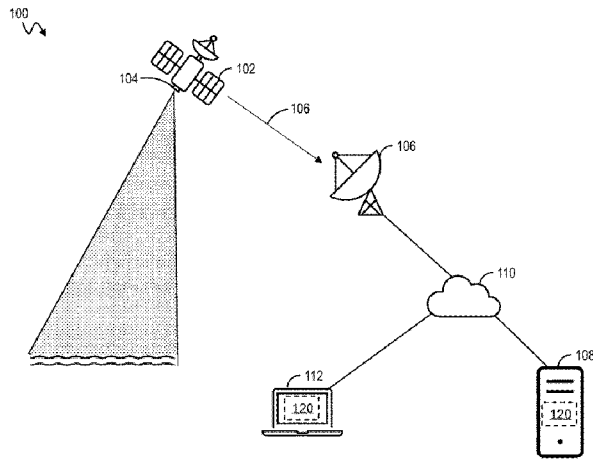


FIG. 1

(57) Abstract: Systems and methods for change detection and classification on SAR imagery are provided. The method includes extracting a first spatial patch as a first image chip from a reference SAR image and a second spatial patch as a second image chip from a comparison SAR image, the first and second spatial patches having the same patch size; generating first and second histograms from the first and second image chips, respectively, the first and second histograms having N bins; determining a first set of N bin variables from the first histogram and a second set of N bin variables from the second histogram; measuring a difference between the first and second sets of bin variables using a separation threshold; generating a similarity image comprising a similarity value indicating a level of similarity between the first and second image chips; and reporting changes to the reference SAR image based on the similarity image.

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SYSTEM AND METHOD FOR CHANGE DETECTION AND CLASSIFICATION ON SAR IMAGERY USING A HISTOGRAM-BASED METHOD

Technical Field

[0001] The following relates generally to change detection and classification on earth observation data, and more particularly to systems and methods for performing change detection and classification tasks on synthetic aperture radar (SAR) imagery.

Introduction

[0002] It is often desired to examine areas of Earth's surface over a period of time to see what changes are indicated and what might be the causes. One way to do this is through the analysis of earth observation data collected by satellite, such as optical and synthetic aperture radar (SAR) imagery. Example potential applications include oceanography (e.g., the detection and characterization of oil spills) and forestry (e.g., forest classification for biomass estimation).

[0003] For oil spills, one of the key oil characteristics is the detection of actionable oil. Actionable oil, which tends to have thickness values greater than approximately 50 μm , refers to areas of an oil spill that can be targeted for the application of dispersants or skimmers. In contrast, non-actionable oil (sheen) cannot be readily cleaned-up. Accordingly, an understanding of oil thickness is desired.

[0004] In order to estimate forest biomass change using remote sensing data, a crucial step is to classify observations into different types of forests.

[0005] High resolution optical data can be used to accurately classify different forest types; however, data can be affected by cloud cover, which limits the ability to monitor large areas regularly.

[0006] It may be desired to monitor forest cover change, such as may result from natural causes, illegal logging, or encroachment. Recently, efforts have been made to extend this service to quantify changes in forest biomass.

[0007] Unlike optical sensors, SAR sensors have the unique advantages of being able to acquire images day and night (24 hours in all weather conditions), and repeatedly capture the images in the same imaging geometry with the same beam mode, which is

important for robust change detection. Combined with wide imaging swaths, this is particularly beneficial for the operational monitoring of biomass changes over large regions.

[0008] When processing SAR imagery, generally, large backscatter changes are easy to detect by comparing individual pixels, such as by setting a high threshold and looking for pixels about that threshold. Example techniques that may be applied include pairwise ACD and persistent change detection (PCD).

[0009] In areas of homogeneous medium backscatter, however, detecting changes by comparing individual pixels can be difficult. For example, setting a medium single threshold may result in many irrelevant decisions and setting a high threshold can produce false negative.

[0010] Accordingly, there is a need for an improved system and method for performing change detection and classification tasks on synthetic aperture radar (SAR) imagery that overcomes at least some of the disadvantages of existing systems and methods.

Summary

[0011] A method of performing change detection and classification on SAR imagery is provided. The method comprises: extracting, by one or more processors, a first spatial patch as a first image chip from a reference SAR image; extracting, by the one or more processors, a second spatial patch as a second image chip from a comparison SAR image, wherein the first and second spatial patches have the same patch size; generating, by the one or more processors, first and second histograms from the first and second image chips, respectively, the first and second histograms having N bins; determining, by the one or more processors, a first set of N bin variables from the first histogram and a second set of N bin variables from the second histogram; measuring, by the one or more processors, a difference between the first and second sets of bin variables using a separation threshold; generating, by the one or more processors, a similarity image comprising a similarity value indicating a level of similarity between the

first and second image chips; and reporting, by the one or more processors, changes to the reference SAR image based on the similarity image.

[0012] The method may be performed for a plurality of spatial patches including the first spatial patch in an area of interest in the comparison image, wherein the plurality of patches are generated by applying a moving window technique to the comparison image.

[0013] The N bin variables may be bin percentages associated with each of the N bins.

[0014] The difference between the first and second sets of bin variables may be measured using a correlation technique.

[0015] The first image chip may be a pre-generated class sample chip obtained from a training image created from a single image or a stack of images.

[0016] The method may further comprise masking out areas in the similarity image using an optimized separation threshold.

[0017] The similarity image may be a maximum similarity image.

[0018] The similarity image may comprise a plurality of pixel values where each pixel value represents a histogram difference between a reference patch and a comparison patch at a pixel location, and wherein the pixel value may be quantified between -1 and 1, wherein a lower value indicates less similarity and a higher value indicates a greater similarity.

[0019] The comparison SAR image may include a plurality of polarization layers and only a subset of the polarization layers are used.

[0020] The reference SAR image may be an average SAR backscatter image generated from a plurality of SAR backscatter images acquired over time.

[0021] The changes to the reference SAR image may be reported as an alert product comprising a masked similarity image displayed in a user interface at a user device.

[0022] The patch size and the separation threshold for classification may be optimized using a point set classification optimization test, wherein the separation threshold is defined as a minimum histogram difference measurement.

[0023] The point set classification optimization test may automatically classify a point set using one or more image chips, specified classes, and test parameters including a candidate patch size, and generates point set classification results.

[0024] The point set classification optimization test may be performed for each of a plurality of candidate patch sizes to determine the patch size.

[0025] The inputs to the point set classification optimization test may include a number of specified classes for classification, a number of points where for each class one selected point is treated as a class sample point, and a specified patch size, and outputs of the point set classification optimization test may include the separation threshold and numbers of total classified points for each class.

[0026] The method may further comprise displaying the point set classification results to a user for confirmation or rejection.

[0027] The method may be used to perform oil spill detection.

[0028] The method may be used to perform forest type classification.

[0029] There is also provided a computer system that comprises at least one processor configured to: extract a first spatial patch as a first image chip from a reference SAR image; extract a second spatial patch as a second image chip from a comparison SAR image, wherein the first and second spatial patches have the same patch size; generate first and second histograms from the first and second image chips, respectively, the first and second histograms having N bins; determine a first set of N bin variables from the first histogram and a second set of N bin variables from the second histogram; measure a difference between the first and second sets of bin variables using a separation threshold; generate a similarity image comprising a similarity value indicating a level of similarity between the first and second image chips; and report changes to the reference SAR image based on the similarity image.

[0030] There is also provided a non-transitory computer readable storage medium storing processor-executable instructions which, when executed by at least one processor, cause the at least one processor to perform a method of performing change detection and classification on SAR imagery. The method comprises: extracting, by one or more processors, a first spatial patch as a first image chip from a reference SAR image; extracting, by the one or more processors, a second spatial patch as a second image chip from a comparison SAR image, wherein the first and second spatial patches have the same patch size; generating, by the one or more processors, first and second histograms from the first and second image chips, respectively, the first and second histograms having N bins; determining, by the one or more processors, a first set of N bin variables from the first histogram and a second set of N bin variables from the second histogram; measuring, by the one or more processors, a difference between the first and second sets of bin variables using a separation threshold; generating, by the one or more processors, a similarity image comprising a similarity value indicating a level of similarity between the first and second image chips; and reporting, by the one or more processors, changes to the reference SAR image based on the similarity image.

[0031] Other aspects and features will become apparent, to those ordinarily skilled in the art, upon review of the following description of some exemplary embodiments.

Brief Description of the Drawings

[0032] The drawings included herewith are for illustrating various examples of articles, methods, and apparatuses of the present specification. In the drawings:

[0033] Figure 1 is a schematic diagram of a system for change detection and classification on SAR imagery, according to an embodiment;

[0034] Figure 2 is a flow diagram of a method of spatial histogram classification of SAR imagery, according to an embodiment;

[0035] Figure 3 is a flow diagram of a method of histogram-based classification of SAR imagery, according to an embodiment;

[0036] Figure 4 is a flow diagram of a method of oil spill detection of SAR imagery, according to an embodiment;

[0037] Figure 5 is a flow diagram of a method of forest classification of SAR imagery for biomass estimation, according to an embodiment

[0038] Figure 6 is a block diagram of a computer system for change detection and classification on SAR imagery using an area-based histogram method, according to an embodiment; and

[0039] Figure 7 shows two example histograms generated and which may be compared using the systems and methods of the present disclosure, according to an embodiment.

