REMOVAL OF ARTIFACTS TO IMPROVE IMAGE CHANGE DETECTION USING DFrFT

Dissertation submitted in the partial fulfillment of requirement for the award of degree of

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Submitted by

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DECLARATION

I, Batish Vij, hereby declare that the work which is being presented in the dissertation entitled, **"Removal of Artifacts to Improve Image Change Detection using DFrFT"** in partial fulfillment of the requirement for the award of degree of Master of Engineering in Electronics and Communication submitted in Electronics and Communication Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Kulbir Singh**, Associate Professor, ECED and refers other researcher's work which are duly listed in the reference section.

The matter presented in this dissertation has not been submitted in any other University/Institute for the award of degree.

Date: 15/07/14

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It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

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ABSTRACT

Image change detection is increasingly becoming one of the major areas of research in image processing. Detecting regions of change in multiple images of the same scene taken at different times is of widespread interest due to a large number of applications in agricultural surveys, urban studies, environmental monitoring, video surveillance, remote sensing, medical diagnosis and treatment, civil infrastructure, forest monitoring, underwater sensing and driver assistance systems. The changes may be due to object movement, insertion, deletion, removal or deformation, and the changes are usually affect the spectral signatures at same pixel locations of two sets of images of the same scene. A key issue in change detection is that it should include only significant changes not the insignificant due to artifacts like, illumination variation, partial translation, large daylight changes and shadowing effect etc. The removal of these artifacts helps in implementing this image change detection system in various applications, like remote sensing, video surveillance and civil infrastructure etc, more accurately. Although there are a number of methods, their applicability is restrained by limitation of the information they are evaluated upon, the type of image acquisition available and need of information to be retrieved after change detection etc.

The present dissertation undertakes a study of image change detection using FrFT along with intensity normalization and thresholding. FrFT has been used as it provides extra degree of freedom to detect accurate changed regions. The use of intensity normalization and thresholding ensure that change is based on appearance or disappearance of objects only, with removal of above mentioned artifacts. Intensity normalization helps in making mean of mutitemporal images equal. Thresholding has been applied to classify pixels as changed or unchanged. In the end, gradient co-relation has been used for classifying the changes obtained from difference image depending upon the value of correlation coefficient.

Change detection results have been analyzed, using precision and recall parameters values, by using three methods namely, DCT, DFrFT and presented method. Results have shown that DCT method is poorest among DFrFT and presented method. By calculation, very large values of recall value have been obtained for all image sets using presented method, it shows that desired objects are detected. The overall improvement in recall

value is 0-34% to DFrFT method. However, precision value for presented method is 6-82% more as compared to DFrFT method which means very small numbers of false regions have been detected.

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LIST OF ABBREVATIONS

CD	Change Detection
DSM	Digital Surface Model
CN	Cluster Neighborhood
SAR	Synthetic Aperture Radar
EMLS	Expectation Maximization based Level Set
PCA	Principal Component Analysis
LPT	Log Polar Transform
SVM	State Vector Machine
APT	Adaptive Polar Transform
SIFT	Scale Invariant Feature Transform
RANSAC	Random Sample Consensus
MGRF	Markov Gibbs Random Field
PRT	Personal Rapid Transit
ATS	Advanced Transport Systems
FT	Fourier Transform
FrFT	Fractional Fourier Transform
DCT	Discrete Cosine Transform
DFT	Discrete Fourier Transform
CVA	Change Vector Analysis
PCC	Post Classification Comparison
DMC	Direct Multidate Classification
LSMA	Li–Strahler Reflectance model
ANN	Artificial Neural Networks
VI	Visual Interpretation

Chapter 1
Introduction

1.1 Preamble

Change detection is an important field of study which is increasingly being researched and analyzed to find new change detection method with more accuracy. A new change detection technique could only be useful if it is straightforward and actualize. Another aspect that needs to understand, whenever a new technique is introduced, is to see the precision with which this new technique locates changes in the image and gives appropriate results related to the changes and trajectories of change in an image. All through the historical backdrop of change detection, variety of change detection systems have been created and new methods keep on developing as the requirement for correctness and exactness is increasingly felt in current technologically oriented world. However it is still exceptionally hard to discover a suitable method for change detection for a particular research purpose or study zone. The need to pick the proper technique for change detection requests a careful examination and cautious study of major impact factors.

