Final Year Project
Final Report

Change Detection in Synthetic Aperture Radar Videos

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1. Abstract

In this research, a change detection technique which can be utilized in identifying important changes in SAR videos has been proposed. Even though most researches have done on change detection in multi temporal SAR images, implementing a methodology to identify changes in SAR videos in a near real time manner has unique challenges such as the inherent speckle noise which will increase the false positive rate of the detection, rotation of the reconstructed SAR video frames due to the movement of the airborne vehicle, dynamic background and the overlapping of the area in consecutive video frames, non-uniform backscattering of SAR pulses and shadowy modelling of objects in video frames which doesn't provide much information about the appearance model of the objects. We propose an algorithm based on the combination of optical flow calculation using Lucas Kanade method (LK method) and blob detection to detect the changes, and we feed the detected changes along with optical flow calculations to a centroid tracking algorithm to track the detected changes throughout the video.

2. Introduction

Synthetic Aperture Radar or SAR is a form of Radar that can be used in creating two dimensional or three-dimensional reconstructions of objects. SAR imagery uses the motion of radar antenna over a target region to provide a finer spatial resolution than a normal beam scanning radar. In order to achieve this task, we mount the Radar antenna on a moving platform such as aircraft or spacecraft etc. The images were taken from SAR are very large in resolution and therefore it is very computationally expensive to generate such images and do further processing in real time manner.

But with today's technology it is possible to generate SAR videos which are created using SAR imagery. One interesting quality in this kind of SAR videos are that they are very high in resolution and did not get affected by the environmental conditions such as fog, smoke etc. Therefore, these videos can be used in applications such as surveillance, rescue missions, landscape change detection etc. The only problem that remain in this is that these videos contains high amount of noise and glare effects due to the uneven reflections that occur from various objects in considering area. Also, these videos contain a circular motion due to the specific method of generating SAR images and this motion also affects when we need to use SAR videos in a meaningful application.

In our research we are hoping to reduce effects in SAR videos such as noise, glares, frame movements etc. and try to build a change detection system which can be used in previously mentioned applications such as surveillance, rescue missions, tracking etc. Also, we are looking forward to develop this algorithm to work in a real time application and with a considerable accuracy as well.

3. Problem Statement

Most of the research that has been carried out, were about change detection in temporal images using SAR imagery which means, detecting changes between images that have acquired on different dates. We are going to address the problem of detecting changes in real time, given a SAR video which consists of a sequence of image frames with a dynamic background. As the capturing radar rotates, the SAR video generated, has a dynamic background and a rotation around the axis of the frame. Comparing each frame in the video, we need to identify the changes in real time. The problem can be addressed in multiple steps.

1. Image Registration - Addressing the issue of rotation of axis of each image frame in the video
2. Dynamic Background modelling - Addressing the issue of dynamic background in each image frame
3. Speckle Noise Reduction - Avoiding the noise in the video frames
4. Real time change detection

Real time change detection in SAR videos plays a major role in interactive applications like military mission planning applications, disaster recovery management applications, country border surveillance, identifying lost people during war periods, monitoring dynamic weather conditions etc. Real time change detection is very important for time critical applications which are used to get information and have access to human unreachable situations.

4. Motivation

There are various practical applications which can utilize the change detection using SAR videos.

1. Military applications remote terrorist location identification

   Remote terrorist locations which are unreachable from the army camps can detected by this approach. Images feed that is derived from the radar pulses can be used to identify movements of enemy troops, whether they're reaching towards the army camp, whether there are injured soldiers or whether they're attacking the army camps in frontline.

2. Surveillance

   This can be used for surveillance of traffic jams, human surveillance for security concerns, ship detections etc. Mainly this approach is much beneficial for surveillant of the locations which are unreachable from humans.

3. Rescue Missions

   It can be amidst a forest where a group of people have lost or middle of the sea that a human is left alone in the boat or a person or a group of people might have caught to a natural disaster like wildfire, hurricane, earthquakes. They might have needed an immediate help and this needs to be conveyed to the relevant rescue teams. This approach can be used to notify relevant authorities in such situations.

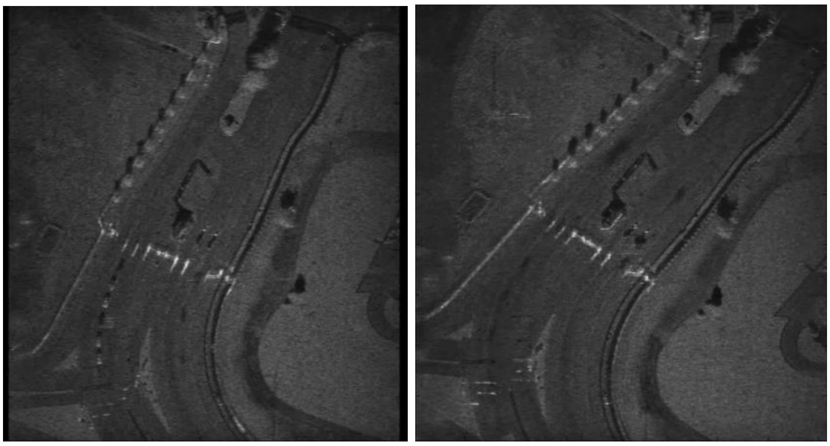
4. Search and Tracking

   All these above mentioned 3 areas can be identified as search and tracking. Therefore, major motivation of this project is to apply this method for search and tracking in real life applications.

5. Research Objectives

The main objective of this research is to develop an algorithm which can be used in SAR videos to detect changes in real time addressing the issue of image registration. As SAR videos often contains considerable amount of noise and glare like artifacts we are hoping to develop a filtering method that can reduce such problems as well. Obtaining an acceptable amount of accuracy is also considered as an objective as well. Thus research objectives can be briefed as follows.

5.1 Develop an algorithm for image rotation correction



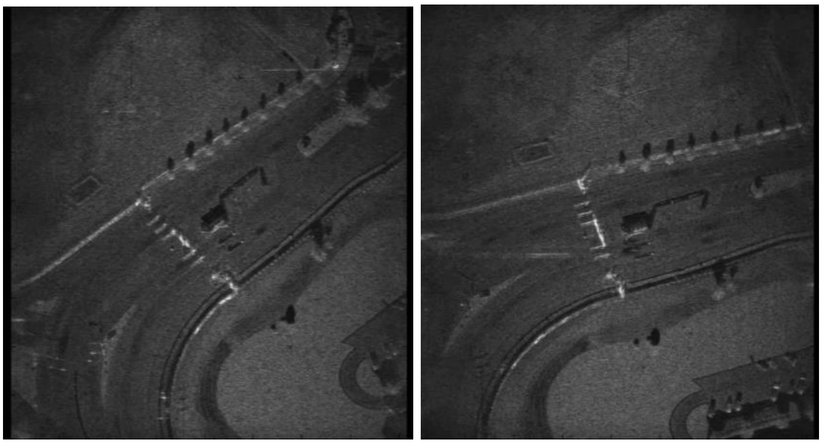


Fig 1-4: Image frames extracted from SAR video

Fig 1-4 are consecutive frames that were captured from a SAR video. We can observe that frames were rotated around the axis due to the angular motion of the airborne satellite. In order to detect the changes, this rotation should be corrected, and the frames should be adjusted based on a reference frame.

5.2 Develop an algorithm to detect changes in SAR videos

We are interested in identifying changes. Changes can be movements of objects which can be either human or object movements. Those are the only true positive changes. Change detection algorithm ideally should not be sensitive to noise, shadows, glare. We are only interested in identifying moving objects. Recognition of the type of the object (e.g. Whether it is a vehicle, human) is not included in our objectives.

Fig 5: Speckle Noise in the image frames

The Fig 5 frame shows how glare or reflection effect might lead to false positives if the change detection algorithm is sensitive to such noise. Therefore, we need to discard such effects in order to increase the accuracy of the algorithm.

5.3 Develop an algorithm for object tracking

After identifying the interested change, we need to be able to locate the object in consecutive frames and track. This helps to use the system that we develop in before mentioned use cases such as Surveillance, rescue mission etc.

Fig 6: Moving objects in the frame

Fig 6. is an image frame captured from a SAR video. The cars on the road are the only moving objects in the whole video. Requirement is to track these vehicles throughout the video frame. By tracking down the moving objects in the frames will help the user to properly identify the moving objects and take necessary actions. Therefore, this part acts as an important step in the system design process.

5.4 Improve algorithm to function with good accuracy

Effect of speckle noise, glare and reflections are inevitable. We need to find good mechanisms to cope up with those effects and to reduce the impact on false alarm rates. Also, after developing the system we need to make sure that it can be used in real time applications as well.

Therefore, as the final step, it is required to improve and enhance the algorithms to perform considerably well in the given use cases. This step acts as the user experience enhancement stage and will be focused last after developing the complete system prototype.

6. Research Methodology

In order to achieve the identified objectives, following main obstacles were detected.

1) Speckle noise in the SAR videos due to the method of generation
2) Dynamic background
3) Hard to find object movements
4) Identification of the moving objects in the scene
5) Tracking the identified objects

After analysing the problems mentioned, four main research steps were identified. Below the research methodology which consists of 4 stepwise procedures have been identified.