Detailed Description

[0040] Various apparatuses or processes will be described below to provide an example of each claimed embodiment. No embodiment described below limits any claimed embodiment and any claimed embodiment may cover processes or apparatuses that differ from those described below. The claimed embodiments are not limited to apparatuses or processes having all of the features of any one apparatus or process described below or to features common to multiple or all of the apparatuses described below.

[0041] One or more systems described herein may be implemented in computer programs executing on programmable computers, each comprising at least one processor, a data storage system (including volatile and non-volatile memory and/or storage elements), at least one input device, and at least one output device. For example, and without limitation, the programmable computer may be a programmable logic unit, a mainframe computer, server, and personal computer, cloud-based program or system, laptop, personal data assistance, cellular telephone, smartphone, or tablet device.

[0042] Each program is preferably implemented in a high-level procedural or object-oriented programming and/or scripting language to communicate with a computer system. However, the programs can be implemented in assembly or machine language, if desired. In any case, the language may be a compiled or interpreted language. Each such computer program is preferably stored on a storage media or a device readable by a general or special purpose programmable computer for configuring and operating the

computer when the storage media or device is read by the computer to perform the procedures described herein.

[0043] A description of an embodiment with several components in communication with each other does not imply that all such components are required. On the contrary, a variety of optional components are described to illustrate the wide variety of possible embodiments of the present invention.

[0044] Further, although process steps, method steps, algorithms or the like may be described (in the disclosure and / or in the claims) in a sequential order, such processes, methods and algorithms may be configured to work in alternate orders. In other words, any sequence or order of steps that may be described does not necessarily indicate a requirement that the steps be performed in that order. The steps of processes described herein may be performed in any order that is practical. Further, some steps may be performed simultaneously.

[0045] When a single device or article is described herein, it will be readily apparent that more than one device / article (whether or not they cooperate) may be used in place of a single device / article. Similarly, where more than one device or article is described herein (whether or not they cooperate), it will be readily apparent that a single device / article may be used in place of the more than one device or article.

[0046] The following relates generally to change detection and classification on Earth's surface using remote sensing data, and more particularly to change detection and classification on Earth's surface using SAR data. Embodiments of the systems and methods use an area-based classification by histogram algorithm.

[0047] The present disclosure uses an area-based method in which change is quantified by an area histogram difference. Typically, changes between two different images are detected by comparing pixel against pixel, which may be referred to as a pixel-based method. In contrast, the area-based method of the present disclosure detects changes between two images using a group of spatial pixels (or "patch" of pixels). The patch of pixels is acquired from the same location in the two images and the results compared.

[0048] The systems and methods of the present disclosure use an area-based histogram algorithm for classification of SAR imagery in which histograms generated from two different SAR images are compared. In an embodiment, rather than comparing the pixel values of two point sets, the algorithm compares a bin percentage difference between the images (or patches) being compared for each bin used to create the histograms. So, if each bin percentage represents one variable and N number of bins are used to create the histograms, then there are N variables to compare. A correlation method is then used to compare the two sets of bin percentage variables.

[0049] According to the present disclosure, a histogram from a sample chip derived from a SAR image is used as a signature for each homogenous ground feature. The change of the histogram is quantified using the area-based histogram comparison method described herein. Embodiments of spatial change detection may be performed by pairs of images, and changes detected by the histogram method may be generated as an alert product to report the changes to the reference image. In other embodiments, pre-generated class sample chips are used which are obtained from a training image which is created by one single image or a stack of images, and classification products are generated by the similarity function from the area-based histogram method.

[0050] The term “patch” as used herein refers to a group of spatial pixels in a SAR image. The patch has a patch size, which may be defined as a number of rows (R) by a number of pixels (P) in each row (e.g., P x R patch size). For example, a patch size of 11x13 has 13 rows, with 11 pixels in each row. Patch size may also be referred to as “window size” and “patch” may be referred to as “window”. In an embodiment, the patch size is determined by applying an optimization test or software tool to a point set classification as described herein. A patch may also be referred to as a “spatial image”, “image chip”, or simply “chip”.

[0051] The term “moving window” as used herein refers to moving the window or patch over the image during the comparison process to collect data from a different subset of pixels in the image. In an embodiment, the moving window means comparing each window after window by moving right one pixel and, if towards the end of the line (or pixel row), then moving the window to the beginning of the next line (pixel row). Comparing two

images for the purpose of change detection or classification includes the use of moving windows taken from each of the images being compared. In some embodiments, such as where a single image detection is being performed, one window from the image is compared to one or more sample chips that each have the same window size.

[0052] The term “similarity image” refers to an output of the comparison of a SAR image to one or more other SAR images or sample chips (derived from SAR images) using the area-based histogram method. The similarity image is generated or determined using the area-based histogram method described herein. In an embodiment, in the similarity image, each pixel value represents the measurements of the specified patch (centered at the pixel location) to a comparison patch. The comparison patch may be a sample chip or a patch with the same patch size and patch location taken from another image. In an embodiment, the value is between -1 and 1, where the smaller the value, the less similar the two patches being compared and the higher the value, the more similar the two patches being compared.

[0053] The term “maximum similarity image” as used herein refers to a particular type of similarity image that may be used when at least one of the defined classes has more than one sample chip. The maximum similarity image is generated by performing the similarity test of the plurality of available sample chips and keeping the maximum value as the output of the test (i.e., the similarity image). The maximum similarity image may have the same content and information contained therein as a similarity image generated using one class sample chip. Like a standard similarity image, the maximum similarity image provides a similarity measurement or value.

[0054] The term “masking” or “masking out” and its variants refers to controlling which pixels in a similarity image are kept and which are not based on a masking threshold. The threshold may be determined from the test using ground truths. Masked out may be unqualified pixels or qualified pixels, depending on the embodiment. Masking out may be applied to or performed on a similarity image generated according to the present disclosure. The threshold used for masking may be determined from a point set classification optimization test, as described herein, which is a supervised classification test. Specified cases are defined by the ground truths. A point set is created to cover all

different classes such that one class is represented by at least one point. Each point is classified into one of the specified classes or belong to an “N/A” class, which cannot be classified by the optimization test using the histogram method. The class separation threshold and numbers of classified points are reported. Finally, the separation threshold is applied to the similarity image to generate a mask image. The mask image may be used as an alert product.

[0055] The term “detection product” or its variants refers to a data structure, such as a file, that includes the location and potential classification information of a detection (i.e., whatever the system is trying to detect or classify). The detection product may be a shape-based vector file. In an oil spill detection application, the detection product may indicate the locations of oil spill alert areas and may report an estimation of oil thickness for detected oil spill areas. The detection product may include a chip image extracted from the SAR image, where the extracted chip image contains the detection (e.g., oil spill). In an oil spill detection application, the detection product may include an oil spill chip image extracted from the compact polarimetry layers of the SAR image. In some cases, a detection product may be referred to as an “alert product”, such as where it alerts a viewer to areas of the image corresponding to detections.

[0056] In embodiments, a detection product may be a raster mask or a shape file that indicates areas of detection in the SAR image (e.g., areas of oil spill detection or alert).

[0057] The term “classification product” or its variants refers to a data structure, such as a file, which visualizes different class assignments or classifications of different portions of the SAR image overlaid the SAR image. For example, the classification product may be a colour coded raster image (where different colours indicate different classifications) or a shape of a classification vector product where each polygon represents one class.

[0058] The term “polarization layer” or “layer” or their variants refer to compact polarimetry layers such as CPR, DCP, DLP, DOP, and H. It should be noted that different SAR polarizations can have a different detection sensitivity. For example, CPR has been determined to be better than other layers for detecting oil spill areas. This requires a solid

knowledge and experience of SAR polarimetry to specify which SAR polarizations are suitable to be used for a certain type of change detection application. In another example, R2 VV is more sensitive to detect young regeneration forest than R2 HH. Therefore, for forest harvest monitoring, it is recommended to acquire VV polarization for the data planning.

[0059] The systems and methods of the present disclosure may be used to perform land cover classification or ocean cover classification. Ocean cover classification may include oil and water classification. Particular embodiments of the systems and methods may be directed to oil spill detection and classification (e.g., thickness estimation) and forest classification for biomass estimation.

[0060] In a particular embodiment, the present disclosure uses an area-based change detection and classification by histogram method to identify oil spill areas and classify different types of oils spills in terms of oil thickness. The method may quantify a difference between an oil spill area and a water area. The method may classify different detected oil spill areas into one of a plurality of oil spill types. The method may do so based on unique signatures in terms of their backscatter histograms in SAR images over different oil spill areas. In a particular embodiment, the system uses compact pol SAR data as input and generate an oil spill area extent and classification of the oil spill over the extent as output.

[0061] In another embodiment, the present disclosure uses an area-based histogram method to classify different types of forest cover in SAR imagery. This may include performing forest classification by multiple SAR polarization bands.

[0062] The present disclosure provides an alternative to pixel-based change detection methods by providing an area-based method or algorithm to quantify a histogram difference between two SAR image spatial patches with the same patch size. One patch may be extracted as an image chip from a reference image. The other patch may be extracted from a comparison image. Rather than comparing the pixel values of two point sets, the algorithm compares a bin percentage difference between the images (or patches) being compared for each bin used to create the histograms. So, if each bin percentage represents one variable and N number of bins are used to create the

histograms, then there are N variables to compare. A correlation method is then used to compare the two sets of bin percentage variables.

