Fusion of high resolution SAR images with optical and GIS data and its application to change detection in urban areas

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Abstract: SAR images are perfectly suited for change detection, given that they are not affected by different sun illumination conditions and/or clouds. There is potential to improve the SAR change detection results by taking into account prior knowledge of the scene, which can be obtained from other sources of information such as high resolution optical images and data from Geographic Information Systems (GIS). In this paper we will describe how information about the scene geometry and a classification of the scene into different semantic classes can be obtained from the optical and GIS data, and how this information can be transformed to the slant-range coordinate system of SAR images so that it can be easily used in the change detection process. Finally, we will show some initial results that illustrate the benefits of using this information about the scene during the change detection.

1 Introduction

One of the most interesting applications of remote sensing data is the detection of changes due to human activity. This can be applied to the monitoring of urban areas, and can also facilitate urban planning. Ideally, we want to be able to detect changes in certain areas of interest as often as possible. Currently, there are many Earth observation satellites on orbit which have high resolution capabilities and can acquire images of any point on Earth every few days. From the different types of sensors available, Synthetic Aperture Radar (SAR) sensors are better suited for this task, because unlike optical sensors, they are able to operate day and night in all weather conditions. Also, because SAR is an active sensor, the acquired images do not change with the sun illumination conditions, which means that any significant differences between two acquired images will be only due to a change in the imaged scene. This is an important advantage when doing change detection. However, one big disadvantage of SAR sensors is that the interpretation of SAR images of complex scenes, like urban areas, can be a difficult task. This is due to radar specific imaging effects like speckle noise, multiple-bounce propagation, layover and shadowing.

Traditionally, when doing SAR change detection, two or more images of the same scene and acquired at different times are first co-registered (i.e., aligned so that each pixel represents the same location in all images). Then, the amplitude (for incoherent change detection) or the amplitude and phase (for coherent change detection) of the SAR images is compared for every pixel. Typically, the results are shown in a new image that highlights the changes in some color. However, these color images still need to be visualized and interpreted by a human. Modern sensors are capable of acquiring large amounts of data in short periods of time, which means that

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the visual interpretation of all these images is no longer feasible. Therefore, a reliable unsupervised approach that detects changes from a series of SAR images is needed.

Several unsupervised change detection techniques employing very high resolution SAR images can be found in the literature. Most of these are automatic thresholding techniques that work with individual pixels such as the ones presented in (QUIN et al. 2014; SU et Al. 2015). This means that after computing a change detection metric, such as the log-ratio operator (BAZI et al. 2005), a threshold is set automatically and then the pixels below/above this threshold are set as unchanged/changed. In the last few years, a few promising examples of unsupervised change detection approaches that take advantage of some available prior knowledge about the imaged scene have been presented. In BOVOLO et al. (2013), which has a focus on surveillance applications, the authors develop custom feature detectors based on the objects that they expect to find in certain areas of interest of the SAR images. This approach seems to provide very good results, but it needs to be customized for each scene. In TAO & AUER (2016) the authors detect changes on existing buildings and facades by using SAR images together with a Digital Surface Model (DSM). Their approach has the advantage of being capable of working with images acquired with different incidence angles. However, it cannot be used to detect new buildings or any other type of changes. Looking at these results it appears that, if available, prior knowledge about the scene can be used to improve the results of the SAR change detection process.

In this paper we will investigate what kind of information about a scene can be extracted from optical images and GIS data, and how this information can be introduced as prior knowledge into the SAR change detection process to improve the change detection results. Initially, in section 2 we will describe the steps that must be performed in order to achieve this, and some examples using a dataset from the city of Oslo (Norway) will be shown. Finally, the obtained conclusions and the next steps that should be taken to further advance this work will be outlined in section 3.

2 Methodology

In this section, we will describe the different steps for using prior knowledge about a scene together with SAR images, and take it into account when doing SAR change detection. We will obtain this prior knowledge about the scene from optical images and GIS data. The information extracted from these sources must be transformed to match the slant range geometry of SAR images so that it can be used in the SAR change detection process. A simple block diagram showing the different steps of the proposed workflow can be seen in Fig. 1.