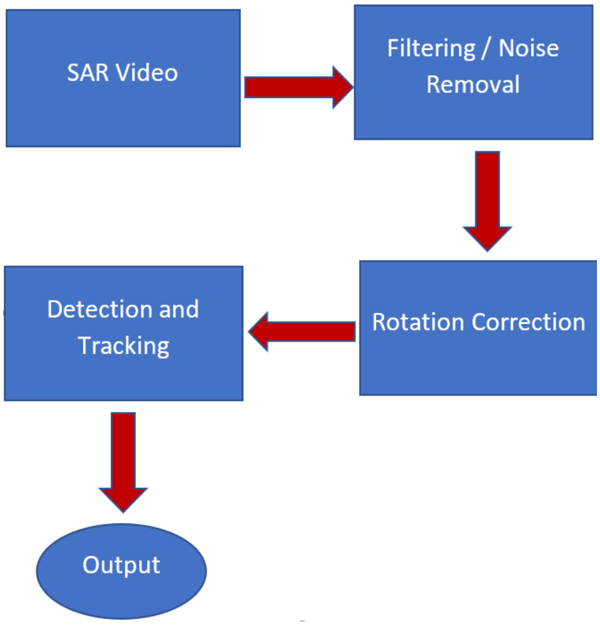


Fig 7. Solution major steps

6.1 Image filtering step

Images that are captured from the airborne vehicles consists of speckle noise, glare, shadows and reflections from the objects. Therefore, we need a mechanism to deal with these problems which might lead to false positives. We need to,

a. To achieve more clear images to next steps
b. To remove speckle noise
c. To enhance the features of the image

This is the initial step of the methodology. Only after obtaining filtered images, we can get a better result for the image movement and tracking stages. Therefore, initial research on this subject is hoped to be helpful in upcoming system steps.

6.2 Image rotation correction

As explained in research objectives, we need a method to handle the effect of movement of airborne vehicle which circulates around an axis while sending pulses to derive images. In this step it is expected to analyse each frame of the video and correct each of their rotations by warping the images to the initial frame. Usage of image feature and using homographic transformation matrix to analyse the required transformation is expected.

For change detection process, this step is used for correcting video frames.

6.3 Image Movement detection

Major part of this research is to identify interested changes in the consecutive images set. There can be two types of change: interested changes and uninterested changes. Uninterested changes can be caused due to glare and speckle noise. Objects and human movements are identified as interested movements. Therefore, in this step we need,

a. To identify the moving objects in the frame.

b. To Ignore the unwanted movements in the frame

Therefore, it is required to identify all the possible movements that can be found in the frame and then ignore the movements/ changes that occur due to dynamic background, noise and reflections in this step.

6.4 Object tracking

As the last stage of the 4-step process, we are interested in tracking the objects/changes that we identified. We need to be able,

a. To track the identified object

b. To notify the user regarding the unusual movement

The research is done mainly focusing on the above-mentioned steps and experimentation is done accordingly.

7. Background and Previous Work

Synthetic Aperture Radar (SAR) is an important modality for remote sensing applications since it has the capability of generating high resolution images significantly invariant to the climate changes, weather and lighting conditions. Tensor-product based transformation of radar return pulse histories are applied to obtain a spatial representation of target objects. SAR imagery uses the motion of radar antenna over a target region to provide a finer spatial resolution than a normal beam scanning radar [1][2].

ViSAR is a SAR imaging mode which is utilized to generate images at a higher rate than a conventional SAR, hence can be viewed as a video derived from consequent set of image frames. Since images generated from ViSAR systems have a higher resolution despite the adverse climate changes, these systems can be utilized in many day/night surveillance or tracking applications such as all-weather military and civilian applications, weather, land and marine traffic monitoring, rescue missions and surveillance [3].

Most of the research that has been carried out, were focused on change detection in temporal images using SAR imagery which means, detecting changes between images that have acquired on different dates. In this paper, we are going to discuss how change detection can be applied on real time Synthetic Aperture Radar (SAR) videos which are generated by consecutive image frames taken by an airborne platform which moves in a circular path around a particular geographical area.

We propose a new method for change detection using the combination of Lucas Kanade method and blob detection followed with various pre-processing steps for filtering and image enhancement. Since SAR video generation can be paralleled and can be extended to do in real time [4], applying change detection on SAR videos can be useful for real time surveillance operations in military situations, ship detection, rescue operations in the aftermath of natural disasters, traffic monitoring and searching and tracking for various other applications.

SAR pulse emitter and receiver are located on an airborne platform which travels along a circular path, therefore it has the effect of covering the same geographical area with different angles which helps to build a complete image of the scene. To derive images from SAR pulse data Frequency domain approaches such as range Doppler imaging and time domain processing algorithms such as Back-propagation were utilized. Due to the support for higher resolution and lesser assumptions about the image, Back-propagation produces better quality constructions compared to frequency domain algorithms [1].

SAR videos are generated by rendering sequence of consecutive SAR pulse reconstructed images. In this paper, a SAR video provided by Sandia Laboratories website and videos generated by our SAR simulator are used for evaluation purposes. Our SAR simulator was developed based on RaySAR [5] to produce circular SAR videos.

There are various problems associated with SAR video manipulation for change detection. Since the airborne vehicle from which the pulses are emitted, moves in a circular motion, the image frames that generated are rotated around a particular axis. Therefore, before applying change detection, either rotation should be corrected to make the background static or the change detection methodology should be invariant of dynamic background.

Speckle noise is inherent in generated SAR videos due to the doppler effect backscattered signals. Hence such noises should be filtered to reduce false positive rates. Various researchers have introduced various techniques to filter the speckle noise of SAR images, image registration techniques of satellite images and change detection techniques for satellite and optical images. Since SAR videos are generated from reconstructed consecutive SAR image frames, these techniques can be applied for our purpose.

Radar illuminate objects from its own lighting source, thus radar is a sensor which belongs to the active category. Radars might or might not produce images since it belongs to the microwave category in electromagnetic spectrum. Doppler radars which are used to calculate the speed are an example for non-image producing radars. Parallel to the flying line of the platform (that is airborne or satellite) image strips of the ground are generated by imaging radars. [1] The mechanism of imaging radars can be explained as follows. Radar antenna of the satellite sends pulse to the ground which hits the objects and scatter in an omni-directional manner. This pulse which is reflected by the object is called scatter. Some of the scatter is returned to the antenna. Scatter which is received back by antenna, is called backscatter. The intensity and the strength of the backscatter and the time it took to bounce back to antenna are measured. Pixel values of the images captured by antenna are measured from the intensity and amplitude of the backscatter. The distance to the objects on the surface from the satellite antenna pointer is measured by the time taken for the backscatter reflection. [2]

Synthetic Aperture Radar (SAR) which utilizes the motion of radar antenna provides finer resolution than generally used radars. The main drawback which must be thoroughly considered, when dealing with SAR imagery is the speckle noise which presents in the images. This speckle noise gives a dark and white intermingled appearance in the imagery. As a result of coherent accumulation of radar which is reflected from multiple elementary scatters, speckle noise is generated in the imagery. This speckle noise can be reduced using various techniques, but never can be eliminated without losing the details of the imagery. [3] - [7]

Change detection is a broad topic which was discussed under both optical and radar imagery. Change detection is discussed under pixel and object-based techniques. [8] By grouping neighbouring pixels based on spectral, textural and edge features, Object Based Change Detection techniques utilize the rich features based format for analysing pixel regions. [9] Based on the spectral properties of the image, it is divided into homogeneous sections in object based technique. Pixel based approach is done through a pixel-by-pixel comparison. Further this technique can be divided into supervised and unsupervised approach. In supervised change detection, multi temporal images are classified based on external information which is known as the post-classification approach. [10] Volpi et al. (2013)[11] discusses about a supervised approach which is not based on post classification method. They have done the multi temporal image classification using combination of support vector mechanism (SVM) and spectral properties. The main issue of the supervised change detection as identified by Yousif et al. (2013) [10] is the need of external information about the imagery.

Compared to Supervised Change Detection techniques, Unsupervised change detection techniques use information only included in the imagery itself. Using this technique, image frame can be identified either as changed or unchanged. Thus, unsupervised techniques only include two classes. [12] These techniques can be explained in multiple steps. Images are pre-processed to reduce the speckle noise. Then a difference image is created from image pixel-by-pixel subtraction or any other method which detects the different pixel values which are deviated from the defined threshold value. The difference image is used to create the change detection map. And the map demonstrates the changed and unchanged areas comparing each neighbouring frame. [3], [13] - [14] Thresholding on image or a histogram can be applied in this method. The main drawback of Unsupervised Change Detection, as explained by Yousif et al. (2012) is that it does not elaborate and specify about the change that has been taken place. However pixel based methods are sensitive to “salt and pepper” (black and white intermingling of images) noise. [6], [7], [9]

Another aspect that should be taken into consideration is the dynamic background of the image sequence. Since the video frame has a dynamic circular moving background, first and foremost background modeling techniques should be done. [15] Background modeling and subtraction which has been widely used for change detection and target detection prones to false alarms in dynamic background since the background model contains only temporal features. Temporal only methods lack the knowledge of the neighbourhood pixels of the concerned pixel. Thus it will conclude dynamic background also as a moving object which will cause a false alarm. A new pixel wise nonparametric change detection algorithm has been proposed. The background is modelled by spatiotemporal model using sequences of frames and sampling them in neighbourhood region randomly. Thus this model contains both spatial and temporal knowledge about the background which leads to better performance in change detection in dynamic background. [15]

Various recent papers have been discussed about using correlation filters for object tracking in satellite images. They have yielded a lot of promising results in the field of target tracking. Yu-Jia-Sun et al.(2017) has explained in their paper about a method named KCF tracker(Kernelized Correlation Filter) combined with 3 frame difference algorithm for object detection and tracking in satellite videos. As the KCF tracker achieves poor results because the target is too small in satellite videos, they have combined KCF tracker with 3 frame difference algorithm to improve the output results. [16]

Even though majority of the papers are discussed around identifying temporal changes using satellite imagery, the problem that we address, requires identifying changes in near real time manner and, instead of images, we are dealing with SAR videos which are generated from sequence of images. In order to tackle this problem, key challenges that we have identified, are as follows.

1. Rotation of video frames
2. Speckle noise and other noises which lead to false positives
3. Near real time change detection

Related work can be compared against the approach we have described in research methodology. As for the initial step of filtering the images in order to reduce the speckle noise, we implemented various techniques that were mentioned on the papers.[3]-[7] The papers have explained image coregistration techniques using feature matching operators such as SIFT, ORB. They have experimented them on optical images and the key difference is that we have applied those techniques to co-register two consecutive SAR image frames derived from the video. The object tracking algorithms were implemented on identifying and tracking objects in optical images, therefore it was less complicated to draw the bounding box compared to our use case of SAR image frames. Therefore we need to further improve these methods to get them adjusted to our context.