[0063] The present disclosure also identifies patch size and separation threshold as important parameters in quantifying the histogram difference and doing accurate classification using the histogram method.

[0064] Patch size plays a significant role in quantifying the histogram difference. While a histogram difference calculated with a smaller patch size may not well represent a typical sample (a unique signature for a specified class), it is very sensitive to the change. A larger patch size can represent the sample well but loses sensitivity. Accordingly, in order to more effectively detect histogram changes, a method of computing an optimal value of the patch size is needed and is provided herein.

[0065] Also, in order to do an accurate classification, the separation threshold parameter is very important. If the separation threshold is too small, two classes may not be separated very well. If the separation threshold is too large, a class may miss lots of areas.

[0066] The present disclosure also provides an optimization function for classifying a point set that can be used to determine an optimized value for the patch size and the separation threshold for the classification by the histogram method. To find an optimized patch size, for each candidate patch size, a point classification optimization test is conducted. From all tests with all different patch sizes, the optimal patch size is selected.

[0067] In an embodiment, the point set classification optimization test is used to compute an optimized separation threshold (ST), where separation threshold is defined as a minimum histogram difference measurement value), as described in the following. The inputs include (1) N number of specified classes for classification, (2) M number of points ($M > N$) where, for each class, one selected point is treated as a class sample point, and (3) a specified patch size. The outputs include (1) the separation threshold and (2) the number of total classified points for each class.

[0068] During the point set classification optimization test by the histogram method, any point has to be classified into one class (where the histogram difference to its class

sample point is bigger or equal to ST) or is masked as an unclassified point (where the histogram difference to any points from the specified classes is less than ST).

[0069] The conditions of a successful classification require meeting two conditions.

[0070] A first condition is that, for any two points from any two different classes specified in the classification, the histogram difference is less than ST.

[0071] A second condition is that, for any two points from the same class, the histogram difference is greater than or equal to ST.

[0072] The optimized separation threshold is determined by the optimization test iterations.

[0073] The next iteration is set ST as the previous ST/2 (i.e. 0.5). It is tested if M points can be classified. If one point exists that belongs to class A where the histogram difference to A's represented point is greater than ST, and it also belongs to class B, the ST is determined as unsatisfied. The threshold is then increased by the previous ST/2 + the previous ST/4. Otherwise, the separation threshold is determined as over-satisfied. The threshold is decreased by the previous ST/2 – the previous ST/4. Such iterations are applied until the optimal threshold is obtained (the difference of the two continuous thresholds is less than 0.0001).

[0074] Once the optimized separation threshold is determined, the difficulty of the classification can be estimated, where the larger the value, the harder of the classification, and the smaller the value, the easier the classification.

[0075] The point set classification optimization test provides a novel method to set the optimal patch size and the optimal separation threshold for change detection and classification. In an example, 31 point set classification optimization tests were performed, where the input patch size was set from 11x7 to 21x25 (pixel height by pixel width), input specified classes were oil and water, and the input point set was 96 points. For each patch size, there is one point set classification test and the results from the test.

[0076] Referring now to Figure 1, shown therein is a system 100 for change detection and classification on SAR imagery, according to an embodiment.

[0077] The system 100 includes a spacecraft 102. The spacecraft 102 may be an earth observation satellite. The spacecraft 102 collects synthetic aperture radar (SAR) data of Earth's surface via one or more SAR sensors 104 disposed onboard the spacecraft 102. The SAR sensor 104 may collect SAR data in one or more polarizations. The SAR data is processed by the system 100 to perform change detection and classification tasks using an area-based histogram method or algorithm. Example applications of the system 100 include forest classification for biomass estimation and oil spill detection and characterization. The system 100 may be used for change detection and classification for land cover or ocean cover.

[0078] It should be noted that while a single spacecraft 102 is shown in Figure 1, it is to be understood that embodiments of the system 100 may include multiple (in some cases, many) spacecrafts collecting SAR data. Accordingly, spacecraft 102 is a representative spacecraft in such embodiments.

[0079] The spacecraft 102 downlinks SAR data 106 to a ground station 106 (or ground terminal). The SAR data 106 may be raw SAR data. The manner of communication is generally known. In other embodiments, there may be a plurality of ground stations 112 and the number of ground stations 112 is not particularly limited. The ground stations may be located in multiple geographic locations.

[0080] The system 100 further includes a server system 108 in communication with the ground station 106 over a communication network 110. The server system 108 is a data processing device configured to perform image processing on SAR imagery. The network 110 may be a wide area network, such as the Internet. Communication in this context may include sending and receiving data.

[0081] The system 100 further includes a user device 112 in communication with the server system 108 over communication network 110. The user device 112 is a data processing device configured to receive input from a user and display data generated by the server system 108. The user device 112 is configured to display a graphical user interface that allows a user to interact with the data generated by the server system 108, including output data generated by the server system 108 performing change detection and classification tasks on SAR data. The user interface may include a series of user

interface screens for receiving user input and display output data generated by the server system 108.

[0082] The server system 108 executes a SAR image processing application 120 for change detection and classification. The user device 112 provides a user interface of the application 120. The application 120 is configured to execute an area-based histogram algorithm or method. The application 120 is configured to classify results derived from SAR imagery using the area-based histogram algorithm. The area-based histogram algorithm may perform, for example, forestry classification or relative thickness estimation (e.g., of oil spills).

[0083] The application 120 may include a plurality of software tools, modules, or functions (which may be collectively referred to as a “toolkit”). The application 120 includes an optimization tool and a similarity measure tool. The optimization tool is used to determine an optimal setting for proper patch size and separation threshold to be used in later comparison and classification tasks. The similarity tool compares two histograms generated from first and second SAR images using the patch size and separation threshold determined by the optimization tool and determines a similarity measure (or similarity value) indicating similarity between the two compared images. The similarity measure is analyzed by the similarity tool and classifications are assigned. The similarity tool may generate and output a detection or classification product. The detection or classification product may be a file that is generated and stored by the server system 108 and sent to the user device 112 for display and review.

[0084] The application 120 may be configured to perform any one or more of single image detection, image-pair based detection, and image stack-based classification as described herein. In the case of image stack-based classification, an average backscatter image may be generated from a plurality of backscatter images. This may be used to create a temporal average backscatter image (e.g., 15 images captured at regular intervals, the average backscatter image is generated by averaging 15 images from the stack).

[0085] Referring now to Figure 2, shown therein is a method 200 of spatial histogram classification, according to an embodiment.

[0086] In embodiments using SAR imagery with multiple polarizations or polarization layers, such as compact polarimetry, the method 200 may be performed for each polarization or polarization layer in the SAR image. This may be done to evaluate which layers are good. For example, the values of the separation thresholds and total number of classified points (as described below) may be reviewed to determine results.

[0087] The method 200, or portions thereof, may be encoded as computer-executable instructions which, when executed by one or more processors, cause the computer system to perform the method 200. In an embodiment, the method 100 may be implemented as part of application 120 of Figure 1.

[0088] The method 200 may be implemented using system 100 of Figure 1. In particular, the method 200 may be implemented at the server system 108, the user device 112, or some combination thereof.

[0089] At 202, the method 200 includes selecting a SAR reference image. The reference image may be representative of normal conditions.

[0090] At 204, the method 200 includes defining control points in the SAR reference image. Control points may be defined manually by a user through a user interface. In an example, a point set of 96 control points that cover oil and water areas in a reference SAR image are created and 2 class chips are defined.

[0091] The reference image is separated into a plurality of classes (e.g., oil and water in an oil spill detection application) representing different surface conditions. In an embodiment, shapefiles may be drawn in regions of the reference image that are characteristic of each class in the plurality of classes. Each class must have at least one control point.

[0092] At 206, the method 200 includes defining chips for each control point in the SAR reference image. The chips may also be referred to as spatial images, patches, or windows.

[0093] At 208, the method 200 includes configuring parameters including patch size and separation threshold.

[0094] Patch size parameter plays a significant role in quantifying the histogram difference. While a smaller patch size calculated histogram difference may not well represent a typical sample (a unique signature for a specified class), it is very sensitive to the change. A larger patch size can well represent the sample but loses sensitivity. In order to properly detect the histogram changes, a way to compute the optimal value of the patch size is needed. Also, in order to do an accurate classification, the separation threshold parameter is very important. If the separation threshold is too small, two classes may not be separated very well, and if the separation threshold is too big, a class may miss lots of areas.

[0095] A developed optimization function has been developed to classify a point set. The optimized function can be used to determine an optimized value for the patch size and the separation threshold for the classification. To find an optimized patch size, for each patch size, a point set classification optimization test is conducted, and from all tests with all different patch sizes, the optimal patch size is selected.

[0096] An embodiment of a detailed procedure of a point set classification optimization test which is used to compute the optimized Separation Threshold (ST, is defined as a minimum histogram difference measurement value) will now be described. The inputs are N number of specified classes for classification, and M number of points ($M > N$) where for each class, one selected point is treated as a class sample point, and the specified patch size. The outputs are the separation threshold and numbers of total classified points for each class. During the point set classification optimization test by the histogram method, any point has to be classified into one class (where the histogram difference to its class sample point is bigger or equal to ST) or is masked as an unclassified point (where the histogram difference to any points from the specified classes is less than the Separation Threshold (ST)). The conditions of a successful classification have to meet two conditions: (1) any two points from any two different classes specified in the classification, the histogram difference is less than ST; (2) any two points from the same class, the histogram difference is bigger or equal to ST; (3) the optimized separation threshold is generated by the optimization iterations. The initial ST is set as 1, we know we can have N points classified into N classes and each class has one class sample point (at least we have a base solution). The next iteration is set ST as the previous ST/2 (i.e.