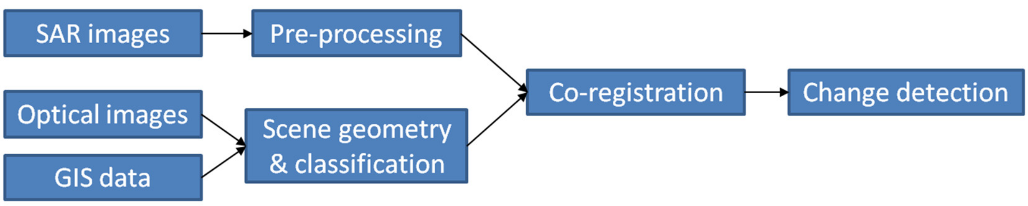

Fig. 1: Block diagram of the proposed workflow for adding information from other sources to the SAR change detection process.

As it can be seen in this block diagram, initially some pre-processing needs to be applied to the SAR images, and information about the scene geometry and a classification of the scene into different semantic classes must be obtained from the GIS and optical data. Then, the information extracted from this data must be co-registered with the SAR images, so that they can be used together during the change detection step. Finally, the changes can be detected by using the SAR images together with the scene knowledge that was obtained from the GIS and optical data. All these steps will be described below.

2.1 Pre-processing of the SAR images

Applying some pre-processing to the SAR images before using them for change detection can help to improve the obtained results. One important task that needs to be performed is the reduction of the speckle noise which is present in all SAR images, as this noise makes it harder to discriminate between the changed and unchanged classes, increasing the number of false alarms. One simple and well established technique for reducing the speckle noise is multi-looking, which significantly improves the radiometric quality of SAR images in exchange for a worse spatial resolution. Depending on the resolution of the SAR images and the size of the smallest changes that must be detected, a worse spatial resolution might not be acceptable. In these cases some other speckle filters can be used, such as the well-known Lee filter (LEE 1986), which attempt to reduce the speckle noise while keeping the spatial resolution of the original SAR image.

After reducing the speckle noise of all the SAR images to be used for change detection, these images must be co-registered. The co-registration of SAR images acquired by the same sensor is not especially difficult, and can be solved using different methods. One of these methods is the geometrical registration presented in (SANSOSTI et al. 2006). Besides being accurate, this method is also very flexible, as it can also be applied to images acquired with different incidence angles and/or different orbits, and not only the typical repeat-pass case.

Once the speckle noise of the SAR images has been reduced and all the images have been co-registered, they are ready to be used for change detection.

2.2 Extracting information about the scene from optical images and GIS data

Although the pre-processed SAR images could already be used for change detection as is, we have already established that there is potential to improve the change detection results if we also use prior information about the scene. This will be especially helpful in urban areas, which are typically very complex scenes in SAR images because of the important role that effects such as layover, shadow and multiple-bounce play in these areas. In order to make our approach fully unsupervised and as general as possible, we will extract this prior information about the scene automatically from other common types of data: optical images and GIS data. More specifically, we will obtain information about the scene geometry in the form of Digital Surface Models (DSM) by photogrammetrically processing stereo optical images, and a classification of the scene into different semantic classes (e.g., buildings, roads, vegetation, etc.) from GIS data (i.e., vector maps).

2.2.1 Extracting information about the scene geometry from stereo optical images

Optical images provide complementary information to the SAR images. Besides being much easier to interpret, the optical images can also be used for obtaining accurate height information in the form of photogrammetric Digital Surface Models (DSM). These DSMs provide us with important information about the scene geometry which can be used to find the layover and shadow areas of the SAR images, as we will describe later in section 2.3.1. The shadow and layover areas of the SAR images play an important role in urban areas, and it has already been shown how their knowledge can be exploited to detect changes in existing buildings (TAO & AUER 2016).

