A Scalable Probabilistic Change Detection Algorithm for Very High Resolution(VHR) Satellite Imagery

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Abstract—In this paper, we are trying to implement a change detection algorithm for a landscape VHL satellite image. Identifying these changes requires an accurate and scalable algorithm that is robust to geometric errors. The pixel based algorithms do not take into consideration the surrounding spatial information and therefore not very effective when we consider at a large scale like a VHL image. Hence a probabilistic change detection algorithm is being re-implemented [6]. Introducing a patch based framework results in a better classification of windows rather than a pixel by pixel approach. However, the resulting algorithm is computationally more expensive and hence the code is parallelized to run on multiple clusters. The paper presents a sliding window based approach where the neighborhood characteristics are taken into consideration.

Keywords-Probabilistic Change Detection; Satellite Image Processing; Spatial Data Mining; Parallelization

I. INTRODUCTION

Settlements are coming up quick and fast around the world. In order to keep track of the urbanizations of the regions it is essential to have an automated mechanism. Timely monitoring of these changes is essential as the government has to keep track of them and plan for a better civilization. There are many other use cases like disaster management where the landscape changes need to be tracked for infrastructure development in these zones. The integration of remote sensing, GIS, and other simulation systems can provide valuable assistance to a comprehensive decision support system. Detection of new settlements is one of the key criteria in identifying new settlements.

The traditional systems for identifying change rely on per pixel based information and do not take into consideration the surrounding information. This usually leads to misclassification and a poor accuracy due to manual control over the threshold values. The limitations of these systems are that they are point based and there is difficulty in mapping the same area to different pixels in VHL images. The images acquired by the same satellite might be varied due to different extrinsic factors like environment conditions, angle of camera and time of the day.

In this paper, we will implement the approach used in "A Scalable Probabilistic Change Detection Algorithm for Very High Resolution (VHR) Satellite Imagery". A grid based approach is introduced, where the changes are determined by using the probabilistic characteristics of the patches. The sliding window approach proves to be a better resolver for detection algorithms. The code will be parallelized as the proposed solution significantly increases the computation time.

II. RELATED WORK

A. *Multi-sensor remote sensing image change detection: An evaluation of similarity measures*

This paper looks at the various methods to detect changes and overcomes the limitations of the previously determined methods to do so. Generally, all change detection measures require the initial image to be geo-spatially registered in order to record the changes at different instances of time and to measure the extent of change. The hypothesis based on which the measures are developed is based on the assumption that the underlying basis of the images remain the same regardless of whether the images are obtained from different sensors at different times since they are different representations of the same reality. This paper looks at improving the existing measures to overcome their limitations. The major limitation of the previously discovered methods is that they use pixel based change detection and hence, they can detect changes in images which are captured by the same sensor i.e; they cannot apply the methods to images that are captured on multiple sensors. This paper looks at various similarity measures such as:

- Mutual information: Gives the relationship between difference of probabilities and entropy.
- Maximal information gain: Captures the dependence relationship between two variables.
- Distance covariance: Measures association between random variables by using the distance between them.

- Distance correlation: Measures the correspondence between two random variables.
- Local self similarity descriptor: Measures similarity between visual entities based on matching internal self similarities.

The paper uses a sliding approach to calculate the normalized measures of the above stated measures. The experiments are performed on three datasets out of which two are artificial datasets and one is a real time dataset. The real time dataset contains images from the KachaGarhi camp in Pakistan. When the data is preprocessed, all the images are geo-registered and the SAR image is de-speckled to remove speckle noise.

Although these methods have various advantages over the traditional pixel based change detection methods, when the experiments were performed on optical and SAR images, it was seen that all the measures generated false positive results even when there was no change in the images.

B. *Probabilistic Change Detection Framework for Analyzing Settlement Dynamic Using Very High-resolution Satellite Imagery*

This Paper serves as the base for the change detection algorithm used. First we need a high-resolution imagery from pre- and post-event dates. These images should then be geo-registered so a one-to-one(pixel) correspondence is established between the two images. Once the images have been registered, change detection techniques can be applied to obtain a map that shows possible changes (affected regions).