0.5). It is tested whether M points can be classified, and if there exists one point that belongs to class A where the histogram difference to A's represented point is bigger than ST , and it also belongs to class B, the ST is determined as unsatisfied. The threshold is then increased by the previous $ST/2$ + the previous $ST/4$. Otherwise, the ST is determined as over-satisfied, and the threshold is decreased by previous $ST/2$ - the previous $ST/4$. Such iterations are applied until the optimal threshold is obtained (the difference of the two continuous threshold is less than 0.0001). Once the optimized separation threshold is calculated, we can estimate the difficulty the classification can be estimated where, the larger the value, the harder of the classification, and the smaller of the value, the easier the classification. Using the point set classification optimization test, a novel method is used to set the optimal patch size and the optimal separation threshold for change detection and classification.

[0097] At 210, the method 200 includes computing a histogram for each chip using the parameters from 208 and the chips from 206.

[0098] At 212, the method 200 includes computing similarity scores between the histograms computed at 210 in an attempt to classify the control points.

[0099] At 214, the method 200 includes classifying the control points based on the similarity scores from 212.

[0100] At 216, the method 200 includes reviewing and confirming the point set classification results. In an embodiment, this includes displaying the point set classification results in a user interface for review and confirmation by a user. The user may either confirm or accept the results, and thus the configured parameters, via the user interface.

[0101] If the point set classification results are not confirmed at 216, then the method 200 proceeds to 208, where the parameters are varied (reconfigured into new parameters) and the process from 208-216 is repeated. In general, the best results may be seen where the number of correctly classified control points is maximized and the histogram similarity between classes is minimized (i.e., balancing correct classification of control points and histogram similarity).

[0102] If the point set classification results are confirmed at 216, then the method 200 proceeds to 218.

[0103] At 218, the method 200 includes classifying the SAR reference image. This is done by computing a histogram for each pixel in the SAR reference image using the optimized parameters from 208 and computing a similarity score between the histograms.

[0104] At 220, the method 200 includes generating a shapefile and mask to a defined area of interest ("AOI"). The AOI is a user-defined area. The AOI may be provided by a user through a user interface (e.g., at user device 112). Classification is performed over only the AOI. This may include masking invalid areas in the image. There may be one shapefile per class in the plurality of classes. Manually created shapefiles (buffered) may be used to mask results.

[0105] Using the method 200 of Figure 2, an entire image may be classified very quickly. The same configuration can be used to classify multiple images. The classification may be masked to the AOI (i.e., only results inside the AOI are relevant).

[0106] Referring now to Figure 3, shown therein is a method 300 of histogram-based classification, according to an embodiment. The method 300 may be executed after method 200 of Figure 2. The method 300 may be used to compare a first SAR image to one or more other SAR images (or chips derived therefrom) to detect changes and classify surface conditions.

[0107] The method 300, or portions thereof, may be encoded as computer-executable instructions which, when executed by one or more processors, cause the computer system to perform the method 300. In an embodiment, the method 100 may be implemented as part of application 120 of Figure 1.

[0108] The method 300 may be implemented using system 100 of Figure 1. In particular, the method 300 may be implemented at the server system 108, the user device 112, or some combination thereof.

[0109] At 302, the method 300 includes retrieving a SAR image for change detection or classification by area-based histogram method.

[0110] At 304, the method 300 includes generating a spatial image from the SAR image using a moving window technique such as described herein. The spatial image may also be referred to as a patch, a chip, or a window. The spatial image includes a subset of the pixels in the SAR image.

[0111] At 306, the method 300 includes computing a spatial histogram for the spatial image from 304. The spatial histogram has N bins. The number of bins, N, may be configurable (e.g., by the user).

[0112] At 308, the method 300 includes computing a first set of bin variables of the spatial histogram and a second set of bin variables of a reference spatial histogram for the N bins.

[0113] The reference spatial histogram is generated from a reference spatial image (or chip or patch). The reference spatial image is generated from another SAR image (reference SAR image). In some cases, the other SAR image may be a second SAR image being compared to or may be a sample chip derived from another SAR image.

[0114] In an embodiment, the bin variables are bin percentages for each of the N bins in the respective spatial histograms. In such a case, the first set of bin variables includes bin percentages for each of the N bins for the first spatial histogram and the second set of bin variables includes bin percentages for each of the N bins in the reference spatial histogram.

[0115] At 310, the method 300 includes measuring the difference between the first and second sets of bin variables from 308.

[0116] In an embodiment, a correlation technique is used to determine the difference. Generally, correlation refers to a statistical approach or formula that measures strength between variables and relationships. To determine how strong a relationship is between two variables, a coefficient value is determined, which may range from -1.00 to 1.00. Correlation can measure the similarity between two variables which need to have the same size. The input to the correlation is two histograms with the same bin setting. Since the values of two chip images are not being compared, but rather their distributions in terms of the histograms are being compared, different image chip sizes can be used

(e.g., the patch size is tested for an optimal setting, e.g., if the patch size is too small, it is not a typical sample, and if the patch size is too large, the sensitivity is not strong).

[0117] At 312, the method 300 includes performing 304-310 for each additional spatial image (image chip or patch) from the SAR image. A moving window technique may be used to generate successive image chips from the SAR image.

[0118] At 314, the method 300 includes generating a similarity image. The similarity image comprises a similarity value for each spatial image (patch). The similarity value indicates a level of similarity between the spatial image and the corresponding reference spatial image. This is the histogram difference measurement from 310.

[0119] In an embodiment, the similarity image contains a plurality of pixel values where each pixel value represents the measurement of the specific patch (centered at the pixel location) to the comparison patch (the comparison patch may be a sample image chip or the same patch location from another image). The value is between -1 and 1, with a lower value indicating less similarity and a higher value indicating greater similarity.

[0120] In some embodiments, the similarity image is masked out. This includes applying a threshold to the similarity image to control which pixels in the similarity image are kept and which are not. The threshold may be determined from testing using ground truths.

[0121] In some embodiments, the similarity image is a maximum similarity image. A maximum similarity image may be generated and used if for one class there is more than one sample chip. For the comparison patch, a plurality of sample chips (e.g., all available sample chips) may be used to do the similarity test and the maximum value from the tests used/kept. The maximum value is then used for the similarity image (i.e., maximum similarity image). Such an approach may be used for image stack-based classification tasks. Using multiple class samples (multiple sample image chips for one or more classes) and the maximum similarity image may improve detection in terms of increasing the detection areas. For example, in a forest classification application, if samples for forest boundary cases and solid forest area are included, then the detection results may be improved over those that would be achieved using only solid forest area.

Contents of a maximum similarity image (from multiple class sample chips) may be the same as a similarity image from a single class sample chip.

[0122] The method 300 may be used to perform single image detection, image pair-based detection, and image stack-based classification. For a single image, detection means to detect the changes from the sample chips by the single image.

[0123] For a single image detection, such as in an oil spill detection task, the histogram method may quantify the histogram difference in a range of -1 and 1 between the sample chips and the moving windows with the same patch size from a single SAR polarization image and generate the similarity image which may be masked out as an alert product by the threshold. The sample chips are prepared in advance by a point set supervised classification by the histogram method, such as method 200 of Figure 2.

[0124] For an image pair based detection, such as in a land use change detection task, the histogram method may quantify the histogram difference in a range of -1 and 1 between the two moving windows with the same patch size from a pair of SAR images with the same polarization and generates the similarity image, which may be masked out as an alert product by the threshold.

[0125] For an image stack based classification, such as in a forest classification task, the histogram method quantifies the histogram difference in a range of -1 and 1 among specified forest sample chips and the moving windows with the same patch size from a temporal average SAR stack image with the same polarization as the sample chips, and generates the maximum similarity image for classification. The sample chips are prepared in advance by a point set supervised classification by the histogram method, such as method 200 of Figure 2.

[0126] Referring now to Figure 4, shown therein is a method 400 of oil spill detection from SAR imagery, according to an embodiment. While the method 400 is described in the context of oil spill detection, it will be understood how such method may be modified and applied to detect other surface conditions in SAR imagery. Method 400 may be considered a single image detection task or application of the histogram method of the present disclosure.

[0127] The method 400, or portions thereof, may be encoded as computer-executable instructions which, when executed by one or more processors, cause the computer system to perform the method 400. In an embodiment, the method 100 may be implemented as part of application 120 of Figure 1. In some embodiments, operations performed as part of the method 400 may be performed automatically without user input. In other embodiments, operations performed as part of the method 400 may be performed in response to a user input (e.g., provided via a user interface at user device 112).

[0128] The method 400 may be implemented using system 100 of Figure 1. In particular, the method 400 may be implemented at the server system 108, the user device 112, or some combination thereof.

[0129] At 402, the method 400 includes preparing, by one or more processors, one or more polarization layers from a single SAR image. Preparing includes training. The SAR image may be referred to as a new SAR image.