In order to obtain a DSM from stereo optical images, these images need to be photogrammetrically processed. Initially, the orientation obtained from a Global Navigation Satellite System (GNSS) and/or Inertial Measurement Units (IMU) can be refined by using Ground Control Points (GCP) in order to achieve better positional accuracy if needed. Then, a dense stereo matching algorithm, such as the popular Semiglobal Matching algorithm presented in (HIRSCHMULLER 2008), must be applied to obtain the height values. Once the height values are available, the images can be orthogonally reprojected with enforced homogeneity constraints to generate a true orthoimage (VILLAMIL-LOPEZ et al. 2016). Depending on the sensor used for acquiring the images and the extension of the scene to be imaged, several images might need to be processed into a mosaic that covers the whole extent.

For the dataset of the city of Oslo that will be used throughout this paper, a set of UltraCam-X images were processed using the approach described above. The obtained true ortho mosaic and DSM have a ground pixel spacing of 20 cm and can be seen below in Fig. 2, which shows a small area near the Oslo train station.

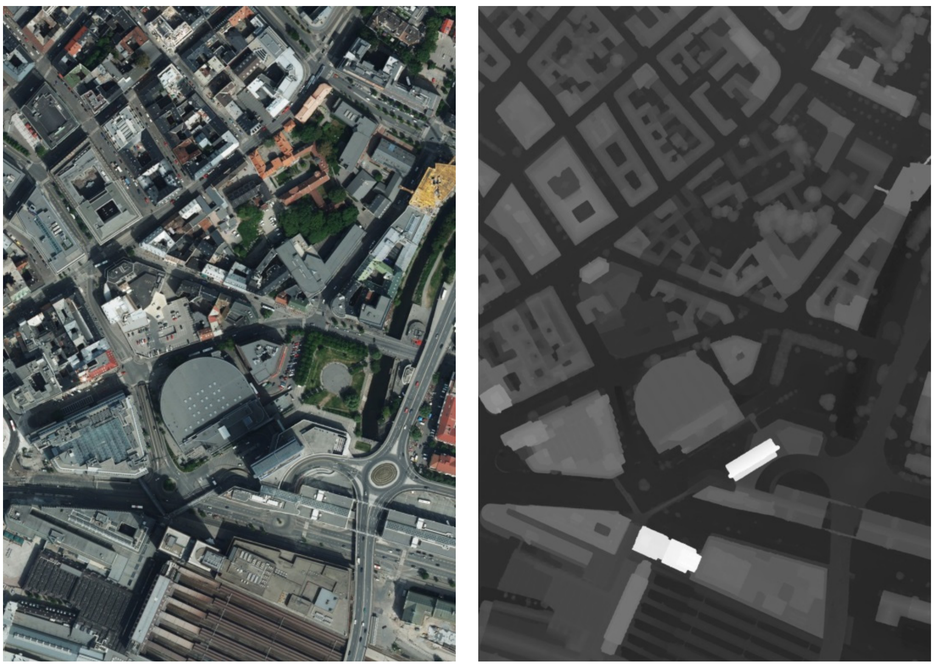

Fig. 2: True orthoimage (left) and DSM (right) from a small area near the Oslo train station, obtained from a set of optical images by using the approach described above

2.3 Classification of the scene into different semantic classes using GIS data

In addition to the information about the scene geometry that we obtained from the optical images, we can also use data from Geographic Information System (GIS), like vector maps, to obtain additional information about the scene. These maps can provide a classification of the scene in different categories, such as buildings, roads, vegetation, water, etc. This classification can help to improve the results of the change detection (e.g., by allowing us to detect changes using different thresholds for different types of surfaces). Besides, once a change has been detected, knowing in which type of area it took place can help us to distinguish between different types of changes. Vector maps are formed by a series of shapes which have an associated tag/category and with their coordinates specified in a certain map projection. In order to use this information in the change detection these shapes need to be projected into the SAR images, as it will be described later in section 2.3.2.
A great source of free high-quality vector maps is the OpenStreetMap (OSM) project, in which data is added and made freely available by volunteers. The amount of data in OSM and its quality is constantly increasing, although data quality varies worldwide (HAKLAY 2010; ZIELSTRA & HOCHMAIR 2012). The global OSM dataset can be imported and organized into a PostGIS database, which allows to quickly find features of a given type which are located within a certain region. An example of the classification that can be obtained by using OSM data can be seen below in Fig. 3, which shows an optical view of Oslo and the corresponding OSM data for four classes: roads, buildings, vegetation and urban ground.