In this study, a semi-permanent IDP camp near Peshawar, Pakistan is examined. Changes in the camp were detected using high-resolution imagery. The probabilistic change detection framework used in this paper provides an automated procedure to identify these types of settlement changes.

This paper has taken into account the following change detection techniques-

- **Image Differencing -** given two univariate images the first image (time 1) is subtracted from the second (time 2), that is:

$$I_{diff}(i,j) = I_2(i,j) - I_1(i,j)$$

  where (i,j) refers to the pixel location with respect to the origin. Each pixel is assigned a label of change or no change by thresholding the change magnitude.
    - *Advantage:* computationally cheap, sensitive to noise
    - *Disadvantage*: setting the appropriate threshold value

Ratio of Means - robust to common multiplicative noise.

$$I_{Ratio} = \frac{I_2(i,j)}{I_i(i,j)}$$

- **Change vector Analysis -** Calculates the vector difference between the time-trajectory of successive time periods. The length of a change vector, given by:

$$S = \sqrt{[(B_1 - B_2)^2 + (G_2 - G_1)^2}$$

  It indicates the magnitude of change and the direction of change given by:

$$\alpha = arctan[\frac{(B_2-B_1)}{(G_2-G_1)}]$$

  which indicates the nature of change, where B and G are independent spectral bands.
- **Inner Product and Spectral Correlation Analysis -** In the inner product analysis, the spectral values of a pixel in an image are considered as vectors. The difference between two multi-spectral vectors is measured as the cosine of the angle between them so that if two multi-spectral vectors are coincident with each other, then their inner product is and between -1 and +1 otherwise. In the spectral correlation analysis, the mean of the multi-spectral vectors is used which reduces atmospheric and other imaging effects.

Limitations of all the existing methods - All the methods are point-based, that is, the comparison (e.g., difference, ration, etc.) is done at the individual pixel and it is difficult to establish a pixel-to-pixel correspondence in very high-resolution imagery.

Probabilistic Change Detection Framework

The key components of the proposed probabilistic change detection framework are as follows:

1. Divide the image into grids (square or rectangle). The optimal grid size is dictated by pixel resolution, typical objects found in the imagery, and the number of image bands (dimensions). The quality and computational cost of the algorithm depends on the size of the grids.
2. Model data from each grid as a Gaussian distribution. Therefore, at each grid i,we have two Gaussian distributions $P_{t1}(i)$, $Q_{t2}(i)$ for time t1 and t2 respectively. All the multi-dimensional feature vectors from each pixel in the grid, are generated by multivariate Gaussian distribution described as -

$$p(x|y_i) = \frac{1}{\sqrt{(2\pi)^{-N}|\sum j|}} e^{\frac{-1}{2}(x-\mu_j)^t|\sum j|^{-1}(x-\mu_j)}$$

The standard multivariate Gaussian distribution is described by the parameters mean (μ) and covariance matrix (∑) These parameters are estimated for each grid separately from the corresponding image data.

3. Compute distance between Gaussian pairs - grids are compared (same location) from two different times by computing the probabilistic distance between corresponding Gaussian Distribution $P_{t1}(i)$, $Q_{t2}(i)$. KL divergence is used as a distance measure.

4. GMM parameter estimation and component discovery - To generate the final change map, we need to find thresholds on the KL Divergence. For that, the KL divergence data is modeled as a GMM and a clustering technique is applied to generate the map.

5. Estimate GMM Parameters - The sample data set D={xi}1nis generated by the mixture density:

$$p(x_i|\theta) = \sum_{j=1}^{K} \alpha p_j(x_i|\theta_j)$$

Here $p_j(x_i|\Theta_j)$ is the probability density function corresponding to the mixture j and parameterized by:

$$\theta_j \text{, and } \Theta = (\alpha_1, ..., \theta_K, \theta_1, ..., \theta_K)$$

Denotes all unknown parameters associated with the K-components mixture density. EM algorithm is used as a technique to estimate the parameters for estimation maximization.