Lucas-Kanade method is a widely used differential method for optical flow estimations. Motion estimation is considered a very important field as independent estimations of motions at each pixel in the image can be computed separately. Patel et. al.(2013) [17] has discussed about how Lucas Kanade method can be applied for detecting changes in optical images which is termed as optical flow(motion of the pixels). Since we are interested in identifying changes in consecutive pixels of the frame, we used this approach to determine the motion pattern of SAR image frames.

Thus in order to apply those techniques that were being introduced in those papers, we had to do certain adaptations to adhere to the context of our problem.

8. Progress Chapters

8.1 Chapter one

8.1.1 Introduction

As explained in problem statement, we have to follow a stepwise approach to solve the associated problems in change detection using SAR videos. In this methodology chapter attempts taken to reduce the effect of speckle noise which should be filtered to avoid false positives in change detection algorithm, the research done to remove the effect of rotation and the approaches carried out to track the detected changes are discussed.

8.1.2 Literature Review

8.1.2.1 Speckle Noise

As a result of the coherent imaging mechanism, SAR images are accompanied by speckle noise unlike optical images. Speckle noise in SAR images are generated as a result of random interference of many elementary reflectors within one resolution cell [4], [5] and is multiplicative in nature. It is observed that speckle noise can affect the quality of the image, image segmentation, classification, extraction of regions of interest and target detection. Hence pre-processing techniques should be applied to reduce the effect of speckle noise. Ideal speckle filter should be adaptable and preserve image statistics, structure of the image and should have simplicity and effectiveness in speckle noise reduction [6].

Different despeckling techniques are suggested by researchers, where each has its own pros and cons. Converting the nature of speckle noise from multiplicative to additive can be done via log transformation. However, the drawback of log transformation is that it changes the statistical characteristics of the speckled image. Although it can be recovered using inverse log transformation operation, still there remains issues [7]. This is also referred as homomorphic transformation. It is mathematically proven that multiplicative operation is costlier than addition, hence the computational image restoration time is reduced in this nature transformation process compared to direct multiplication.

Mean filter, Median filter, Lee filter, Refined Lee filter and Lee Sigma filter are the most common and simple despeckling techniques used in SAR imagery [8],[6]. In mean filter, considering a specified window, central pixel is replaced by the mean of the neighbouring pixels. While mean filter smoothes out the image, it also smoothes the edges of the image [8]. As mean filter does not consider the homogeneous, flat areas of the image, it shows a low-edge preservation [9]. Boxcar filter which is a type of mean filter has been used for Polarimetric SAR classification of agricultural region [10]. By replacing the central pixel of the specified window with the median of the neighbouring pixels, image is smoothed out by the median filter. Segregated noise points in the image can be despeckled using Median filter [11]. Lee filter which uses the Minimum Mean Square Error filter principle reduces the speckle to a considerable level, however edges of the image also get blurred. As an improvement to this Lee filter, Refined Lee filter approach is capable of preserving the edges of the image while reducing the noise [8].

Speckle noise filtering methods can be further categorized as linear filtering, nonlinear filtering, partial differential equation (PDE) filtering, hybrid methods, and filtering methods that are based on the discrete wavelet transform (DWT). Mean filter and Gaussian filter are examples of linear filters which convoluted image with symmetric mask and then redefine each pixel value as a weighted average of neighbouring pixel values. In Gaussian filter, Gaussian function of 2-D is used as the convolution mask. Gaussian filter shows a great performance in despeckling with small variance. However blurring phenomena is visible near edged area [5]. Edge regions can be extracted using nonlinear filtering techniques such as median filter, a bilateral filter (BF), and a non-local mean (NLM) filter [12], [13].

8.1.2.2 Image Registration

Image registration can be defined as the process of transforming different sets of data into one coordinate system, also can be interpreted as the process of aligning two or more images having a geometrical overlapping area. Images can be taken at different times, from different angles or from different sensors [14]. The procedure for registering two remote sensing images have several steps: (a) Preprocessing, (b) Feature Selection, (c) Feature Correspondence, (d) Determination of a transformation function and (e) Resampling. Out of these aforementioned steps, feature selection, correspondence and transformation function can be implemented using numerous approaches [15]. Feature selection step will be based on the orientation of particular features of the image such as regions, lines, curves and corners or the geometric distribution of the pixels in the image. Core techniques used for feature selection, correspondence and determination of a transformation function can be categorized into similarity metric based methods, methods using a combination of simulated annealing and genetic algorithm, pyramid or triangular and coarse-to-fine based methods, methods using points, edges, corners, road-junctions and road point extraction as the base, segmentation, point scatter and learning based methods, Fourier transformation and wavelet based techniques and Miscellaneous methods. Similarity metrics such as mutual information, histograms among others, correlation coefficients which were used as a measure of determining the accuracy have been evolved as a method for image registration. Images which are misaligned by small rigid or affine transformations can be registered using a correlation based statistical approach [14],[16]. Point matching problem of image registration was addressed by implementing a genetic algorithm approach which employed a nearest neighbourhood based method[17]. To rectify and correct the rotation and translation of SAR images, edge feature consensus method was incorporated for coarse to fine registration[18]. Straight lines, junctions and T-points are significantly visible in man-made structures[14]. For registration of city images, straight lines are considered as an important feature. A hybrid approach of combining area based techniques with feature based techniques was often employed as an effective solution for satellite image registration [19],[20].

Image registration process is based on identifying the control points which precisely locates the corresponding image coordinates of the images need to be aligned. Control points can be selected manually or by semi or fully automatic techniques. However manual selection of control points is time consuming and not applicable for near real time image registration. There have been discussed various methods for semi or fully automatic control points selection. Existing automated methods fall into two categories which are feature based or area based approach. In feature based methods, features such as curvatures, moments, areas, contour lines or line segments are used to perform registration. Since these features are in variant of climate changes and grey scale changes, feature based methods have shown comparatively accurate results in registration. However these methods are effective only when features are well presented and preserved. Therefore, area-based image registration methods are still widely used in registration [21].

8.1.3 Experimental Evaluation and Discussion of results

8.1.3.1 Speckle Noise Removal

8.1.3.1.1 Tested approaches

In order to process video frames to enhance its features and remove noise artifacts etc. application of various filters was considered.

Hence the images that have a Gaussian type of noise distribution application "Median Blur" filter is considered. Application of it, reduced the noise in the considering frame to some extent. But practical difference was very minimal and sometimes affected the frame feature to get blurred as well.

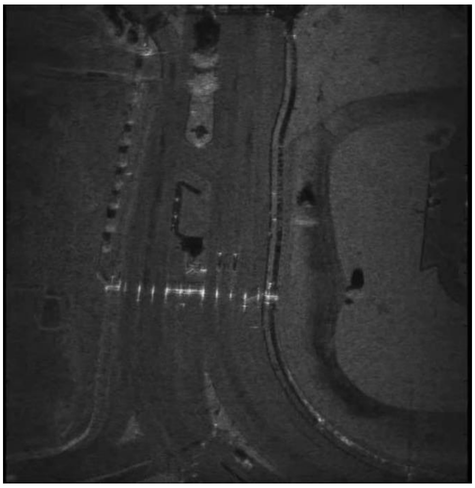


Fig 8: Original SAR image frame

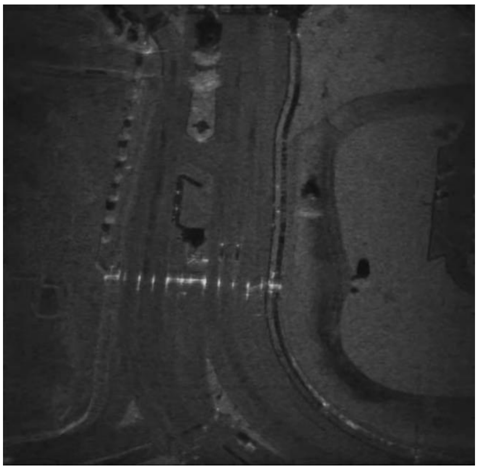


Fig 9: Median Blurred Image

Such problems were also occurred due to other kinds of noise removal filters as well and even if the process reduced the noise margins for some level, high computational power or proper tuning was required. Therefore, as a solution, usage of a sharpening filter along with a Median Blur filter was considered for further processing.

Fig 10: Sharpened image

Fig 11: Sharpened and Median Blurred Image

Then the main focus in this step was to enhance the image feature to a considerable extent. In order to achieve the mentioned task application of Sobel and Laplacian of Gaussian filters were considered as they emphasize the edges of an image. But the results were not performed as expected.

Fig 12: Sobel Filtered image

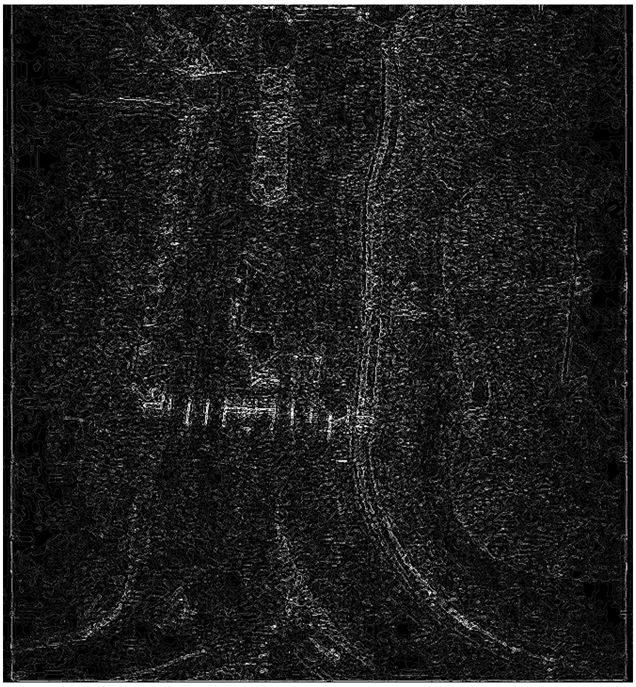


Fig 13: Laplacian of Gaussian Image

As these filters, usually focus on the image intensity gradient such image gets affected by the noisy artifacts of the frame and perform very poorly in this use case. Therefore, in order to enhance the image features, usage of custom filters were considered.