Fig. 3: Optical view from Oslo (top) and classification obtained using OpenStreetMap vector data (bottom). The classes are: roads (gray), buildings (red), vegetation (green) and urban ground (brown)

2.4 Co-registration of the SAR images with the GIS and optical data

Even though all the SAR images have already been co-registered during the pre-processing step, we still need to co-register them with the GIS and the optical data so that later, in the change detection step, we are able to use the information that we extracted from these sources. This means that we need to transform these different types of data to the same coordinate system. One possibility would be to simply orthorectify the SAR and optical images to the map projection used by the GIS data. However, this is not ideal, as there would be some issues in the layover regions of the SAR images, where multiple points located at different positions are imaged into a single SAR image pixel. To avoid these issues, it is desirable to transform the GIS and optical data into the azimuth and range coordinate system of the SAR images. Initially, we will describe how to transform the optical image (and the DSM we obtained from it) to accurately match the SAR images. Finally, we will briefly mention how to do the same for the GIS data, although this task is much easier.

2.4.1 Transforming optical data to the SAR slant range geometry

The co-registration of SAR and optical images was traditionally a difficult task due to the big radiometric and geometric differences that exist between these two image types. However, the high geolocation accuracy of current state-of-the-art SAR and optical sensors makes this much simpler, by allowing us just to use the geometric information instead of having to use more complex feature or intensity based registration methods. Recently, we presented a method for the co-registration of SAR and optical images using this geometric information, which is capable of handling the ambiguities that appear in the layover areas by using a DSM. We describe this method in detail in (VILLAMIL-LOPEZ et al. 2016), but it will also be summarized below.

For any given pixel in a SAR image, we know the corresponding sensor position and the distance between the sensor and all the points that are imaged in this pixel. By using this information and the range and Doppler equations presented in (CURLANDER 1982), we obtain a circle which defines all the possible locations of these points. By intersecting this circle with the DSM obtained from the optical images, we can find how many points are imaged in this pixel and get their respective locations. With this information, we can easily obtain the shadow and layover areas of the SAR image, and also the pixels in an optical image that correspond to each pixel in the SAR image. The optical image can then be resampled to the coordinate system of the SAR image, obtaining the co-registered optical image.

In order to find all these intersections in an efficient way, we need to be able to perform fast and accurate geocoding (i.e., convert between image and ground coordinates and vice versa). The Rational Polynomial Coefficients (RPC) are a set of polynomials that can be used for fast geocoding, and they can be computed for a SAR image as described in (ZHANG et al. 2011). The loss of accuracy due to the use of RPC instead of to the physical SAR sensor model described in (CURLANDER 1982) is negligible, with errors typically below millimeter level. The optical data has already been processed to a true orthoimage, as we described before in setion 2.2.1, which makes the conversion between image and ground coordinates trivial for this type of data.

Once the conversion between image and ground coordinates can be done efficiently for both types of data, we need to find the intersections between the circle that describes the possible locations of a SAR pixel and the DSM. This process is illustrated in Fig. 4, which shows a very typical case that appears in most SAR images of buildings, where the reflections from the building's roof, façade and the ground are imaged in the same SAR image pixel. In the top-left of this figure, a SAR image of a building with a pixel highlighted in red can be seen. The ground coordinates of this pixel are computed for different height values using the RPC, and the obtained points are projected into the DSM (top-right of Fig. 4). Then, the height value of each of these points can be compared with the corresponding DSM height values. Finally, as it can be seen at the bottom of Fig. 4, the obtained intersections give us the location of the scatterers which can be imaged in the highlighted SAR pixel.