Image Change Detection (CD) plays a very important role in modern infrastructure. The aim of CD is to spot and characterize any change between two images captured at different time instants. Change dealing out on imagery data includes the detection of a set of pixels that have undergone a significant change relative in a previous data sequence. These changes may arise due to object movement, addition, deletion, removal or distortion etc. The consequence of these changes is the variation in the spectral signatures at same pixel locations of two sets of images of the same scene.

The process of change detection is of widespread interest since it is having a wide variety of applications in diverse domains like agricultural surveys [31], remote sensing [30], analysis of urban changes [28], motion detection [8], underwater sensing [10], video surveillance [43], damage assessment [25], environmental monitoring [42] and medical diagnosis [39]. Despite the diversity of applications, change detection researchers employ many common processing steps and core algorithms [45].

1.2 Image Change Detection

The process of change detection is summarized in the flowchart below [32]:

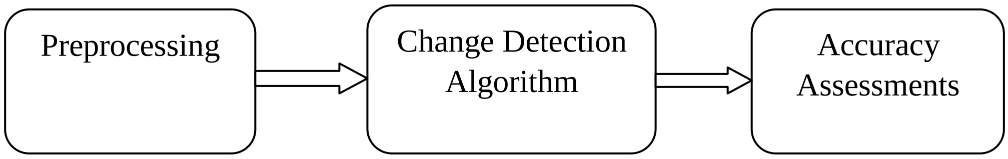


Figure: 1.1 General Scheme of Image Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times [5]. The main goal in change detection is to estimate the "change mask", comprising of set of pixels in the current image that are "significantly different" from the previous image. A key issue in estimating the change mask is that it should include only significant changes not the insignificant such as illumination variation, camera motion or sensor noise etc.

In image change detection scheme contains three basic blocks:

- Preprocessing
- Change Detection Algorithm
- Accuracy Assessments

1.2.1 Preprocessing

Any remotely sensed data, e.g. satellite images, is liable to different errors. These errors could be inner geometric errors, i.e. errors produced by the remote sensing system, the Earth's rotation or curvature. The images could be distorted, due to relief displacement (objects in the image seem tilted) or tangential scale distortion (objects on the edges of the images get compressed). These inner geometric errors are systematic, which means that they can be identified and redressed [32]. Before any change detection algorithm can be applied to images, they have to be amended for geometric and atmospheric differences. This correction is generally done in preprocessing. Preprocessing includes geometric correction, radiometric correction and classification [32].

- The motivation behind geometric correction or co-registration is to uproot the impact of different geometries in the images.

- There are two sorts of radiometric correction, absolute and relative. For absolute radiometric correction, data concerning the environment at the time of image obtaining is required. As this data is very hard to obtain, relative radiometric correction is often utilized instead, where the digital values (DN) of images are changed to a typical scale.
- Depending on selection of change detection algorithm, the images may need to be classified. This implies that the examiner divides the pixels into certain groups, this is possible on a spectral basis (pixels with comparable spectral characteristics are sorted together), spatial basis (pixels having a spatial relationship are sorted together) or temporal basis (pixels might be correctly classified by help of data from two dates).

1.2.2 Change Detection Algorithm

Change detection algorithm is the crucial basic block among the all. Although there are a number of methods, but these techniques can be broadly classified under two main approaches based on the nature of method used for processing the images: unsupervised and supervised. The former technique performs change detection by using only the multitemporal images and in this method no ground truth is needed. The latter is based on supervised classification methods; a training set is required for the learning process of the classifiers. This training set is obtained from the ground truth data [12]. Although the supervised approach exhibits some advantages over the unsupervised one as:

- the capability to explicitly identify the sorts of land cover or land use transitions that have occurred;
- the robustness to the different atmospheric and light conditions at the two acquisition times;
- the ability to process multisensor and/or multisource images;

the generation of an appropriate training set is usually a difficult and expensive task [12]. Further discussion about these methods will be covered in following chapters.

1.2.3 Accuracy Assessments

Accuracy assessment of change detection result has two classes, change and no change. A change pixel that is recognized as unchanged is known as a false negative or miss. A no-change pixel that is distinguished as changed is known as a false positive or false alarm.