Results -

The proposed probabilistic change detection framework was applied on bi-temporal high-resolution multispectral imagery over Kacha Garhi camp, Pakistan. Two images acquired in 2004 and 2009 were used to show the transition. The algorithm accurately detected all the changes highlighted by human experts.

C. *Photogrammetric processing of hexagon stereo data for change detection*

The main idea in this paper is to detect changes in the temporal images that are captured by remote sensing satellites. The change detection techniques described in this paper require the images to be captured at regular time periods. This paper uses the declassified images of the Hexagon satellite data that was part of the Corona operation conducted by the USA. The Corona operation included a number of satellites with onboard film cameras, recovery vehicles to collect the exposed film from mid air. This program was initiated in order to acquire photographic intelligence regarding the arms proliferation from the USSR and China soon after World War II during the Cold War period over two decades in the 1960s and 1970s. There were four satellites launched for this purpose. They were the KH1, KH2, KH3 and KH4. The information obtained was secretly managed and the declassified version of these images were released to the public years later. The Hexagon satellite was launched after the initial success of the Corona program. A series of 20 satellite missions were launched with increased spatial resolutions. This was named KH9. The data obtained by this mission was of high resolution and it is now available all around the world at an affordable price.

The change detection algorithm used in this paper uses Rigorous Sensor Modeling (RSM) and Rational Function Models (RFM). The study is made on a part of Western Ghats in India.

- RSM: Requires the knowledge of sensor and platform geometry. These models are very accurate since they represent the true physical geometry of an imaging system. The RSM is based on the principle of collinearity condition where in the exposure station, an object point and its corresponding image point all lie along a straight line in a 3D space. The internal geometry parameters can be obtained through sensor calibration. The external geometry parameters can be observed using Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU). The collinearity condition is expressed as:

$$x_a = x_0 - f\left[\frac{m_{11}(X_A - X_L) + m_{12}(Y_A - Y_L) + m_{13}(Z_A - Z_L)}{m_{31}(X_A - X_L) + m_{32}(Y_A - Y_L) + m_{33}(Z_A - Z_L)}\right]$$

$$y_a = y_0 - f\left[\frac{m_{21}(X_A - X_L) + m_{22}(Y_A - Y_L) + m_{23}(Z_A - Z_L)}{m_{31}(X_A - X_L) + m_{32}(Y_A - Y_L) + m_{33}(Z_A - Z_L)}\right]$$

The above equations are nonlinear and can be linearized as follows:

$$\begin{aligned} &b_{11}d\omega + b_{12}\,d\varphi + b_{13}d\kappa - b_{14}dX_L - b_{15}dY_L - b_{16}dZ_L \\ &+ b_{14}dX_A + b_{15}dY_A + b_{16}dZ_A = J + Vx_a \end{aligned}$$

$$\begin{aligned} &b_{21}d\omega + b_{22}\,d\varphi + b_{23}d\kappa - b_{24}dX_L - b_{25}dY_L - b_{26}dZ_L \\ &+ b_{24}dX_A + b_{25}dY_A + b_{26}dZ_A = K + Vy_a \end{aligned}$$

These equations are then solved iteratively until the values are close to the initial approximations.

RSM is highly dependent on the platform and has to be changed for different sensors on different platforms. This makes it highly complicated to use.

- RFM: RFM is used in situations where sensor geometry and attitude information is not available since it is not dependent on the physical geometric relations of the sensor, platform and the ground. The RFM can be used to any coordinate system and is not dependent on the software. The Rational functions are the ratio of polynomial models one for the sample and one for the line as given below:

$$s = \frac{P_1(X,Y,Z)}{P_2(X,Y,Z)}$$

$$l = \frac{P_3(X,Y,Z)}{P_4(X,Y,Z)}$$

Photogrammetric processing of Hexagon stereo data is not simple because of the absence of interior orientation parameters of the mapping camera.