[0130] In an embodiment, the SAR image is a compact polarimetry SAR image. The SAR image includes a polarization layers, such as CPR, DCP, DLP, DOP, and H. Preparing the polarization layers may include performing a point set classification test (e.g., method 200 of Figure 2) on the SAR image layers and reviewing the point classification results to determine or evaluate which layers are good [NTD – what does it mean if a layer is “good”?]. Review may include reviewing the values of separation thresholds and total number of classified points to determine results. After the analysis, one or more layers are selected and used.

[0131] At 404, the method 400 includes retrieving, by the one or more processors, pre-prepared oil spill sample chips from a data storage device. The oil spill sample chips are generated from portions of SAR images containing known oil spill areas.

[0132] The oil spill sample image chips are prepared in advance using point set supervised classification by the histogram method as described herein. For example, the oil spill sample chips may be prepared using the method 200 of Figure 2.

[0133] This requires to prepare the sample chips in advance by the toolkit from the point set supervised classification by the histogram method

[0134] In order to detect an oil spill area in real, ongoing SAR data (i.e., the SAR image from 402), the histogram method of the present disclosure is used to determine if any area of the new SAR image is similar to a pre-prepared oil spill sample. To do this, oil spill sample chips (i.e., reference image chips containing known oil spill areas) are generated from SAR images with known oil spill events using the existing polarization layers. Existing polarization layers refers to training data used to prepare the sample chips. The oil spill sample chips may be built from multiple cases of known oil spills, such as in a machine learning approach. Collecting multiple kinds of oil spill sample chips may improve detection quality (like in a machine learning approach).

[0135] At 406, the method includes generating, by the one or more processors, an oil spill detection product using the histogram-based change detection and classification method of the present disclosure (e.g., method 200).

[0136] In an embodiment, the histogram-based change detection and classification method is applied to the one more polarization layers of the SAR image and quantifies the histogram difference in a range of -1 to 1 between the sample chips and the moving windows with the same patch size from a single SAR polarization image and generates the similarity image. One image may have more than one layer. One or more layers can be used as the training image. The smaller the similarity value, the less similar the two patches; the higher the similarity value, the more similar the patches. The patch size setting is obtained from the optimization test of the point set classification using the histogram method as described herein (e.g., method 200 of Figure 2).

[0137] The similarity image may be masked out by threshold. The threshold is tested by ground truths. The masked out similarity image may be used as an alert product, for example alerting to areas in the image where oil spills have been detected.

[0138] In an embodiment, the oil spill detection product may be a shape-based vector file that indicates the locations of oil spills and alert areas. The oil spill detection product may also report an estimation of the oil thickness (in detected oil spill areas). The detection product may include the oil spill image chip (i.e., a patch of the image containing the detected oil spill area) extracted from the compact polarimetry layers.

[0139] At 408, the method includes integrating, by the one or more processors, the oil spill detection product into a processing flow of an earth observation data analysis application, such as a ship detection system, as a value added product.

[0140] Referring now to Figure 5, shown therein is a method 500 of forest classification for biomass estimation from SAR imagery, according to an embodiment. While the method 400 is described in the context of forest classification for biomass estimation, it will be understood how such method may be modified and applied to detect other surface conditions in SAR imagery.

[0141] The method 500, or portions thereof, may be encoded as computer-executable instructions which, when executed by one or more processors, cause the computer system to perform the method 500. In an embodiment, the method 100 may be implemented as part of application 120 of Figure 1. In some embodiments, operations performed as part of the method 500 may be performed automatically without user input. In other embodiments, operations performed as part of the method 500 may be performed in response to a user input (e.g., provided via a user interface at user device 112).

[0142] The method 500 may be implemented using system 100 of Figure 1. In particular, the method 500 may be implemented at the server system 108, the user device 112, or some combination thereof.

[0143] At 502, the method 500 includes preparing one or more temporal average stack backscatter images by one or more polarizations. The SAR image may be referred to as a new SAR image.

[0144] A temporal average stack backscatter image is an average backscatter image generated from a stack of images acquired over time (generated by averaging the images in the stack). Each pixel value in the temporal stack backscatter image is calculated by averaging the pixel values from all images in the stack. All images in the stack of images have the same SAR geometry.

[0145] At 504, the method 500 includes retrieving pre-prepared forests sample image chips. The forest sample chips are generated from portions of SAR images containing areas with known forest type classifications.

[0146] In order to classify different types of forest, samples of different types of forests in terms of SAR sample chips need to be available from the training temporal average stack backscatter image. Sample chips are prepared from the ground truths or optical images and extracted from the SAR backscatter training image. Once the forest sample chips are obtained, they can be compared with the new comparison image to do forest classification based on the histogram method as described herein.

[0147] At 506, the method 500 includes generating a forest classification product using the histogram-based change detection and classification method. A moving window technique as described herein may be used.

[0148] For an image stack based classification such as forest classification, a set of histograms are generated, and the histogram difference is quantified in a range of -1 and 1 among specified forest sample chips and the moving windows with the same patch size from a temporal average SAR stack image with the same polarization as the sample chips. A similarity image is generated for classification from the histogram difference. The sample chips are prepared in advance by a point set supervised classification by histogram method, such as described herein (e.g., method 200 of Figure 2). A specified forest sample chip is prepared for each forest type being classified. It must first be confirmed that the types of forest can be classified technically. For example, high dense forest and very high dense forest are very similar. If they cannot be separated by the method, the two classes may be combined into one class.

[0149] The similarity image is a maximum similarity image generated using the spatial histogram classifier method as described herein in which multiple class chips are used for the comparison patch and the maximum value retained.

[0150] By using multiple class samples and the maximum similarity image, the detection may be improved in terms of increasing the detection areas. For example, if we include the samples for forest boundary cases and solid forest area, the result can be improved over that only including solid forest area.

[0151] The forest classification product may be a colour coded raster image or a shape of a classification vector product where each polygon represents one class.

[0152] At 508, the method 500 includes integrating the forest classification product into a biomass change processing flow. The biomass change processing flow is used to determine and report biomass changes.

[0153] Referring now to Figure 6, shown therein is a computer system 600 for change detection and classification on SAR imagery by spatial histogram classification, according to an embodiment.

[0154] The system 600 may be configured to implement any one or more of the methods described herein.

[0155] Components of the computer system 300 may be implemented at one or more devices, such as server system 108 and user device 112 of Figure 1.

[0156] The system 600 includes a memory 602 and a processor 604 in communication with the memory 602.

[0157] The processor 604 is configured to execute various software modules and components. In some embodiments, modules or components executed by the processor 604 may include server-side software components and client-side software components that communicate with each other in order to provide various features and functionalities of the system 600. In some cases, server-side components may be executed at a server computer and client-side components may be executed at a user device.

[0158] The system 600 includes a communication interface device 606 for transmitting and receiving data to and from other computing devices. The communication interface device 606 may include a network interface device for transmitting and receiving data via a network connection (e.g., local area network, wide area network, etc.).

[0159] The system 600 includes a display device 608 for displaying data generated by the system 600. The display device 608 may be located at a user device, such as user device 112 of Figure 1.

[0160] The system 600 includes an input device 610 for receiving input data from a user interacting with the system 600. For example, a user may use input device 610 to interact with the system 600 through a graphical user interface generated by the processor 604 and displayed via the display device 608. The input device 610 may be

located at the user device, such as user device 112 of Figure 1. A user may input information requests about change detection and analysis of SAR imagery through input device 610.

[0161] The processor 604 executes a SAR change detection and classification application 612. The application 612 may be the application 120 of Figure 1.

[0162] The SAR change detection and classification application 612 includes an optimizer tool 614, a similarity measurement tool 616, an output product generator module 618, and a user interface module 620.

[0163] The memory 602 stores a plurality of SAR reference images 622. The SAR reference images 622 may have multiple polarizations. The SAR reference images 622 are provided as input to the optimizer tool 614. A user of the system 600 interacts with the optimizer tool 614 through the user interface module 620 to define a set of control points (point set 624). The user also defines chips for each control point a point set chip (or patch) 626.

[0164] The user interacts with the user interface module 620 to define or specify classes 628 for the classification and configure test parameters 630 for an area-based histogram classifier algorithm 632 executed by a point set classifier component 634 of the optimizer tool 614. The test parameters 630 include at least a patch size and a separation threshold.

[0165] The point set classifier 634 optimizer tool 614 automatically classifies the point set 624 using the chips 626, specified classes 628, and test parameters 630 and generates point set classification results 636. The point set classification results 636 are displayed to the user via user interface module 620.

[0166] The results are either confirmed or the parameters reconfigured or redefined and the process is repeated until the results are acceptable. The parameters are then stored as optimized parameters or optimized system settings 640. The optimized system settings 640 include a patch size 642 and a separation threshold 644.

[0167] The memory 602 also stores a new SAR image 646. The new SAR image may have multiple polarizations. The new SAR image 646 is to be processed by the

system 600 to detect or classify areas in the SAR image that correspond to certain surface conditions. The new SAR image 646 may be compared to SAR reference images 622 (or chips derived therefrom). It should be noted that the comparison is patch to patch and that the point provides the location.

[0168] The new SAR image 646 is provided as input to the similarity measurement tool 616. The similarity measurement tool 616 executes a spatial histogram classifier module 648.

[0169] The spatial histogram classifier 648 executes an area-based histogram classifier algorithm, such as described herein (e.g., method 300 of Figure 3).