In certain cases something might block the direct line of sight between the SAR sensor and some of these points, which means that the SAR sensor will not be able to see them. For a given SAR pixel, if none of these points can be seen by the SAR sensor, the pixel will correspond to a shadow area; whereas if more than one point can be seen, then the pixel corresponds to a layover area. To check if a point is seen by the SAR sensor, we need to compute the look angle (i.e., the angle between the nadir vector and the line of sight between the sensor and this point) and compare it with the look angle for other points at the same range line (i.e., same azimuth position). A point will be occluded (and therefore not seen by the SAR sensor) if there is another point in the same range line located closer to the sensor and with a higher look angle.

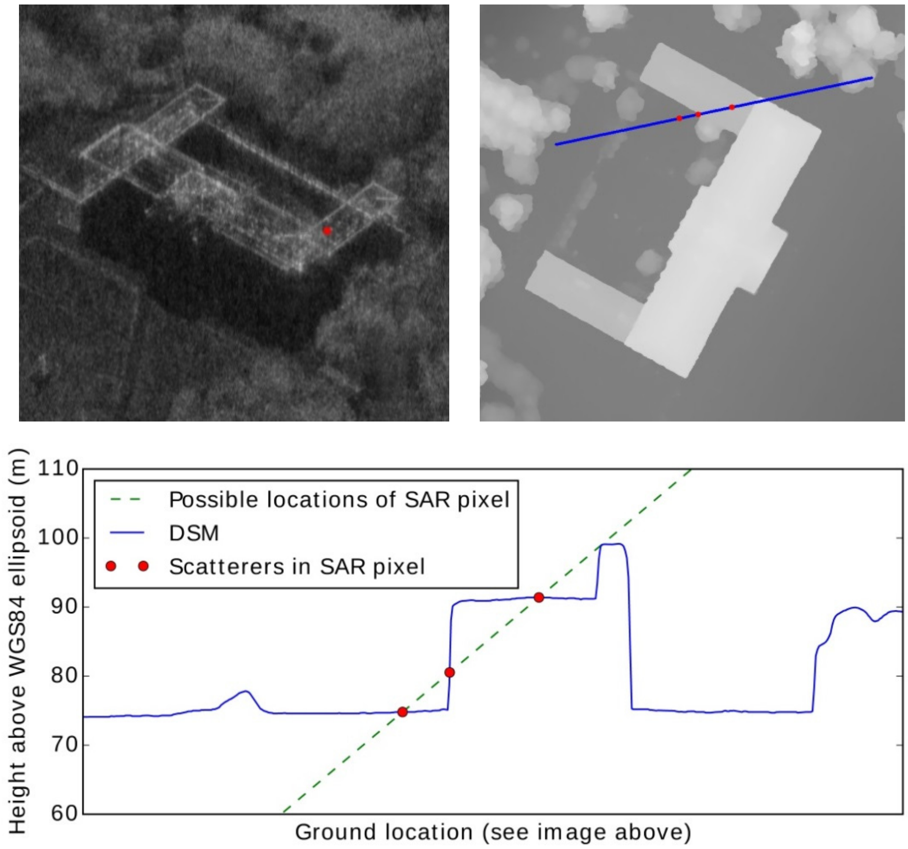

Fig. 4: Finding the location of the scatterers that are imaged in a SAR pixel using a DSM: SAR image with a pixel highlighted in red (top left), DSM with the possible locations of this pixel highlighted in blue (top right), and plot showing the intersections between these locations and the DSM (bottom)

2.4.2 Transforming GIS data to the SAR slant range geometry

The vector shapes from the GIS data need to be projected to the SAR images so that we can use this information later in the SAR change detection step. These shapes are defined by coordinates in a certain map projection (e.g., latitude and longitude or UTM). However, they are typically missing the height coordinate, which we need to project these shapes into the SAR images. Because the shapes in these maps represent objects that are located on the ground surface, we need to obtain those heights from a Digital Elevation Model (DEM) which depicts the terrain height, rather than the DSM that we previously used (which includes the heights of buildings and other structures). Once we know these height values, we can easily project the shapes in the vector map to the SAR images by using the RPCs of the SAR image that we computed before, obtaining a classification of the SAR image in different semantic categories as a result.