	Rigorous Sensor Model			Rational Function Model		
Error	X(m)	Y(m)	Z(m)	X(m)	Y(m)	Z(m)
Min	0.17	0.01	0.18	0.65	0.52	2.08
Max	5.37	7.07	12.02	6.58	5.07	9.79
RMS	2.51	2.28	5.04	2.32	3.75	7.38

Table 1. RMSE after adjustment through RSM and RFM

	Hexagon KH9 data (1973)	Cartosat1 data (2011)
No. of water bodies	17	89
Area coverage (Ha)	1178.79	3479.19

Table 2. Number of water bodies and the area covered in Hexagon and Cartosat-1 data

Looking at the observations shown above, it can be seen that historical data is of prime importance when using remote sensing technology. From this study, it is inferred that KH9 data is similar to Large Format Camera data. Adding a few assumptions to the data makes it possible to determine the internal geometry of the data. Using this information, it can be seen that the accuracy of both RSM and RFM models is higher than that of the traditional one pixel based change detection algorithms.

D. *Change Detection in Forest Ecosystems with Remote Sensing Digital Imagery*

The essential challenge in determining forest cover change information is tackling the remote sensing problem of improving the signal to noise ratio. This paper reviews the methods and the results of digital change detection in forest ecosystems. After reading the following paper we understood the different aspects of how the satellite image has to take care of and what preprocessing techniques are applied before executing the change detection. Because it is a VHR image taken from the satellite, the image is subject to a lot of noise due to a lot of contributing factors like One of the oldest techniques is to build a model like logistic regression which requires rigorous prior detection and labeling data for conversion from forest to non-forest regions.

The paper summarizes the following conclusions which provide us a method to foresee probable challenges while implementing the EM Clustering approach to the VHL images.

1) Vegetation indices are strongly correlated compared to single band responses.
2) The boundary drawn for a spatial image is somewhat blurred when it comes to classification into different regions. Despite it being a VHL image, the below pixel level image degrades the aerial extrapolation of the image.
3) Radiometric calibration is a recommended approach for temporal changes as the best way to simulate the ideal conditions is to remove exogenous differences that may occur due to different environmental factors in which the two images were taken.
4) Image differencing and linear transformations are good approaches for change identification.

Some of the factors that affect change detection algorithms are spatial, spectral, temporal, and thematic constraints. In this paper the previous work has been classified:

1) In mono temporal change delineation, pattern recognition is found to be good enough to provide enough clarity on per pixel boundary detection by using convolutional filters.
2) Delta classification is a method that independently classifies the image pixel by pixel. The advantage of this approach is the classification of the images individually which results in insensitivity to transient changes where no change is present. However, the success of this method is highly dependent on the initial classification.
3) By combining subsets of the dataset (image), a composite statistical measure where the change is present would be significantly different to the sites which are constant.
4) Image differencing and Image rationing are the most logical and easy to use algorithms where the two images are superimposed resulting in a positive, negative or zero difference which can be mapped to changes. The only constraint of this method would be the existence of perfectly aligned images. In the case of rationing, the pixel by pixel ratios also gives a scale of change.
5) Data transformation is one of the primary steps and since the images are VHL, they have to be transferred to smaller dimensions to easy computation. PCA on

multitemporal data is possible after a deeper study if the eigen feature vectors.

6) Change vector analysis was one of the first automated change detection algorithms that transforms the subspace into a vector taking into account the different features of the space like brightness, RGB and image segmentation.

E. A New Approach to Change Vector Analysis Using Distance and Similarity Measures

Change Vector Analysis (CVA) is a bi-temporal method of change detection that considers the magnitude and direction of change vector. This was originally designed for only two spectral dimensions, Brightness(indicated overall reflectance) and Greenness(indicates vegetation). CVA application for >2 spectral bands uses the same calculation of the magnitude but the calculation of the direction can be done with several methods. In many cases, the direction component is disregarded entirely. Two approaches are proposed for calculating the direction component in 3-D CVA :

- Sector coding - defines nominal categories for change direction, complex for >3 spectral bands and under utilizes the data variance.
- Calculating vector direction cosines - offers a practical approach that can be extended to n-dimensional space.

Many multispectral applications do not use the direction component. Direction cosine is used to calculate the direction component using multi-band data. In this paper, a new approach to calculate the spectral direction of change, using Spectral Angle Mapper and Spectral Correlation Mapper spectral-similarity measures is proposed. The major advantage of this approach is that it generates a single image of change information insensitive to illumination variation.