While testing for possible filters we found out that usage of Emboss filter act surprisingly well to the test frames.

Fig 14: Emboss filtered image

Then customizing the Emboss filter gave a considerably good results for the task.

Custom filter:

[-2, -1,   0]
[-1, 1.5, 1]
[0,   1,   2]

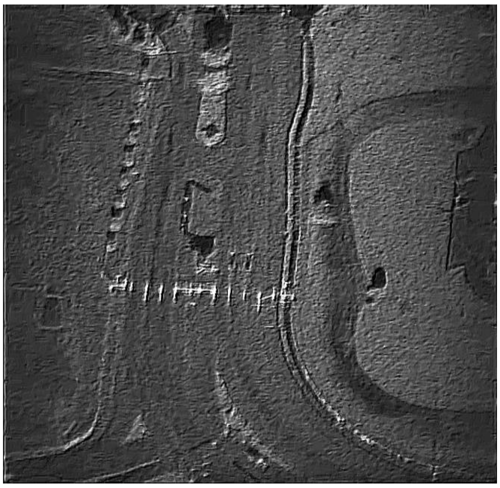


Fig 15: Custom Filter

Custom2 Filter:

[0,   1,   2],
[-1,   1.5, 1],
[-2,   -1,   0]

Fig 16: Custom2 Filter

8.1.3.1.2 Unsharp Masking

Unsharp Masking was used to sharpen the image frames. Consecutive video frames in Figure 17 demonstrate the blurriness of the interesting changes which are the vehicle movements (denoted by a red circle). They are visible as shadow movements to naked eye. Hence the requirement is to sharpen the frames to highlight the moving objects (vehicles) before binarization. Technique of Unsharp masking which is performed as a difference of Gaussian operations can be explained in the following steps.

1. Blurred image is the exact opposite of sharpened image. By duplicating the original frame and performing Gaussian blurring, blurred frame can be obtained.
2. Subtracting the blurred image obtained in step a) from the original image to obtain the image with enhanced edges and sharpness (unsharp mask).
3. Duplicating original image and increasing contrast to obtain high contrast version of the original image.
4. For each pixel of the unsharp mask, if the luminosity is 100\% pixel value of high contrast version image is used, if 0\%, value from the original image is used. Otherwise if the luminosity is in between 0\% and 100\%, weighted average value of both pixel values of high contrast version image and the original image is used.

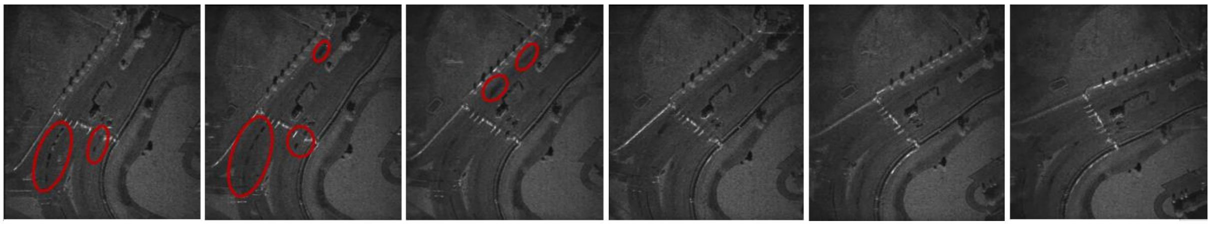


Fig 17: Image frame sequence of a SAR video

8.1.3.1.3 Otsu Binary Conversion

A binary image can be considered as a logical array of 1 s and 0 s. Each pixel of the image can be either black or white. Pixel values of an image (RGB) varies in between range of 0-255. In binary conversion, this range is converted to a 2 level (binary) thresholding. If the pixel value is greater than the threshold, it is replaced by 1, otherwise 0. The Otsu binarization returns a single intensity threshold that separate pixels into two classes, foreground and background. Converting to binary is often advantageous in finding the region of interest for further processing. Moving cars on the road are visible in the enhanced video frames shown in Figure 18.

Fig 18: Binarized and unsharp masking added frames of the video

8.1.3.2 Image Registration

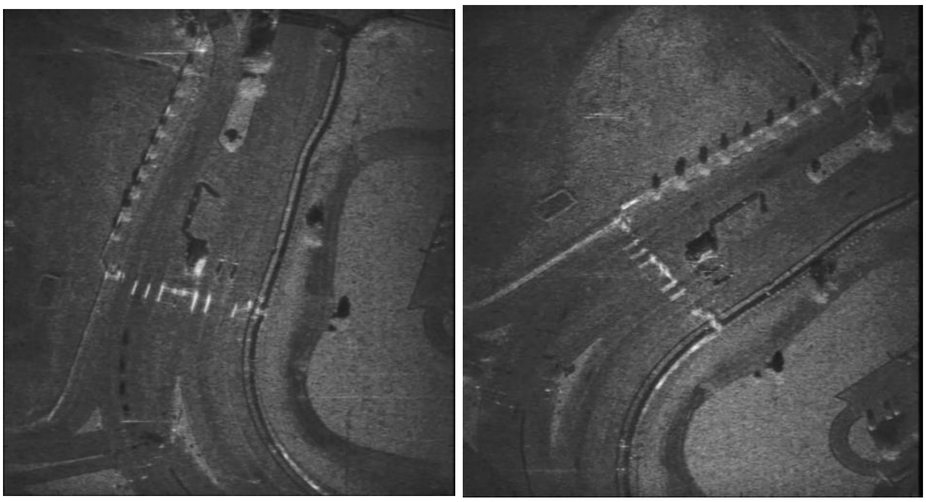


Fig 19: First image frame & Fig 20: Consecutive image frame

Circular SAR videos rotate due to the method of generation and therefore all the points including interesting and non-interesting points change with each frame. Normal change detection algorithms are incapable in such conditions and therefore an approach to reduce the video rotation was considered. As the first part of the rotation correction, feature point identification was done.

For this task several feature extraction methods were tested including Scale Invariant Feature Transform (SIFT)[30], Speeded Up Robust Features(SURF)[31] etc. Algorithms like Harris Corner Detector, Shi-Tomasi Corner Detector was not considered as they do not include any feature descriptors. Oriented Fast Rotated Brief (ORB) algorithm was used as the feature detection and matching algorithm as the comparisons in literature indicated that it is the fastest for mentioned task [32].

After identifying feature points in two consecutive frames in a SAR video, matching feature point was done using Normal Hamming Distance as shown in Figure 21. Then the matched points were sorted according to the distance and filter out the best points. Then these points were used to calculate the Homography matrix and two frames were warped to match the key points using the matrix.

In our scenario, feature matching was needed to be done in a video where the frames rotate around an axis and it was required these frames to be aligned in a way that apparent rotation of consecutive frames are low. Therefore, all the frames were aligned by taking the first frame as the reference. Such an alignment with warping causes frame transitions to be inconsistent and to reduce such problems image stabilization using point feature matching was used.

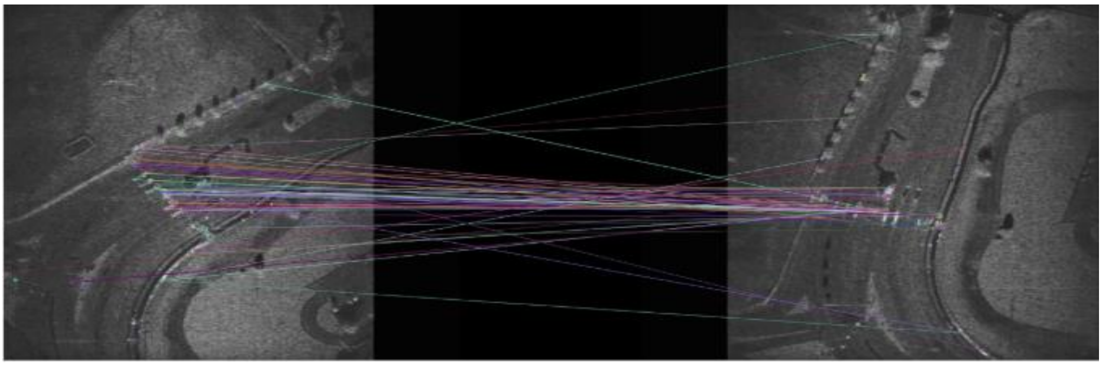


Fig 21: Feature Matching

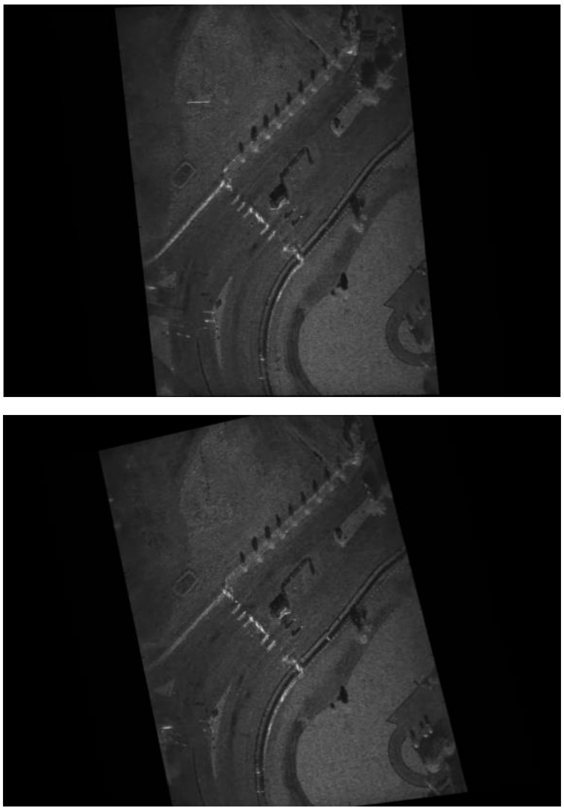


Fig 22-23: Rotation corrected images

(Note that road is aligned to the same direction in both frames in Fig 22 and 23)

8.1.3.3 Blob Detection

Blob refers to the group of connected pixels in a binary image and the goal of blob detection is to identify and mark the connected pixel sets in a given image.