[0170] The spatial histogram classifier 648 generates spatial images 650 from the new SAR image 646 using the optimized system settings 640 and a moving window technique.

[0171] The memory 602 also stores reference spatial images 652, which are generated from the SAR reference images 622.

[0172] The spatial histogram classifier 648 generates a spatial histogram 654, 656 for each spatial image 650 and reference spatial image 652 using the methods described herein. The histograms 654, 656 include the same number of bins (N). Example spatial histograms that may be generated by the system 600 are shown in Figure 7.

[0173] The spatial histogram classifier 648 determines histogram bin percentages 658 for the spatial histograms 654 and reference histogram bin percentages 660 of the reference spatial histograms 656.

[0174] The spatial histogram classifier 648 compares the bin percentages 658, 660 using a correlation technique and determines a similarity score 662 for each comparison.

[0175] The spatial histogram classifier 648 generates a similarity image 664, as described herein, using the similarity scores 662.

[0176] The similarity image 664 is provided to the output product generator module 618, which generates a masked out similarity image 666 by masking out areas in the similarity image 664 that have an associated class that is to be masked out (i.e. alert areas that are being looked for in the SAR images).

[0177] The masked out similarity image 666 may be displayed and reviewed by a user via the user interface module 620.

[0178] The output product generator module 618 may further process the masked out similarity image 666 into a detection or classification product 668, which contains additional information beyond what is provided in the masked out similarity image 666.

[0179] As described herein, the present disclosure provides an area-based histogram method to quantify a histogram difference by comparing the bin percentage difference. The present disclosure also provides a point set classification optimization test. Instead of working on a raster image to do classification, a point set is used and processed to do point classification and then the optimal settings from the point classification (e.g., patch size, separation threshold) are applied to image-based classification. This provides an efficient way of performing classification. The present disclosure also provides a processing flow for estimating and reporting biomass changes. The present disclosure also provides a processing flow for detecting oil spills.

[0180] It should be noted that while the present disclosure describes comparing bin percentage variables by a correlation method, other techniques for comparing histogram graph differences may be used, such as peak point, tail points, and fitting curve. Also, making histogram-based change detection and classification most effective can require identifying and using the most effective input image. For oil spill detection cases, certain CP layers provide better results.

[0181] While the above description provides examples of one or more apparatus, methods, or systems, it will be appreciated that other apparatus, methods, or systems may be within the scope of the claims as interpreted by one of skill in the art.

Claims:

1. A method of performing change detection and classification on SAR imagery, the method comprising:

extracting, by one or more processors, a first spatial patch as a first image chip from a reference SAR image;

extracting, by the one or more processors, a second spatial patch as a second image chip from a comparison SAR image, wherein the first and second spatial patches have the same patch size;

generating, by the one or more processors, first and second histograms from the first and second image chips, respectively, the first and second histograms having N bins;

determining, by the one or more processors, a first set of N bin variables from the first histogram and a second set of N bin variables from the second histogram;

measuring, by the one or more processors, a difference between the first and second sets of bin variables using a separation threshold;

generating, by the one or more processors, a similarity image comprising a similarity value indicating a level of similarity between the first and second image chips; and

reporting, by the one or more processors, changes to the reference SAR image based on the similarity image.
2. The method of claim 1, further comprising performing the method of claim 1 for a plurality of spatial patches including the first spatial patch in an area of interest in the comparison image, wherein the plurality of patches are generated by applying a moving window technique to the comparison image.

3. The method of claim 1, wherein the N bin variables are bin percentages associated with each of the N bins.
4. The method of claim 1, wherein the difference between the first and second sets of bin variables is measured using a correlation technique.
5. The method of claim 1, wherein the first image chip is a pre-generated class sample chip obtained from a training image created from a single image or a stack of images.
6. The method of claim 1, further comprising masking out areas in the similarity image using an optimized separation threshold.
7. The method of claim 1, wherein the similarity image is a maximum similarity image.
8. The method of claim 1, wherein the similarity image comprises a plurality of pixel values where each pixel value represents a histogram difference between a reference patch and a comparison patch at a pixel location, and wherein the pixel value is quantified between -1 and 1, wherein a lower value indicates less similarity and a higher value indicates a greater similarity.
9. The method of claim 1, wherein the comparison SAR image includes a plurality of polarization layers and wherein only a subset of the polarization layers are used.
10. The method of claim 1, wherein the reference SAR image is an average SAR backscatter image generated from a plurality of SAR backscatter images acquired over time.
11. The method of claim 1, wherein the changes to the reference SAR image are reported as an alert product comprising a masked similarity image displayed in a user interface at a user device.

12. The method of claim 1, wherein the patch size and the separation threshold for classification are optimized using a point set classification optimization test, wherein the separation threshold is defined as a minimum histogram difference measurement.
13. The method of claim 12, wherein the point set classification optimization test automatically classifies a point set using one or more image chips, specified classes, and test parameters including a candidate patch size, and generates point set classification results.
14. The method of claim 12, wherein the point set classification optimization test is performed for each of a plurality of candidate patch sizes to determine the patch size.
15. The method of claim 12, wherein inputs to the point set classification optimization test include a number of specified classes for classification, a number of points where for each class one selected point is treated as a class sample point, and a specified patch size, and wherein outputs of the point set classification optimization test include the separation threshold and numbers of total classified points for each class.
16. The method of claim 13, further comprising displaying the point set classification results to a user for confirmation or rejection.
17. The method of claim 1, wherein the method is used to perform oil spill detection.
18. The method of claim 1, wherein the method is used to perform forest type classification.
19. A computer system comprising at least one processor configured to:

extract a first spatial patch as a first image chip from a reference SAR image;

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extract a second spatial patch as a second image chip from a comparison SAR image, wherein the first and second spatial patches have the same patch size;

generate first and second histograms from the first and second image chips, respectively, the first and second histograms having N bins;

determine a first set of N bin variables from the first histogram and a second set of N bin variables from the second histogram;

measure a difference between the first and second sets of bin variables using a separation threshold;

generate a similarity image comprising a similarity value indicating a level of similarity between the first and second image chips; and

report changes to the reference SAR image based on the similarity image.

20. A non-transitory computer readable storage medium storing processor-executable instructions which, when executed by at least one processor, cause the at least one processor to perform a method of performing change detection and classification on SAR imagery, the method comprising:

extracting, by one or more processors, a first spatial patch as a first image chip from a reference SAR image;

extracting, by the one or more processors, a second spatial patch as a second image chip from a comparison SAR image, wherein the first and second spatial patches have the same patch size;

generating, by the one or more processors, first and second histograms from the first and second image chips, respectively, the first and second histograms having N bins;

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determining, by the one or more processors, a first set of N bin variables from the first histogram and a second set of N bin variables from the second histogram;

measuring, by the one or more processors, a difference between the first and second sets of bin variables using a separation threshold;

generating, by the one or more processors, a similarity image comprising a similarity value indicating a level of similarity between the first and second image chips; and

reporting, by the one or more processors, changes to the reference SAR image based on the similarity image.