2.4.3 Sample co-registration results

To check the accuracy achievable with the co-registration methods described in this section, we applied them to co-register the orthophoto and the OpenStreetMap vector data of Oslo described in the previous sections with a SAR image showing an area with a few buildings. The obtained results are shown below in Fig. 5, where we can see how the co-registered optical image is perfectly aligned with the SAR image even in the layover areas. It is interesting to note that although the optical image used was a true orthophoto (i.e., seen from above), after the co-registration the building façades are now visible because they are also visible in the SAR image, and we transformed the orthophoto to the SAR slant range geometry. Regarding the vector maps from OpenStreetMap, we can see that the building footprints and the roads are accurately projected to the same ground locations they occupy on the SAR image. The vegetation areas with some trees are missing from the OpenStreetMap data, but this has nothing to do with the co-registration method, and more accurate maps from a different source could be used if available.

Fig. 5: Example of co-registration results obtained with the described approach: SAR image of a small area of the city of Oslo (left), co-registered optical image (center), and GIS data showing the location of building footprints in red and roads in dark gray (right)

2.5 Using knowledge about the scene in SAR change detection: initial results

Once we have transformed all the different types of data to the SAR slant range geometry, we can use the information about the scene that we have obtained in the previous steps together with the SAR images for detecting changes caused by human activity. As we already mentioned, the DSM can be exploited for detecting changes in existing buildings by looking for changes in their corresponding shadow and layover areas, whereas the vector maps can be helpful for other types of changes by allowing us to detect the changes in different regions separately. An example of using a DSM for detecting changes in existing buildings has already been shown in (TAO & AUER, 2016). Therefore, to demonstrate the potential of the approach presented in this paper we chose not to focus on buildings, but rather on taking advantage of the vector maps for detecting other types of changes. To illustrate this, we will use two TerraSAR-X images of Oslo (with dates of 12.03.2016 and 23.03.2016) acquired with the very high resolution Staring Spotlight imaging mode, together with the OpenStreetMap data that we described previously in section 2.2.2.

The most prominent changes in our dataset correspond to activity at Oslo the city port, such as moving ships and cargo. The detection of these ships serves as a perfect example for showing how vector maps during the change detection for detecting only specific types of changes. For starters, we know that ships will obviously be located on water, and we know which parts of the image correspond to water thanks to the OpenStreetMap data. Therefore, we only need to look for changes in these image regions, and we can set a threshold for detecting these changes by taking into account the SAR amplitude of just the water regions. The histogram of the log-ratio image (i.e., the logarithm of the ratio between the amplitude of both SAR images) was computed for the complete image and for only the water regions, and the results can be seen in Fig. 6.