Blob analysis was used for image segmentation as it is capable of identifying pixel clusters with special features which can be interesting changes or object movements.

1. Frame Acquisition: As the SAR video is created by sequence of image frame, 1st frame is acquired for applying image enhancement and blob detection.
2. RGB to Grayscale conversion: For applying enhancements and extraction of features, image is converted to grayscale. As SAR videos are inherently black

and white, RGB color components are not considered throughout the algorithm.

3. Image enhancement using Histogram Equalization: Histogram Equalization was utilized to adjust image intensities to enhance the contrast.
4. Blob analysis : Blob analysis which is a fundamental concept in computer vision, can be performed to distinguish particular pixel clusters in the image from the background. Blob analysis is applied to find the exact objects in the processed video frames. The objects in the frame which have a clear pixel cluster compared to background and noise, can be either static or dynamic. Since the requirement is to identify changes which can be interpreted as dynamic object movements, the separation of static and dynamic blobs is required. This can be achieved by combining LK method with blob detection. If a pixel cluster can be identified as a clear blob based on the constraints defined on the features of the blob and if it has an apparent motion compared to the previous consecutive frames which can be calculated by LK method, the probability of being an interesting change will be increased.
5. Defining thresholds for features of the blob : In order to identify interesting pixel clusters, constraints for blob features were defined as follows.
    a. By area: Area of the blob is the number of pixels included in the blob. This feature was used to remove blobs which were too small. By setting a minimum and maximum range for area of the blobs, possible objects can be traced down.
        i. min area - Minimum area should be defined considering the ratio of the size of the object to the size of the geographical area captured by the frame.
        ii. max area - area of the circle of which radius is defined as the half of the distance between two-pixel points of the selected pixel distribution of the frame (radius = d/2, where d is denoted in Figure 35).
    b. When generating SAR image frames, objects are modelled by radar pulse reflections from actual objects, hence pixels of the objects usually have higher intensity compared to the background. Since we are

interested in dynamic changes (of objects), pixels are filtered by a pixel intensity range between 0 to 125.

c. By circularity: Circularity of the blob defines how circular the blob is. This circularity can be measured by Heywood Circularity Factor. Since the SAR video frames are high resolution image frames which cover a large geographical area, the ratio between object area and frame size is very small. Hence these objects can be segmented to circular shapes by a threshold of circular factor.

8.1.3.4 Tracking

8.1.3.4.1 Approach 1 - using Kernelized Correlation Filters

In this approach, we are trying to determine a motion model for the object that we expect to track. We have information such as direction of the motion, location of object in previous frames. Therefore new location of the object in the next consequent frame can be tracked using the motion model. Motion model predicts the approximate location of the object. Further an appearance model which encodes the shape of the object is utilized to search in the small neighbourhood of the location which is predicted by the motion model. The motion model predicts an approximate location of the object, hence appearance model is used to finetune the estimate. But the key challenge is appearance model is dynamic in this scenario, as the airborne vehicle is moving. Therefore we decided to use a classifier as an appearance model which can be trained in an online manner. The objective of this classifier is to classify rectangular region of the image as either an object or background. Score in between 0 to 1 is returned indicating whether the object is contained in the image patch. This classifier is trained at runtime.

Initial bounding box which include the object that we are interested in, needs to be provided. (or by an object detection algorithm) Since as the 3rd step, object movements are detected, we can get the input from that step to feed into this step to draw the bounding box. This bounding box is taken as a positive example for the object and the image patches outside the bounding box is treated as the background.

We used Kernelized Correlation Filters tracking approach to this problem. This is a combination of Boosting and MIL (Multiple Instance Learning) tracker. Instead of considering only the current location of the object as positive example, we considered a neighbourhood around the current location to generate several possible positive examples. This is considered as positive bag (negative bag if examples are negative) The collection of images in the positive bag are not all positive examples, only one image needs to be a positive example which is the patch centered on the current location of the object. Therefore positive bag contains the patch centered on the current location of the object, as well as patches of the small neighbourhood around it. Current location of the object may not be precisely accurate. But when it is considered along with a small neighbourhood around it, there is a high tendency that bag might contain at least one image in which, the location of the object is considerably accurate. Therefore we employ this neighbourhood estimate to determine the location of the object.

Also we have identified another interesting fact that multiple positive samples used for consecutive frames have large overlapping patches. As the airborne vehicle moves from one point to another and emit signals through which images are generated, there is a point to point huge overlapping area. Therefore we utilized this feature to reduce the neighbourhood space and increase accuracy.

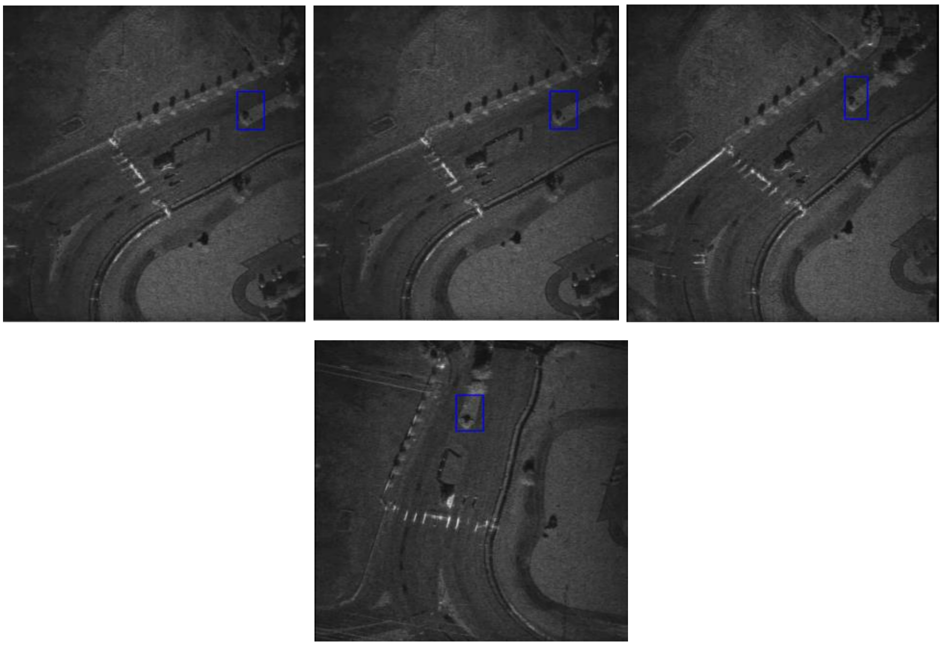


Fig 24-27: Object tracking in consecutive frames

The algorithm is able to track the object in consecutive frames. Object is identified by the bounding box.

8.1.3.4.2 Approach 2 - using centroid tracking algorithm

The approach of centroid tracking can be explained in multiple steps.

1. Draw the bounding box coordinates and compute the centroids of the objects.

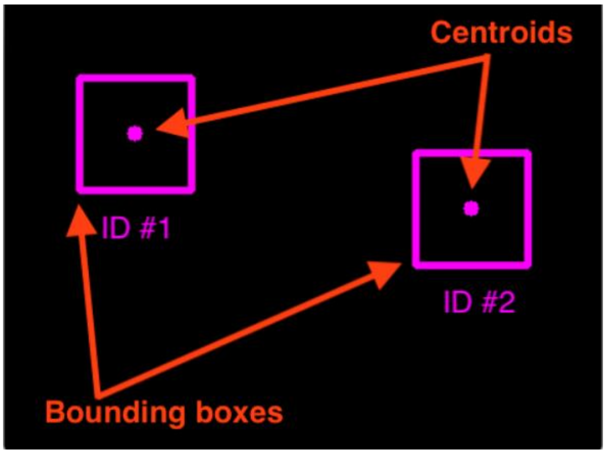


Fig 28: Centroids of detected objects

For each detected object in every single frame, a set of bounding box coordinates is initialized. These bounding boxes can be drawn using an object detector, in this scenario, object detection is done by blob analysis. Since SAR videos don't provide rich texture on the appearance model of the objects, conventional object detection techniques cannot be used in this. After obtaining the bounding boxes, the centroids of the bounding boxes or the centers of the detected blobs are captured as coordinate pairs. Initial set of bounding boxes are given unique ids.

2. Determine the Euclidean distances between previously identified objects and the new bounding box centroids.

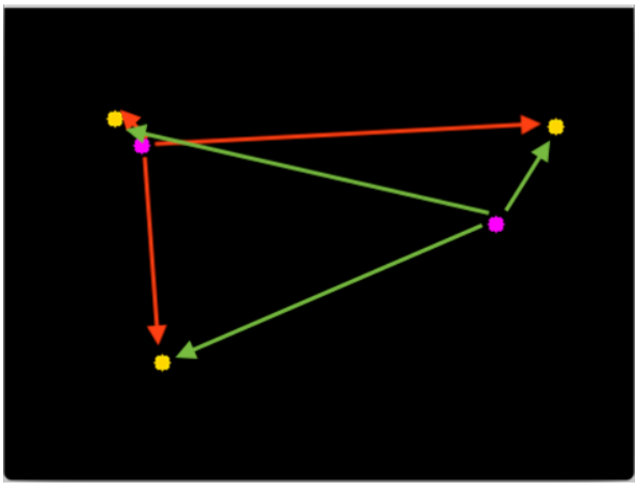


Fig 29: Computing Euclidean distance between each pair

After the initial frame, for every subsequent frame, step 1 is executed. But instead of assigning all centroids with new ids, we need to be able to determine whether we can associate new centroids with previously identified centroids. In the figure 29 centroids in purple depict detected objects in previous frame and centroids in yellow depict centroids identified in current frame. We use Euclidean distances to associate in between centroids in previous and current frame.