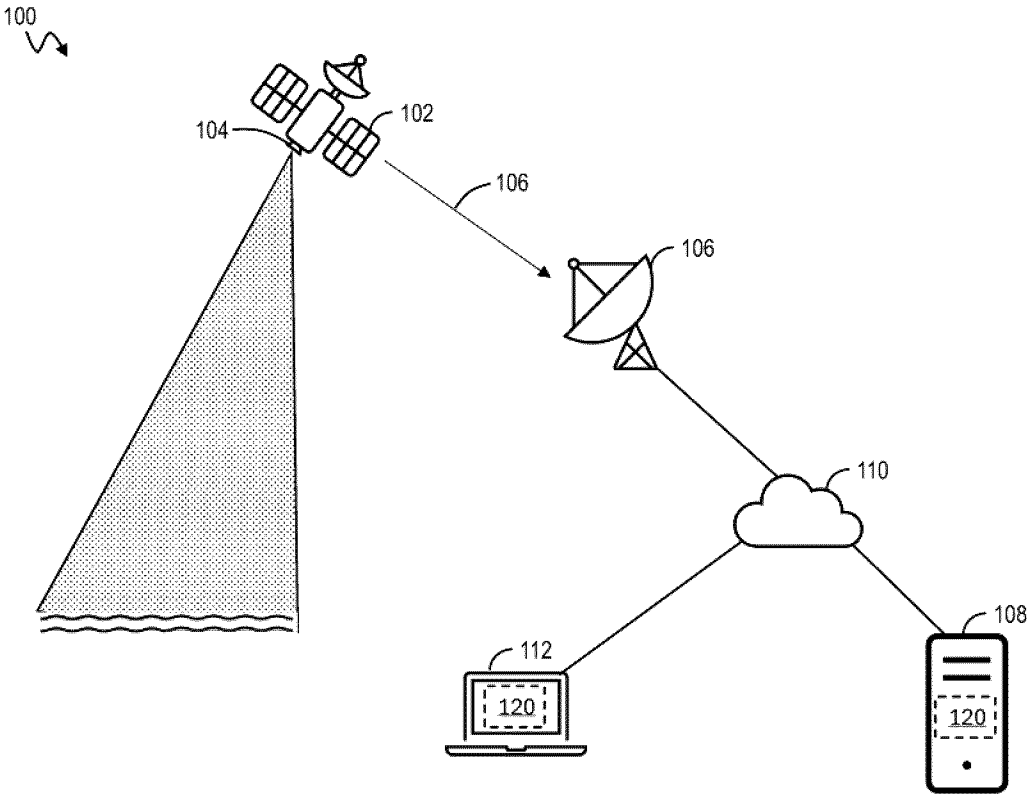


FIG. 1

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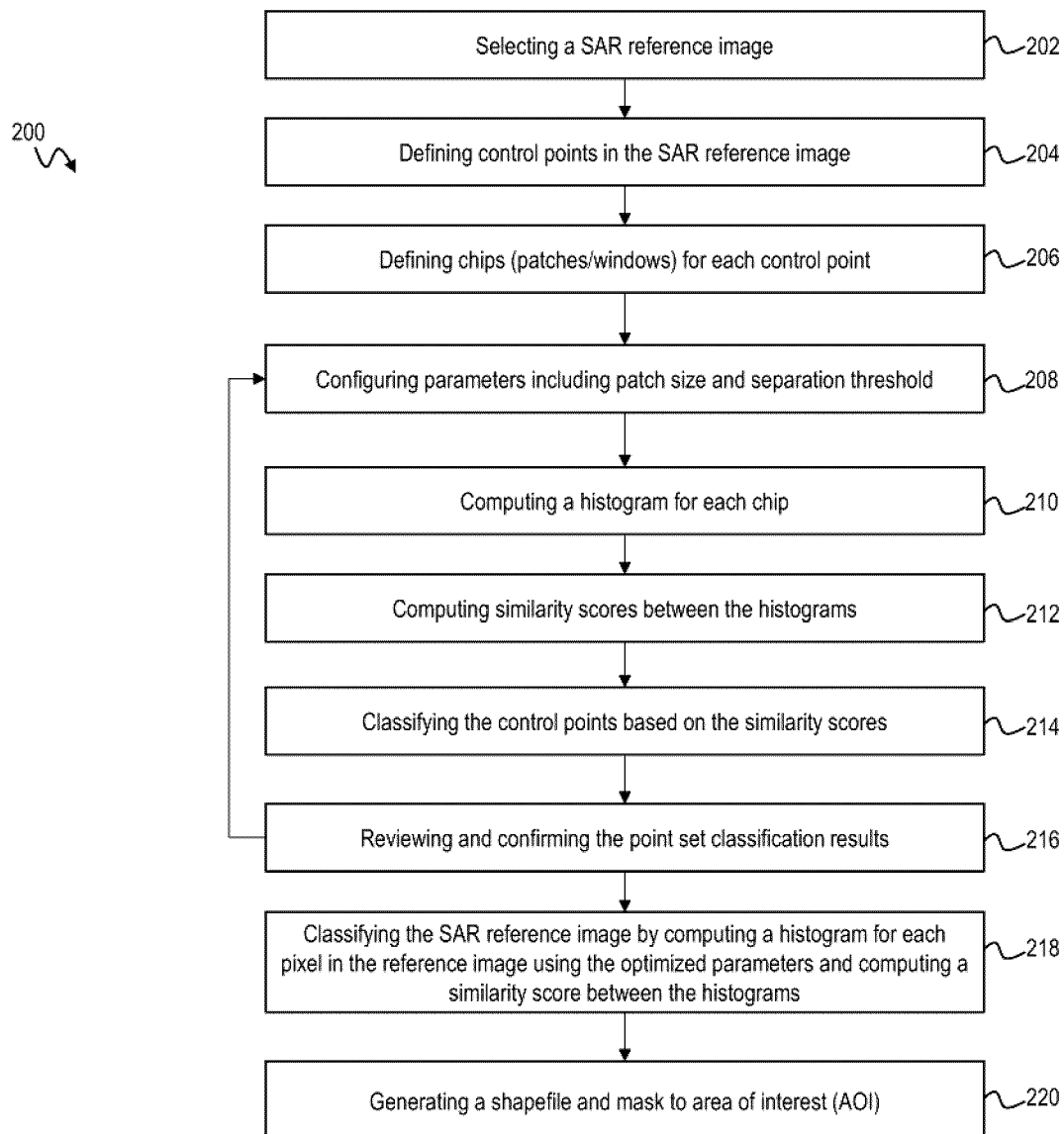