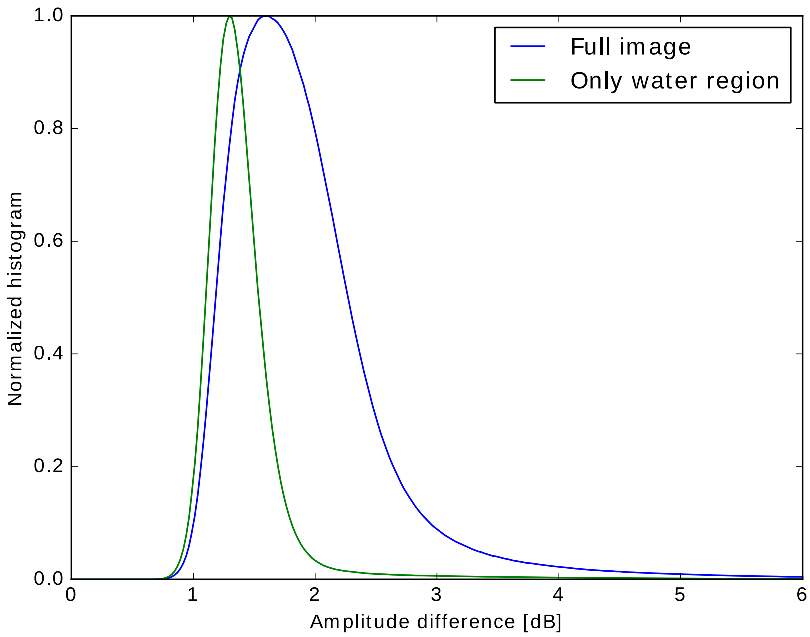

Fig. 6: Plot showing the histogram of the difference between the amplitude of the two SAR images computed for the whole image (blue) and only for the water region (green line)

For finding the threshold to separate the change and no-change classes, an unsupervised thresholding technique such as the ones presented in (BAZI et al 2005; QUIN et. al 2014) can be applied. Looking at the histograms shown in Fig. 6 it becomes clear that computing this threshold for a certain image region (such as water in this case) will provide different results than computing it using the whole image, and it seems obvious that more accurate results will be obtained when computing a specific threshold for each region.
For this simple example of ship detection no automatic thresholding technique was applied, and instead the threshold was set to a fixed 6 dB value. This value was selected by taking into account that ships have bright signatures in SAR images, and the corresponding SAR amplitude is typically at least one order of magnitude (i.e., 10 dB) than that of water (which appears as a dark homogeneous surface). Finally, to remove false alarms due to speckle noise and other detected changes which were not ships, the changes that were too small and therefore could not be ships (which typically have sizes of at least 10 meters) were discarded automatically. This last step was done by analyzing the number of pixels in each of the connected components of the thresholded log-ratio image. The results of this example are shown below in Fig. 7, which shows the bounding boxes of the automatically detected ships in red, painted over a RGB composite image that highlights the changes in orange for easier visuaization.