3. Update the (x,y) coordinates of the centroids of the existing objects.

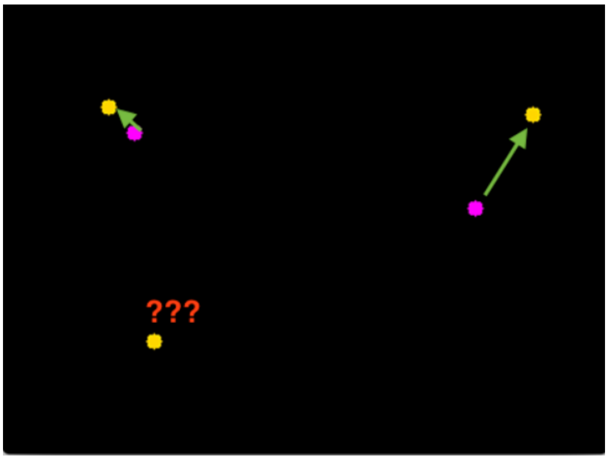


Fig 30: Identified new objects

We assume that the distance moved by a given object in between consecutive frames t and t+1 will be the least compared to distances calculated with other objects. Hence as shown in figure 30 new centroids can be associated with previous centroids using the least measured Euclidean distances. But as shown in the figure 30 there can be points which cannot be associated with the previous centroids. Such points can be registered as new objects by giving new ids.

4. Register new centroids

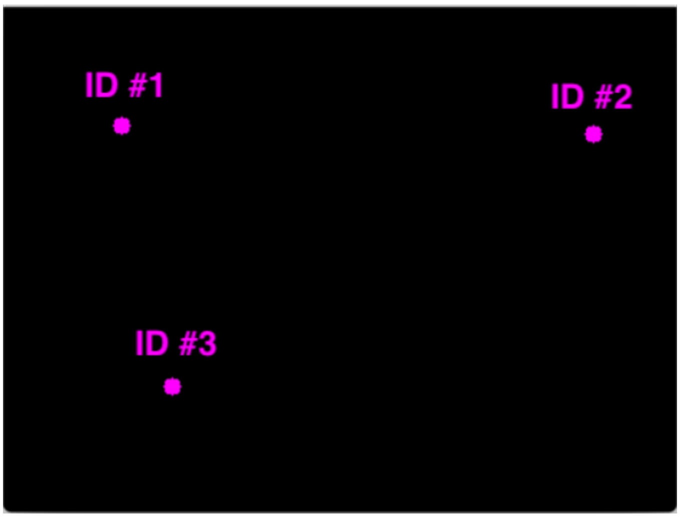


Fig 31: Register new objects and track previous objects

Registering a centroid is a twostep process.

a. Assigning a new centroid id
b. Add the centroid coordinates of the identified object to the existing array of the detected objects in the current frame

As shown in the figure 31 new object is assigned with id 3 where as previously tracked objects are given id 1 and 2.

5. De-register old centroids

In order to handle objects which are lost or disappeared in the frames, we need to be able to deregister such centroids from previous frames. When an object cannot be matched to any existing objects of the current frame for n consecutive frame readings, we deregister the object from the array.

How centroid tracking algorithm tracked the moving vehicles is shown in Figure 32.

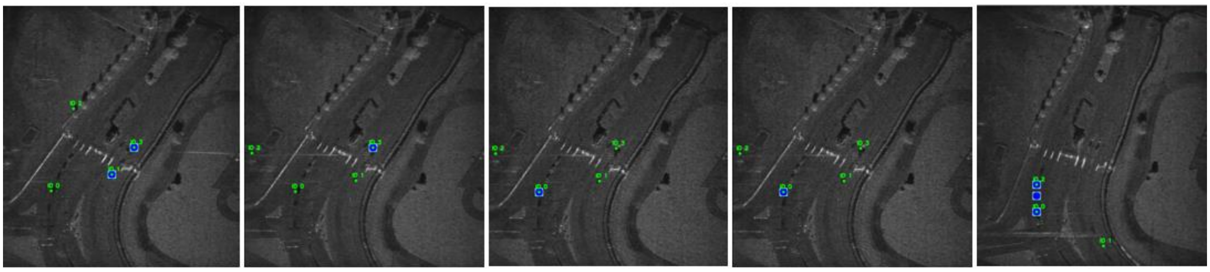


Fig 32: Tracking the detected changes

8.1.4 Conclusion

We experimented various approaches and techniques to address the issues described in the problem statement. Used filters were able to reduce the effect of speckle noise and glare to a considerable level. Even though the attempt to do the rotation correction using image registration was successful, that approach couldn't be integrated with optical flow calculation Lucas Kanade method. It was because image registration caused video frames to lose the smooth switching in between each other. Even though video stabilization techniques were applied to solve the issue, it was still insufficient to apply LK method. Further research should be done how moving camera object detection techniques can be applied to solve this issue of rotation. Even though Kernelized Correlation Filter tracking approach was able to track static objects of the frame, it was determined that KCF tracker was unable of capturing the appearance model of the dynamic objects due to the characteristics inherent to SAR videos. The actual features or the colour segmentations of the objects are not visible as videos are reconstructed using intensity differences between backscattered radar pulses. Also compared to the geographical area covered in a particular frame, object sizes are comparatively small. Hence conventional object detection techniques do not work in this scenario. Hence centroid tracking algorithm was experimented to track the detected changes. And it showed good results compared to conventional trackers. This approach should be further fine tuned to increase the accuracy of tracking.

8.2 Chapter Two

8.2.1 Introduction

As explained in the above sections, SAR videos contains inherent problems such as continuous rotation of frames, noise distributions, glare like artifacts from highly reflective objects, etc. Therefore, in order to properly detect the changes in the system, it was required to filter out the noise and reduce artifacts in the frame. Also finding the points/ objects in a frame which moves cannot be done using traditional change detection algorithms. A new methodology for recognizing such points were also required.

8.2.2 Literature Review

Change detection is a broad topic which was discussed under both optical and radar imagery. Change detection is discussed under pixel and object based techniques [22]. By grouping neighbouring pixels based on spectral, textural and edge features, Object Based Change Detection techniques utilize the rich features based format for analysing pixel regions [23]. Based on the spectral properties of the image, it is divided into homogeneous sections in object based technique. Pixel based approach is done through a pixel-by-pixel comparison. Further this technique can be divided into supervised and unsupervised approach. In supervised change detection, multi temporal images are classified based on external information which is known as the post-classification approach [24]. Volpi et al. (2013) discusses about a supervised approach which is not based on post classification method. They have done the multi temporal image classification using a combination of support vector mechanism(SVM) and spectral properties [25]. The main issue of the supervised change detection as identified by Yousif et al.(2013) is the need of external information about the imagery [24].

Compared to Supervised Change Detection techniques, Unsupervised change detection techniques use information only included in the imagery itself. Using this technique, image frame can be identified either as changed or unchanged. Thus unsupervised techniques only include two classes [26]. These techniques can be explained in multiple steps. Images are pre-processed to reduce the speckle noise. Then a difference image is created from image pixel-by-pixel subtraction or any other method which detects the different pixel values which are deviated from the defined threshold value. The difference image is used to create the change detection map. And the map demonstrates the changed and unchanged areas comparing each neighbouring frame[27],[28]. Threshold on image or a histogram can be applied in this method. The main drawback of Unsupervised Change Detection, as explained by Yousif et al.(2013) is that it does not elaborate and specify about the change that has been taken place. However pixel based methods are sensitive to “salt and pepper” (black and white intermingling of images) noise [24].

Another aspect that should be taken into consideration is the dynamic background of the image sequence. Since the video frame has a dynamic circular moving background, first and foremost background modeling techniques should be done.Background modeling and subtraction which has been widely used for change detection and target detection is prone to false alarms in dynamic background since the background model contains only temporal features. Temporal only methods lack the knowledge of the neighbourhood pixels of the concerned pixel. Thus it will conclude dynamic background also as a moving object which will cause a false alarm. A new pixel wise nonparametric change detection algorithm has been proposed. The background is modelled by spatiotemporal model using sequences of frames and sampling them in neighbourhood region randomly. Thus this model contains both spatial and temporal knowledge about the background which leads to better performance in change detection in dynamic background [29].

Even though majority of the papers have discussed identifying temporal changes of SAR imagery which are acquired on different dates, the problem that we address, requires identifying changes in near real time manner and, instead of images, we are dealing with SAR videos which are generated from sequence of images. In order to tackle this problem, key challenges that we have identified, are as follows.

1. Rotation of video frames
2. Speckle noise and other noises which lead to false positives
3. Near real time change detection

8.2.3 Experimental Evaluation and Discussion of results

8.2.3.1 Change detection

In order to detect interesting changes in a frame such as movements, Lucas Kanade Method for optical flow estimation was used in our application. Optical flow is the motion of objects between consecutive frame as a result of relative movement between the object and the camera. This uses the concept of flow vectors to determine the motion between two subsequent frames of the video. Vectors have both magnitude and direction, hence the flow vector gives an approximation on the amount of deviation of the pixel from current position to the next frame position. We used Sparse optical flow for this purpose which selects sparse set of pixels (interesting features) to calculate its velocity vectors.

Fig 33: Moving objects in the frame

LK method is usually used in sparse feature set and our main focus is to find such points from a frame. Usage of dense optical flow calculation methods are not considered as they cannot be used in real time applications. Therefore as a solution, for each video frame, we choose a uniform distribution of set of fixed points in the video frame and use those points regularly in every optical flow measuring cycle to identify interesting movements. This significantly reduces the computational complexity of the overall optical flow calculation. We can safely assume that interesting movements will pass through one of those selected points in point distribution as the distribution is uniformly spread across the frame. We used a two threshold mechanism based on motion variance and the angle of deviation to select interesting points from the distribution. If a pixel point has a relative motion or an angle of deviation compared to the pixel points of the neighbourhood, it can be considered as an interesting change. Relative motion vector of the pixel point is obtained by LK method. All objects in the frame are subjected to the rotation of the airborne vehicle and therefore objects which are static have the same angle of rotation, whereas moving objects have a deviation in angle of rotation with respect to the static objects. This angle can be measured using the output of LK method.