The magnitude component of the Spectral similarity is calculated in two ways -

1. Euclidean distance
2. Mahalanobis distance

This paper proposes to determine the direction for change from the angle between the two temporal vectors, instead of using the angle between the change vector and the axes of the Cartesian space. Two spectral vectors at different times are considered. Each temporal spectral vector is drawn from the origin through one of the data points. If two points are on the same vector, it indicates no change in spectral shape or contrast, just different degrees of shading. The origin of coordinates represents null reflectance. This approach is insensitive to real change in the albedo of a surface component that mimic darkening due to an illumination variation.

In this study a new algorithm is formulated to calculate the direction of change in CVA using an adaptation of the Spectral Angle Mapper and the Spectral Correlation Mapper. Mahalanobis distance is also used and its use is compared along with Euclidian distances to estimate the magnitude of change.

The proposed method have been applies in the Cerrado region of Western Bahia state of Brazil, which has become the leading region of an expanding agricultural frontier in the northeastern Brazil because of the low land cost, high insolation, flat topography, proximity to population centers in northeastern Brazil, etc.

The two main requirements in the pre-processing for bi-temporal change detection are precise registration of the images and radiometric and atmospheric calibration. In this paper, the images were co-registered from ground control points identified in each image.

Change detection using Spectral Measures

This paper estimates the magnitude of change by distance measures and the direction of change by similarity measures. In this study, the approach is to compare spectra measured at different times. Regardless of how the spectral relationships are defined, such analysis requires a suitable metric to capture the dependencies among variables. The target identification method adopted was based on the best optimum threshold. In the case of spectral classification, the best fit indicates the greatest possibility of a reference material in a given pixel; for change detection it indicates no spectral change in time.

Direction of Vector Change (Correlation Measures)

The main correlation measures that have been employed in spectral classification are cosine correlation in the Spectral Angle Mapper (SAM), and Pearson's correlation coefficient in the Spectral Correlation Mapper (SCM). SAM is a common method of spectral classification and is widely used in geological mapping and space science. In this work, the SAM expression is adapted to change detection (SAMCD) considering the registered pixel X for the first (t1) and second (t2) times:

$$SAM_{CD} = \alpha = cos^{-1} \frac{\sum_{i=1}^{i=N} X_i^{t_1} X_i^{t_2}}{\sqrt{\sum_{i=1}^{i=N} \left(X_i^{t_1}\right)^2 \sum_{i=1}^{i=N} \left(X_i^{t_2}\right)^2}}$$

where "α" is the angle expressed in radians (0–π). The variable "i" corresponds to the spectral band and ranges from 1 to the number of bands (N). Smaller angles represent closer matches and indicate increased similarity between the two temporal spectral vectors.

III. METHODOLOGY

We will be implementing the paper on "A Scalable Probabilistic Change Detection Algorithm for Very High Resolution (VHR) Satellite Imagery".
This paper is based on a probabilistic change detection framework which consists of 4 major steps:

1) The 2 images are taken at 2 different times and they have been geo-registered as a part of the preprocessing step.

2) To process the image, they are divided into n grids and a gaussian multivariate distribution is applied for each grid. Each Grid at a time interval is represented as:

$$f_j(\mathbf{x}|\mu_j, \mathbf{\Sigma}_j) = \frac{1}{(2\pi)^{\frac{d}{2}}|\mathbf{\Sigma}_j|^{\frac{1}{2}}} e^{-\frac{(\mathbf{x}-\mu_j)^T\mathbf{\Sigma}_j^{-1}(\mathbf{x}-\mu_j)}{2}}$$

Where x belongs to the Relation space and sigma is the covariance matrix.

3) The distance between the two patches taken at different time intervals is measured using the symmetrical Kullback-Leibler distance (SKLD) where the distance D (SKLD) is computed by averaging the Bayesian distances.

4) When the distance for all the grids is computed, we perform a Gaussian mixture model with expectation maximization clustering to generate the change map.