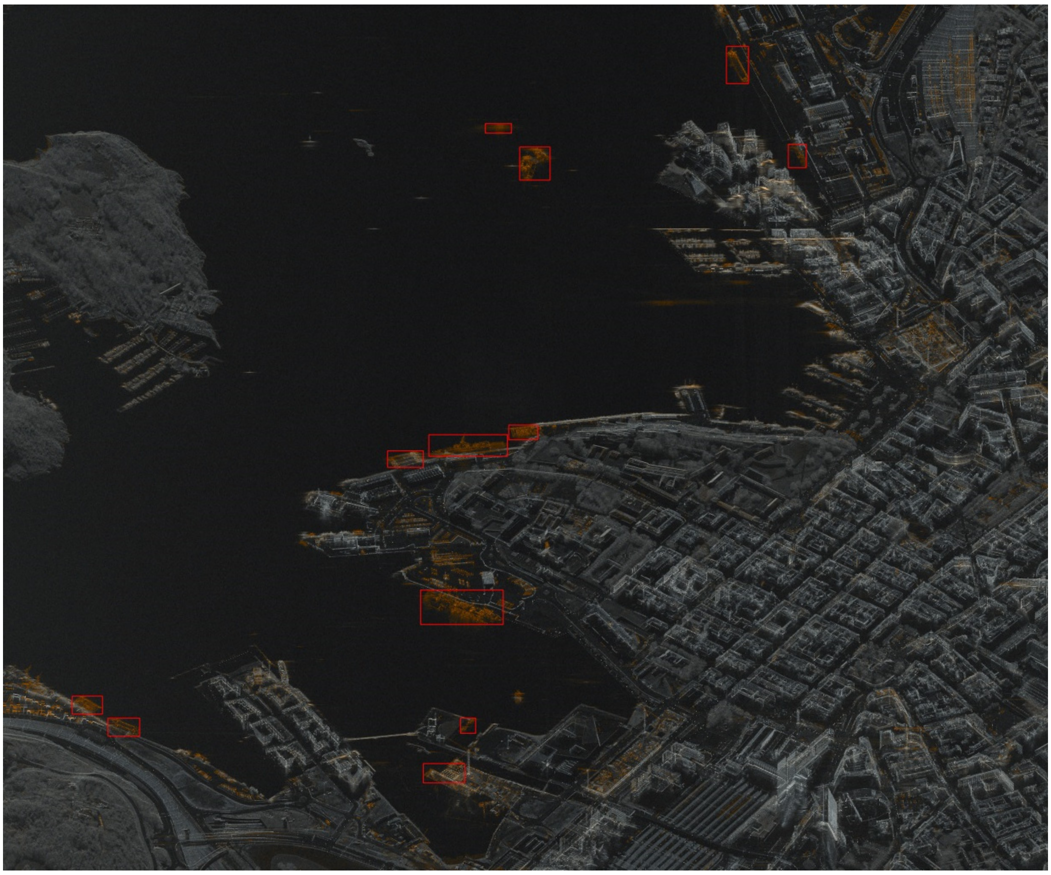

Fig. 7: Results of applying the proposed workflow for detecting ships that arrived/left the port of Oslo. Red rectangles show the ships that were automatically detected. For easier visualization, the rectangles are drawn over a RGB composite of two TerraSAR-X images that highlights the changes in orange

Looking at the results shown in Fig. 7, we can see that all the large ships in this scene were correctly detected. However, one object at the port was erroneously identified as a ship, and three small ships located very close to each other were detected as a single ship. From the results of this simple example, we can establish that the presented method has potential for the unsupervised detection of changes and the classification of these changes (e.g., buildings, ships, etc.). However, these are still initial results which are meant to illustrate the ideas presented in the paper, and more research is needed to be able to robustly detect and identify multiple types of changes, and make it applicable in more scenarios.

3 Conclusions and future work

Remote sensing data can be used for detecting changes due to human activity. Synthetic Aperture Radar (SAR) sensors are better suited for this task than other types of sensors because SAR images are not affected by the sun illumination conditions and/or clouds. However, robustly detecting these changes in an unsupervised manner (i.e., without any human interaction) is still challenging. If available, prior knowledge about the imaged scene can be taken into account during the change detection process to simplify this problem and improve the obtained results. The introduction of this prior knowledge appears especially interesting for urban areas, which are typically very complex scenes in SAR images because of the important role that effects such as layover, shadow and multiple-bounce play in the urban environment. Two interesting sources for this prior knowledge about a scene are GIS and optical data: vector maps provide a classification of the scene into different semantic classes, and stereo optical images can be processed into a DSM that contains accurate information about the scene geometry. The information extracted from these sources needs to be transformed to the slant range geometry of SAR images in order to be used during the change detection step. Another possibility would be to orthorectify the SAR images, but this is not recommended because of the ambiguities that exist in the layover areas, which are very common in urban areas. A complete workflow for extracting this prior knowledge about the scene from GIS and optical data, transforming it to the SAR slant range geometry, and taking it into account during the SAR change detection process has been described in section 2.

Even though we have described the complete workflow, the main focus has been on the initial steps: which kind prior scene knowledge can be useful, where and how to obtain this information, and how to transform it to the geometry of the SAR images so that it can be used together with the SAR images for the change detection. This means that only some initial research has been done on how to exploit this prior scene knowledge for detecting changes with SAR images, and even though we have already shown that there is a big potential, more research is needed to fully take advantage of it.

In addition to this, the potential of other types of GIS data (different than the vector maps from OpenStreetMap which were used in this paper) must also be explored. One very promising source of information for our application is data in CityGML format, which is an open data model and XML-based format for the storage and exchange of virtual 3D city models (Gröger et al. 2012). CityGML is becoming a popular standard, and datasets in this format can be imported and organized into a PostGIS database (which we also used for the OpenStreetMap data) using the 3DCityDB software (Stadler et al. 2009; Kunde et al. 2013). Therefore, the presented workflow should not change much, and the 3D models of buildings which are available within these datasets might eliminate the need of using a DSM.

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