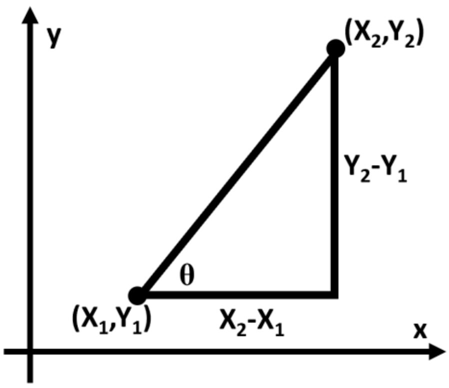


Fig 34: Graphical representation of the motion vector of a pixel

Apparent movement = $\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$

$\tan(\theta) = \frac{(y_2 - y_1)}{(x_2 - x_1}$

8.2.3.2 Optical flow based algorithm

For detecting changes in SAR video following algorithm was developed by us. This method consists of two thresholds to find interesting movements in video frames and its description is as follows.

Define two arrays: interesting points array and counter array and let “t” be the current frame.

1. Define the point distribution of the t^{th} frame.
   Define a set of points distributed throughout frame. This set of points should be fixed for the particular frame and will be checked for optical flow changes. As shown in Fig 35. black color pixels represent the selected pixel distribution of the frame. Pixels are selected such that each pixel is “d” distance away from another. Assume there are N number of pixel points in the distribution of t^{th} frame.

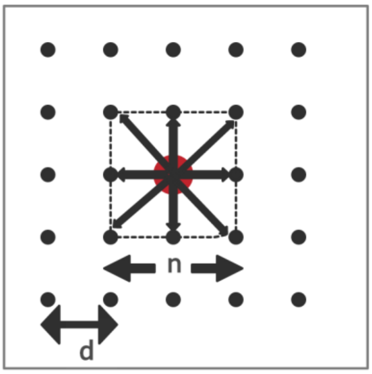


Fig 35: Point distribution of a frame

2. Calculate the optical flow for all N number of pixel points in the distribution.
3. Select interesting points from the point distribution as explained as follows:

Let (x_k, y_k) be a pixel of the pixel distribution of t^{th} frame. This pixel is represented by the red pixel marked in the Figure 35. Define a window size to derive the neighbourhood of the selected pixel.

Let n x n be the neighbourhood window size. Use LK method to calculate the motion vector of the pixels and to derive the angle of deviation. Let k_1, k_2 be the thresholds.

For k=1 to k=N repeat the following:

For the neighbourhood of (x_k, y_k),

A. Apply LK method to all the pixels in the neighbourhood and derive the average motion of the neighbourhood $\underline{v_k}$
B. Derive the average motion angle of the neighbourhood $\underline{\theta_k}$.
C. Derive motion v_k and the angle θ_k of the pixel(x_k, y_k).
D. If $\left|\frac{\underline{v_k} - v_k}{\underline{v_k}}\right| > k_1$ and $\left|\frac{\underline{\theta_k} - \theta_k}{\underline{\theta_k}}\right| > k_2$, mark the point (x_k, y_k) as an interesting point.
E. If (x_k, y_k) is found interesting,
    a. add (x_k, y_k) to the interesting points array.
    b. add an entry to the counter array corresponding to the pixel point (x_k, y_k) and initialize its value to zero .

Counter array is to determine whether a selected interesting point in a particular frame is interesting to all the consecutive frames. The threshold approach of counter array is explained in step 4.

4. If $t \neq 1$,

Let $\underline{V_t}$ be the average sum of the motion vector of all the neighbourhoods of each pixel point in the distribution of frame t,

$$\underline{V_t} = \sum_{k=1}^{N} \underline{v_k}$$

a. Follow steps 1,2 and 3 to find interesting points in the t^{th} frame.

b. Filter already selected points in the interesting points array. Let $\underline{V_T}$ be the average sum of motion vectors from 1^{st} to $t = T^{th}$ frame.

$$\underline{V_T} = \sum_{t=1}^{T} \underline{V_t}$$

Let p_i be a point in interesting points array and its motion vector be v_{pi}. For each point in interesting point array,

1. Check the condition:

    a. $\left|\frac{\underline{v_T} - v_{pi}}{\underline{v_T}}\right| > k_1$, point is again considered interesting. Initialize its counter back to zero.

    b. Otherwise increase counter value by 1.

2. If an interesting point has a counter value larger than the defined threshold value k_3, remove it from the interesting points array.

5. Increment to next frame and repeat from step 1.

Storing interesting points of previous frames helps to identify potential actual moving objects. Also, marking them with a counter to determine whether that point is an interesting point for each frame will be used to reduce calculations.

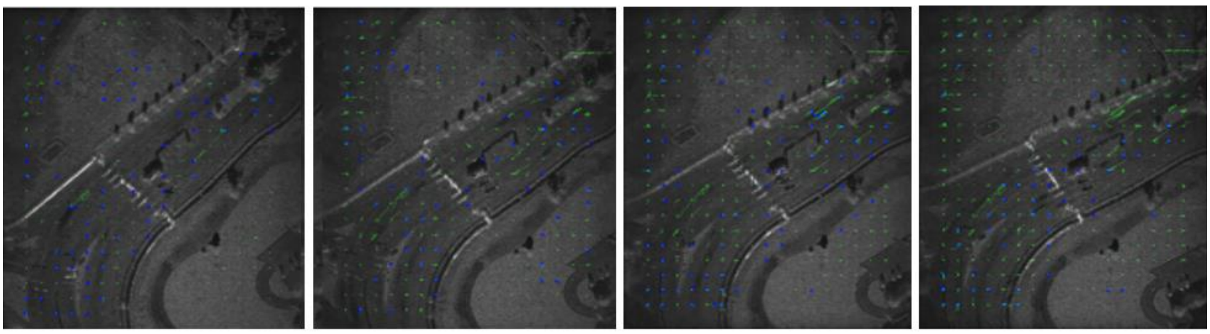


Fig 36: Calculated interesting points and optical flow are shown in video frames

The mentioned procedure requires three threshold values to be given before the execution: threshold of angle and magnitude of motion vector to determine interesting points, threshold to eliminate false positive interesting points from interesting points array (counter value threshold).

After detecting the interesting points a blob detection methodology for increasing the accuracy of detection was considered. In this step blob analysis was used for image segmentation as it is capable of identifying pixel clusters with special features which can be interesting changes or object movements. Theoretical aspects of Blob detection is explained in the previous chapter.

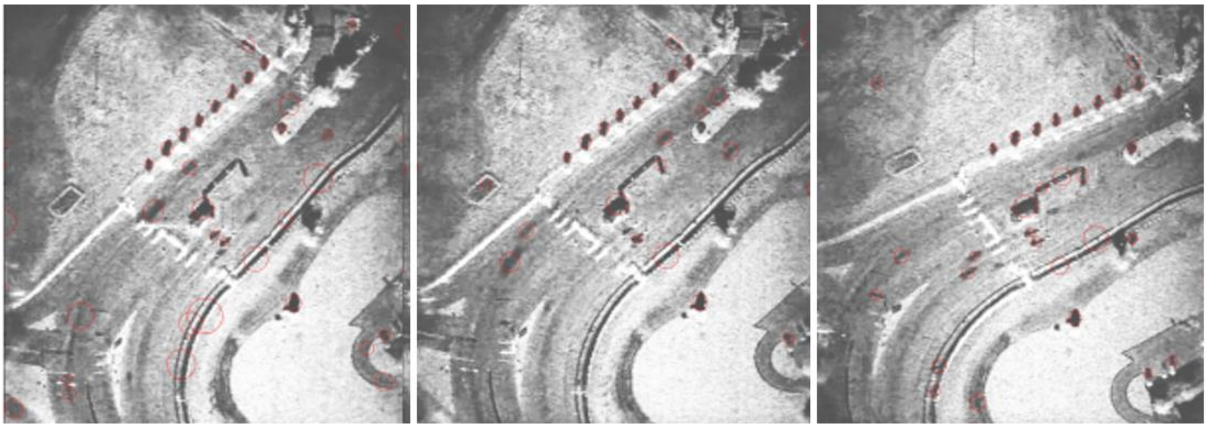


Fig 37: Blobs detected in consecutive video frames

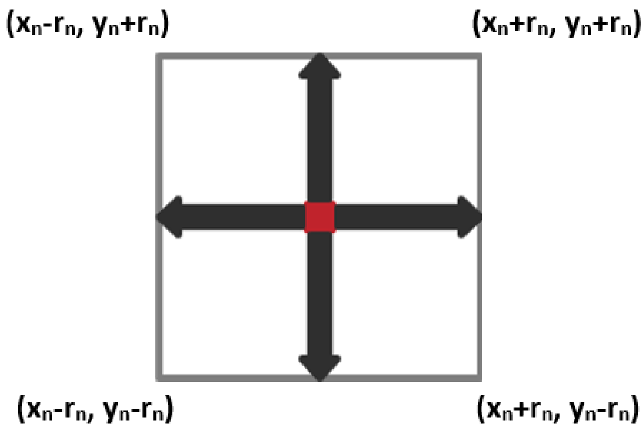


Fig 38: Square of area $4r_n^2$, drawn using (x_n , y_n) as the center

After identifying the blobs in a frame, in order to determine whether an actual change has occurred, the combination of LK method and blob detection is applied in an iterative manner for each frame of the video. The methodology is explained as follows.

1. Interesting points array and the detected blobs of the current frame are considered. Let t be the current frame number.
   a. Let (x_t , y_t) be an interesting pixel point of t^{th} frame and assume there are N number of blobs detected in t^{th} frame.
   b. Let point (x_n , y_n) be the middle point of an arbitrary blob as denoted by the red pixel in Fig 38. Let r_n be the radius of the detected blob. Consider the area of the square which is drawn r_n distance away from horizontal and vertical directions from (x_n , y_n), as shown in Fig 38. Let a_n be the array of pixel points which are within the drawn square for (x_n , y_n).

   c. For n=1 to n=N repeat the following,
      I. Derive (x_n , y_n), r_n, a_n
      II. For all points in a_n check whether (x_t , y_t) is found. If found, mark that point as an interesting change which can be tracked. End the loop.
      III. Otherwise, increment n by 1, to consider the next blob and repeat the loop.

   d. Repeat steps (a), (b) and (c) for all the interesting points of the current frame.