The advantage of this algorithm over the other pixel based approaches is that it uses the characteristics of the image through Gaussian modeling.

Limitations of this algorithm:

1. Since we are using a grid based approach, some of the important features might lose significance as they are present at the edge of the grid which limits the accuracy of the change map.
2. Some of the features which are smaller when compared to the grid size are lost when converting it into a gaussian distribution.

Scalable Sliding window approach:

Data: Images: M_1 and M_2
Result: Change Map
$window.SetSize(W, H)$;
$window.SetPosition(0, 0)$;
$distances \leftarrow 0$;
$change\_map \leftarrow 0$;
while *window does not reach to the end* **do**
  $s_1 \leftarrow$ **RetrieveSubImage**$(M_1, window)$;
  $s_2 \leftarrow$ **RetrieveSubImage**$(M_2, window)$;
  $G_1 \leftarrow$ **ComputeGaussian**(s_1);
  $G_2 \leftarrow$ **ComputeGaussian**(s_2);
  $distances(Window.Center()) \leftarrow$ **S-KLD**(G_1,G_2);
  $window.Move()$
end
$change\_map \leftarrow$ **ClusterGMMWithEM**$(distances)$;
Display$(change\_map)$

Algorithm 1: Sliding Window-based Probabilistic Change Detection Algorithm

Instead of dividing the image into fixed size windows we convolve the pixels by creating a sliding window that covers the complete image. After convolving the window with each set of pixels, the Gaussian mixture is computed for the 2 images that are taken at different time intervals and the SKL-distance is computed. After this, an EM clustering is performed based on the Gaussian mixture model for all the distances to produce the change map.

This algorithm is computationally expensive as the Gaussian distribution is computed for each window. This limitation of the approach is overcome by parallelizing the code using the multi processing library in python.

IV. IMPLEMENTATION

The code was implemented on a Macbook with the following configuration of 16 GB 2133 MHz LPDDR3 RAM and 1.4 GHz Intel Core i5 Processor which has 4 cores. The software used for implementation is Python 3.7 and used the following libraries:

- Opencv (cv2): To perform image processing.
- Joblib and multiprocessing: To perform parallelization.
- Sklearn and scipy: For generating Gaussian mixtures.
- Numpy: For mathematical equations and faster array processing.
- Matplotlib: To plot the change map.

V. RESULTS

The dataset used for this project consisted of two gray scale VHL satellite images of 6972x6984 pixels of dimensions. Initially, the grid based approach was implemented for a small image size of 500x500 with window size of 25x25. This approach failed to capture the changes that occurred at the boundary of the window. To overcome this limitation, the sliding window approach was implemented for various image sizes and window sizes. Initially, a 51x51 window size was run across a 500x500 subset of the image. Fig 1shows four images: the first two images show the original images taken at times t1 and t2, the third image shows the change map that is generated by the algorithm and the fourth image shows the superimposed image of the image at time t2 and the change map generated.

As a result, the resulting change map is likely to make domain experts not to afford to easily assess detailed changes. On the other hand, the result of the proposed algorithm could depict changes in a finer- grained manner by reducing those limitations. As a result of the change map, the task of the domain experts become easier as they have to go through only the high intensity changes in the images. The algorithm could depict changes in a finer-grained manner.