FIG. 2

3/7

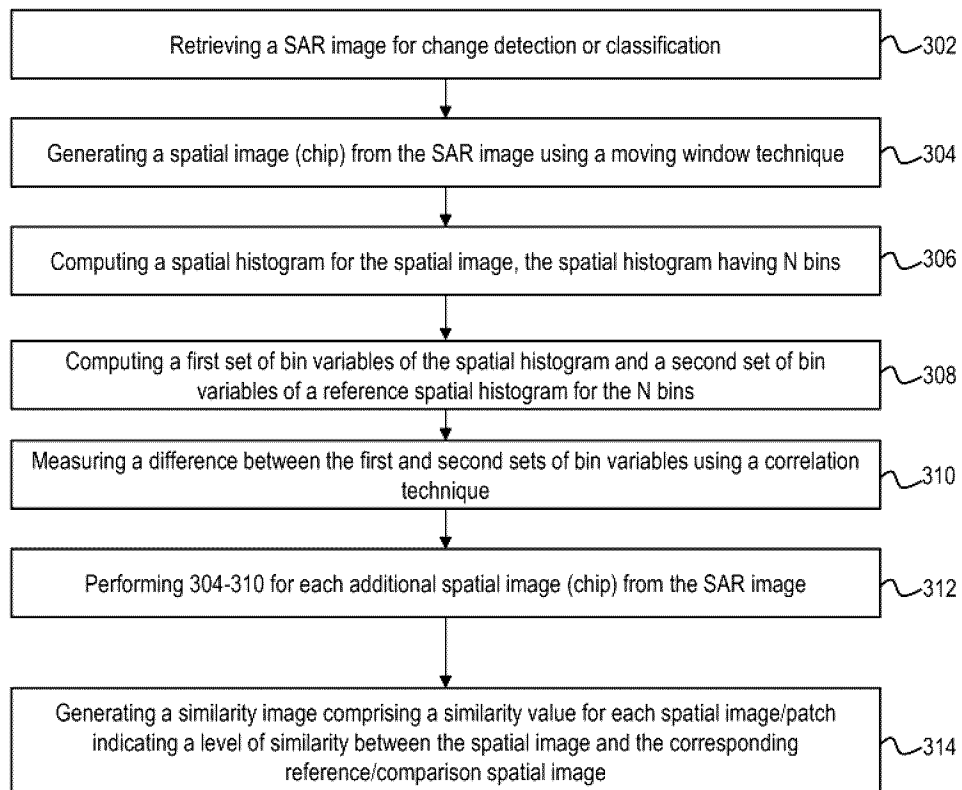
300
~

FIG. 3

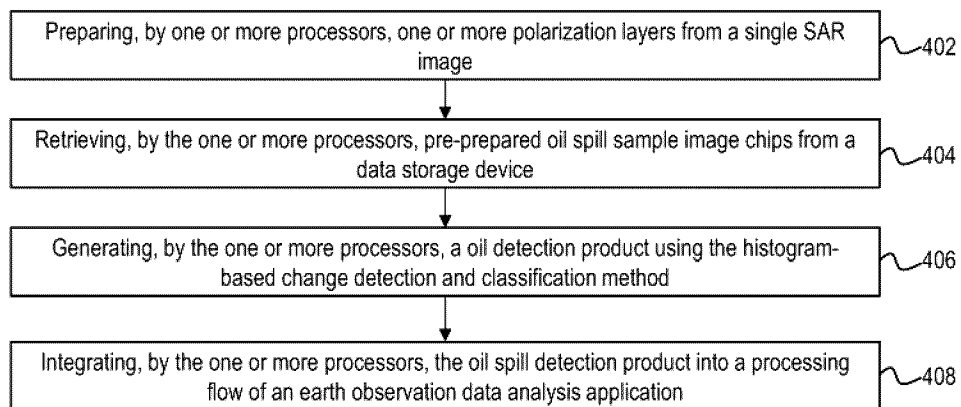
400
~

FIG. 4

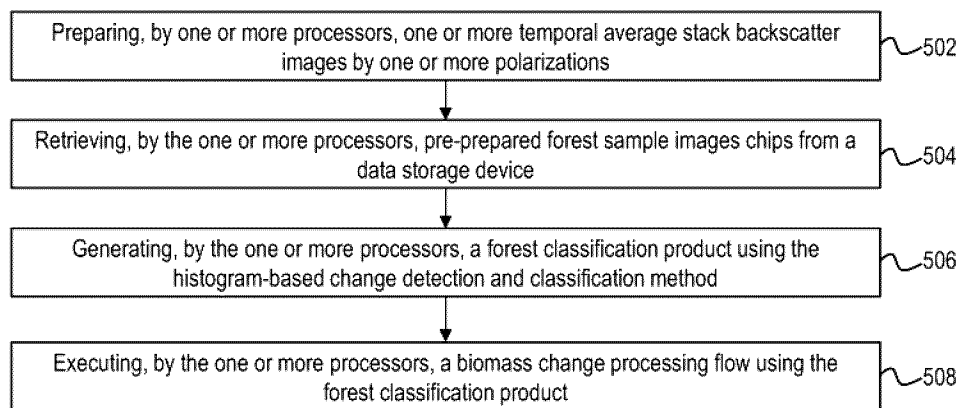
500
~

FIG. 5

600
↘

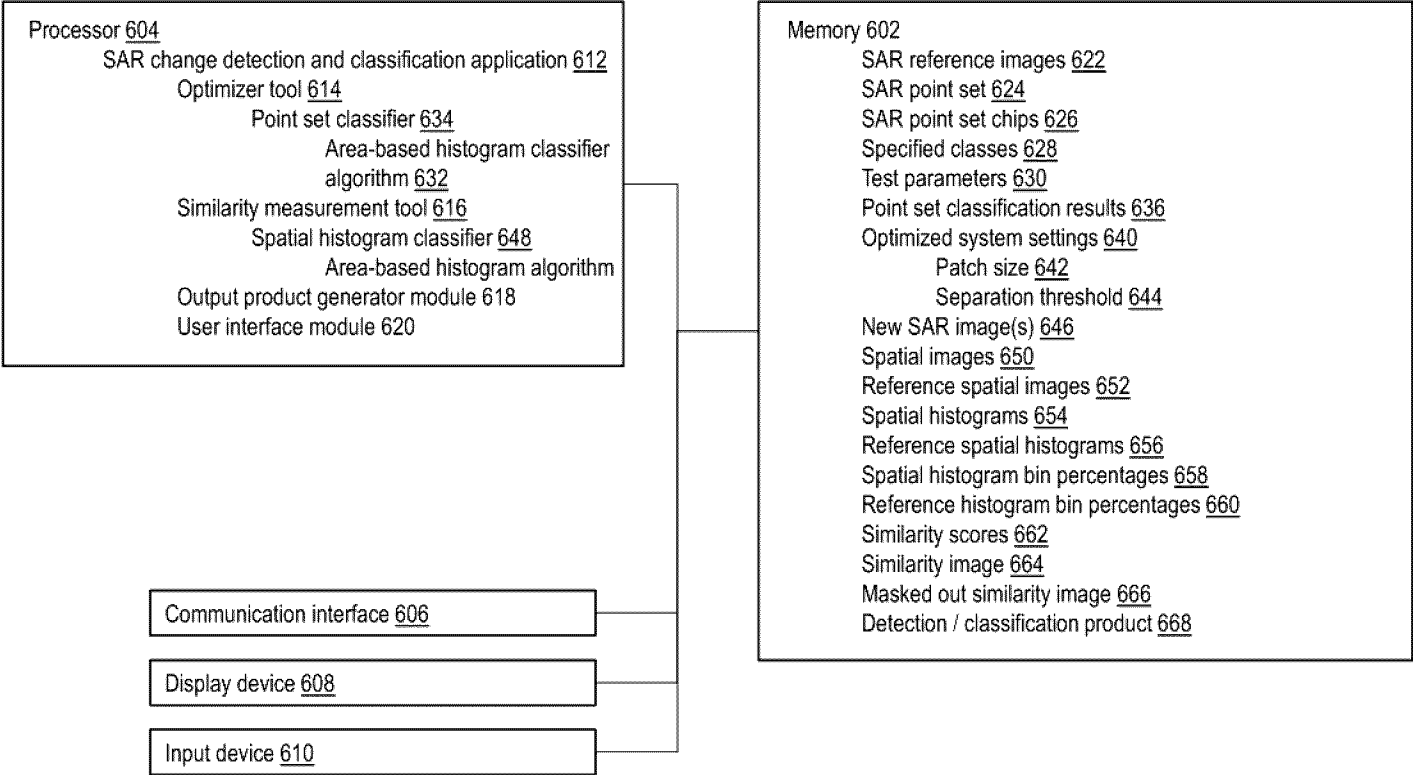


FIG. 6

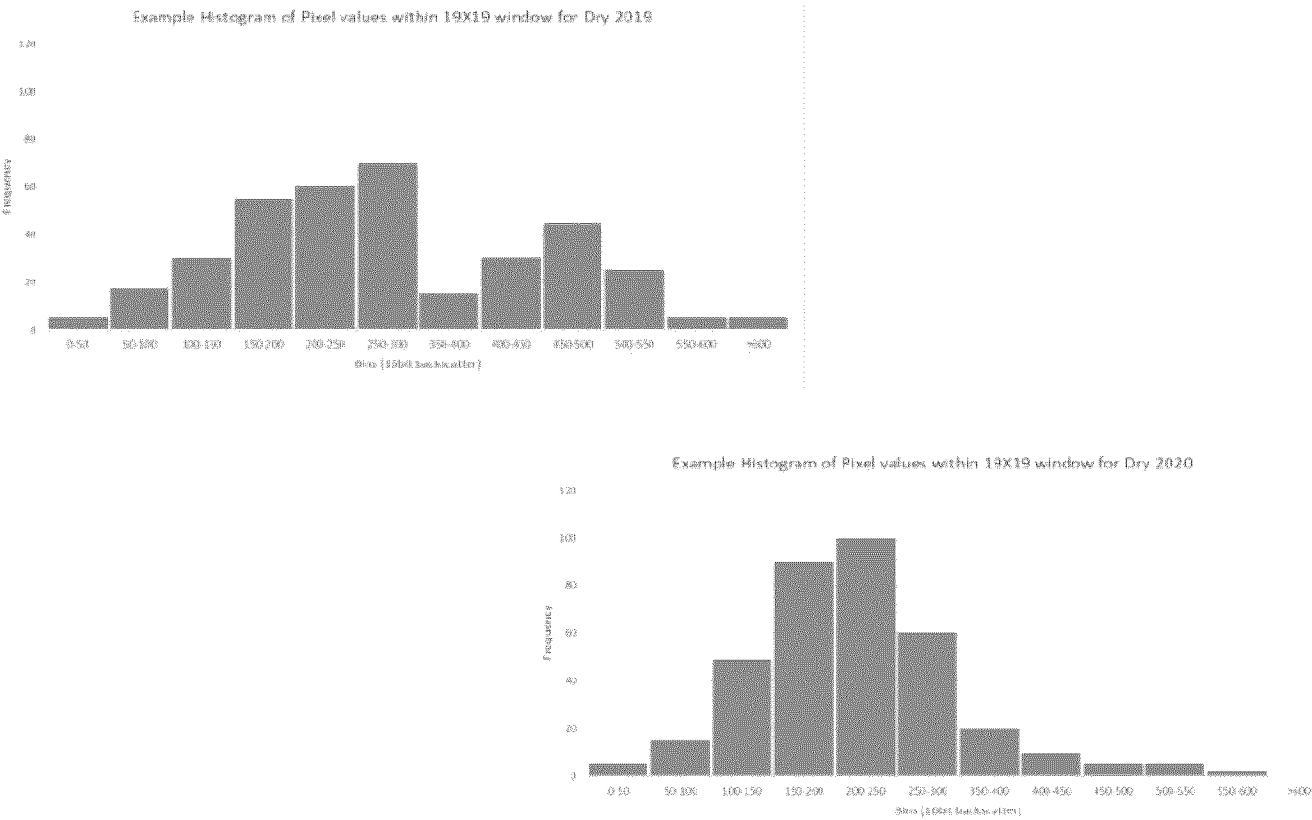


FIG. 7

INTERNATIONAL SEARCH REPORT

International application No.

PCT/CA2024/050819

A. CLASSIFICATION OF SUBJECT MATTER

IPC: *G01S 13/90* (2006.01), *G06V 10/75* (2022.01)

CPC:

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)

IPC: *G01S 13/90* (2006.01), *G06V 10/75* (2022.01)

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic database(s) consulted during the international search (name of database(s) and, where practicable, search terms used)

Databases: Questel Orbit, Canadian Patent Database (Intellect)

Keywords: SAR, classification, image, spatial, compare, similarity, difference, threshold, measure, reference

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	CN114581771A (WANG C. et al.) 03 June 2022 (03-06-2022) *abstract; claims; see entire document*	1-20
A	CN116109931A (MA P. et al.) 12 May 2023 (12-05-2023) *abstract; claims; see entire document*	1-20

☐ Further documents are listed in the continuation of Box C.☒ See patent family annex.

* "A" "D" "E" "L" "O" "P"	Special categories of cited documents: document defining the general state of the art which is not considered to be of particular relevance document cited by the applicant in the international application earlier application or patent but published on or after the international filing date document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified) document referring to an oral disclosure, use, exhibition or other means document published prior to the international filing date but later than the priority date claimed	"T" "X" "Y" "&"	later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art document member of the same patent family
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Date of the actual completion of the international search

12 August 2024 (12-08-2024)

Date of mailing of the international search report

26 September 2024 (26-09-2024)

Name and mailing address of the ISA/CA
 Canadian Intellectual Property Office
 Place du Portage I, C114 - 1st Floor, Box PCT
 50 Victoria Street
 Gatineau, Quebec K1A 0C9
 Facsimile No.: 819-953-2476

Authorized officer

Paul Sabharwal (819) 639-3264

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No.

PCT/CA2024/050819

Patent Document Cited in Search Report	Publication Date	Patent Family Member(s)	Publication Date
CN114581771A	03 June 2022 (03-06-2022)	CN114581771B	25 April 2023 (25-04-2023)
CN116109931A	12 May 2023 (12-05-2023)	CN116109931B	15 March 2024 (15-03-2024)