2. Repeat step 1 for all the frames of the video.

By adhering to the above-mentioned algorithms, we were able to identify the changing objects in the frame with considerable accuracy.

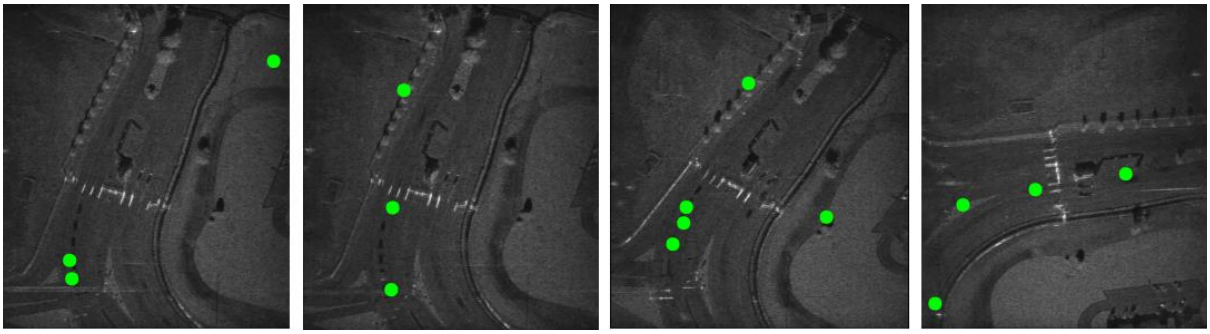


Fig 39: Detected changes

8.2.3.2 Blob based algorithm

Even though the previously mentioned algorithm worked, it consists with following problematic aspects.

- Computational Complexity
- Low framerate processing
- Not accurate (High false positive rate)

In order to remove the above issues, a new approach was considered. In this method instead of having a point distribution throughout the frame detecting blobs was considered.

Following are the steps in this procedure.

1. Initialize interesting points array to None.
2. First detect the blobs in the frame using section 8.2.3.2 mentioned blob detection algorithm.
3. Do the secondary steps of the 4th step to the interesting point array and keep interesting points by keeping a counter (same as the optical flow-based algorithm)
4. Then for each blob in the frame,
    a. Find its middle point

b. Find the neighbouring points for the middle points based on the radius of the blob
c. For all the neighbouring points including the considering point, calculate the optical flow.
d. Find the average optical flow and tan value for the neighbouring points.
e. Mark the considering point as interesting point by comparing average magnitude of optical flow values of neighbouring points and tan values.
f. Add selected interesting blob point to the interesting point array.

5. Mark the interesting points in the frame.
6. Continue the above steps to all the frames of the video.

In this algorithm, additional calculations used for the optical flow distribution was reduced significantly and therefore improve the framerate with reduced computational complexity.

8.2.4 Conclusion

Implementation of our change detection algorithm was tested on SAR videos which were publicly available on Sandia Laboratories Website and videos that were generated by our SAR simulator.

The apparent motion of the pixels which exceeded the two thresholds were marked in blue color, which we defined as interesting points. Apparent motion of interesting points was tracked by LK method throughout the video and it is visible that, movements of the vehicles were traced. Majority of the lines drawn were within the road. Hence it can be assumed that interesting movements were captured as moving objects in the frame are vehicles which were driven on the road. Also it is visible that the majority of the interesting points were marked around the road, which means algorithm was able to capture actual interesting points.

Even though static objects were also detected by blobs, those blobs could be neglected by combining with LK method. The final changes that are detected by the system using both LK method and blob detection is shown.

Even though actual interesting changes were detected in the videos, static objects were captured as interesting changes in some frames, hence caused few false positives. Parameters of blob detection, window size for optical flow calculation of the neighbourhood and pixel step count for determining the pixel distribution of the frame should be further optimized to achieve a higher accuracy.

Following is a table of accuracy details of the initial LK based change detection.

Video	Details	Source	Video duration	Actual Moving objects in the video	Contains static objects	Total number of detected changes	Correctly Detected changes (moving objects)	Falsely Detected changes
Eubank gate and traffic video SAR	VideoSAR footage of a gate at Kirtland Air Force Base. The vehicle traffic is moving through the gate in different velocities and directions.	Sandia Laboratories	00:00:25	42	yes	49	42	7
Simulated SAR video	Video contains both static and dynamic objects. Dynamic objects are the vehicles moving on the road and static objects are the buildings and	Generated by a SAR simulator	00:00:02	6	yes	7	6	1

	trees.							
Total Power AFRL Gotcha Scene	Video is generated by using the backprojection algorithm and an aperture size of 3 degrees.	Raw data courtesy - AFRL/SNA Video Source - RITSAR	00:00:17	0	yes - vehicles are parked in a car park	0	-	0
Solar Tower Video SAR	VideoSAR footage is from a solar tower of Sandia.	Sandia Laboratories	00:00:12	0	yes - trees, tower, buildings, parked vehicles	0	-	0

As the table indicates, it has a good accuracy over SAR videos. But in order to achieve a good accuracy it is required to tune number of parameters properly considering the video resolution, intensity conditions, video to object size ratios etc.

High computational expensiveness can cause the frame rate significantly. Also, low accuracy of the object detection can be seen with unoptimized parameters and various intensity conditions of the SAR video.

8.3 Deviations from the initial methodology

8.3.1 Rotation correction

In the initial research planning phase, we hoped to use rotation correction methodology to stop the frame from being continuously rotated. Main reason for taking such decision was after correcting the frame rotation, then we can use that frame to detect changes using standard change detection algorithms. In order to achieve the aforementioned task, feature detection, homography matrix and affine transformation was used (details are explained in 8.1.2.2 section). After developing the program to correct the frame rotation, results shown in Fig 40 were obtained.

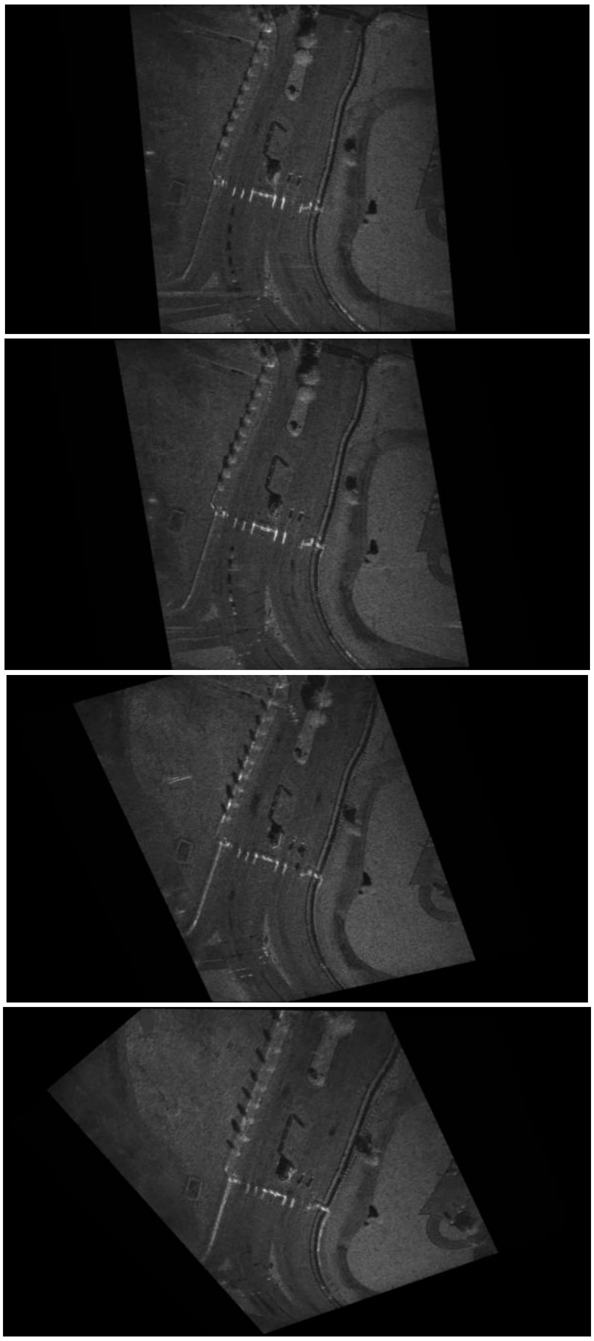


Fig 40: rotation correction implementation.

8.3.1.1 Reasons to drop the rotation correction

Application of rotation correction to a video frame creates several problems to the overall approach. One is heavy computational complexity to detect feature in a frame and match it to the next frame. The other problematic scenario is that, after warping the current frame to the initial frame, overall video frame transitions become glitchy and frame rate drops to a very low level, where we cannot use further processing to identify objects in the corrected frame. Usage of video stabilization techniques also did not help in reducing the glitchiness of the corrected video but added extra computational complexity. Therefore, our team decided not to use the rotation correction in the overall system.

9. Conclusion and Future Work

In this paper an algorithm based on combining of optical flow calculation and blob detection was introduced for detecting changes in Synthetic Aperture Radar videos. In contrast to optical images, videos and multi temporal SAR images, there are unique problems associated with SAR videos. Hence when developing a change detection algorithm for SAR videos, conventional change detection techniques used in above scenarios cannot be applied as it is. The mentioned approach in the paper was a multistep process which was formulated through a modification by combining Lucas Kanade method for optical flow calculation and blob detection. Next, in order to track the detected changes, centroid tracking algorithm based on Euclidean distances along with predicted locations derived by optical flow calculations was applied. In future work, we hope to improve the accuracy of detection by defining better ways to determine the thresholds to filter the interesting pixel clusters (actual moving objects) in the video frames.

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