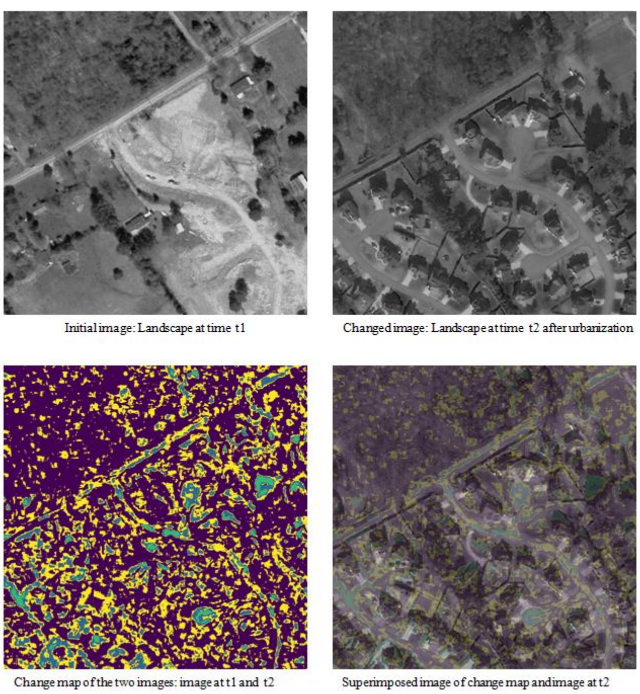
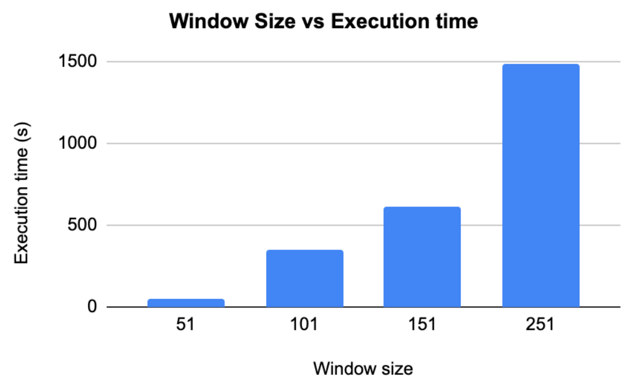
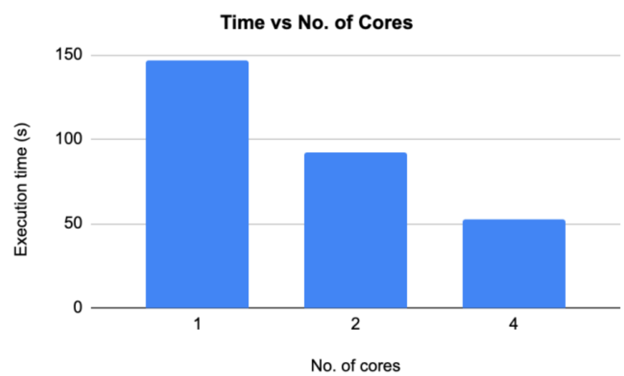


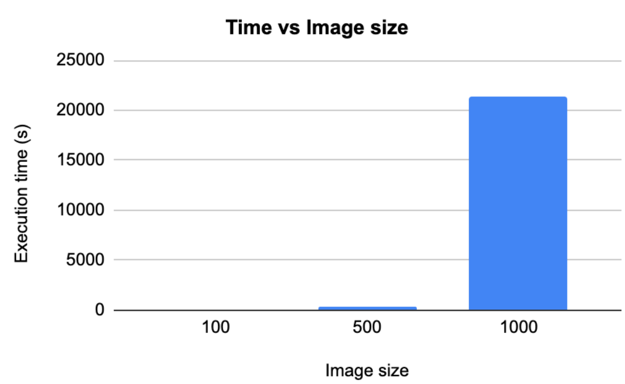
Fig 1: Sliding Window Result

Next we ran a performance analysis on the code. First, the time of the algorithm was observed for each of these windows and the observations indicated an exponential increase because of the time taken to calculate KL Divergence as it involves inverting matrix operation.

The code was parallelized to improve performance and the results were as expected. The code was run on 1, 2 and 4 cores to test the results on the same image and window size. The performance was also evaluated by running it on different image sizes.







VI. CONCLUSION

In this work [6], the existing change detection approaches were explored and two approaches were implemented - Grid based and sliding window. As per the results, the sliding window approach detected the changes in images taken from two different time stamps more accurately.

The proposed algorithm is, however, sensitive to the size of sliding window, which affects the quality of produced change maps and the number of clusters. For parallel change detection, it focused on the "scale- up" aspect of parallelization and compared the performance of the proposed algorithms on different number of cores.

VII. REPOSITORY

The code is pushed to the following GitHub repository: https://github.ncsu.edu/sbalas22/STDM-Project

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