True negatives are unchanged pixels that were distinguished as unchanged. True positives are changed pixels that were recognized as changed [32].

1.3 Need of Image Change Detection

Following few stanzas highlight the necessity of image change detection:

Timely and exact change detection of Earth's surface features is greatly important for understanding relationships and interactions between human and natural phenomena in order to promote better choice making. With headways in remote sensing technologies, change detection focused around high resolution satellite images gives an efficient tool for checking infrastructural development within vast premises.

Automatically recognizing objects and people left in the inner part of vehicles is highly desirable because human monitoring has high running costs and low efficiency associated with it.

Detection/ appearance of items in video frames alongside security systems of surveillance cameras incorporate change detection for fast and efficient working [43].

In medical analysis, detection of missing part of organs and near dissection of scans become easy with image change detection. For example, significance of change detection in MRI scans is highlighted in [36].

Image change detection along with classification algorithms is essential for obtaining out the statistics and hence planning the policies for the development of any geographical area.

To detect the motion in a video stream environment which is a thought to guarantee that the monitoring systems not only actively partake in halting the crime, but do so while the crime is occurring.

Checking Changes of environment is an issue confronted by numerous different institutions. Particularly Government organizations have the duty to identify and record these changes which may occur in urban, forest, agricultural, desert areas, and so forth [14]. Subsequently for gathering information for these at worthy expense and suitable ease, we require dissection of image change detection.

Examine in Environmental Remote Sensing Global and Regional Environmental Applications of Remote Sensing Data Land cover change detection utilizing remote sensing satellite imagery is an influential tool for observing urbanization and the ensuing resulting loss of forest and agrarian.

In Satellite images (acquired at different times/dates), change detection is an important practice that can lead to valuable information about deforestation, water level - imminent floods, tree mortality due to droughts or forest fires, urban infrastructure change – new roads, buildings [21, 22, 48].

1.4 Objectives

Dissertation has following objectives:

1) To study existing techniques of Image Change Detection.
2) To implement Image Change Detection using DFrFT along with intensity normalization and thresholding and comparing the results with other techniques.
3) To Identify the main change objects by removal of artifacts
    - Illumination variations
    - Partial translation
    - Large daylight changes and
    - Shadowing effect in change image.

1.5 Methodology of Research Work

The project involving modified image change detection based on DFrFT constitute of following steps:

Firstly, two images are taken at different time of same scene then intensity normalization is applied on second image to make its mean and variance compatible with the first image. After doing an initial differencing step, the main blocks incorporating fractional functions are the applications of fractional and inverse fractional block with a varying value of fractional parameter. The quantizer selects only appropriate coefficients and round off other to zero. The details of image change detection using DFrFT along with intensity normalization and thresholding will be explained in the later chapters of the dissertation.

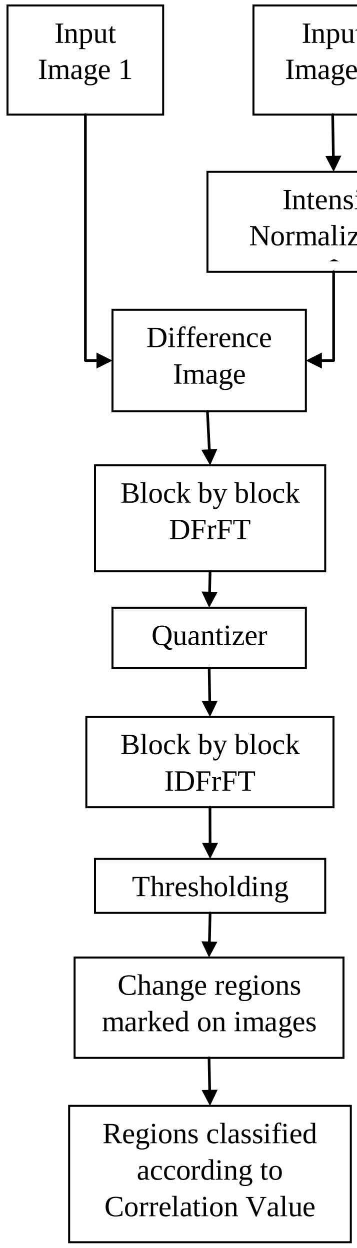


Figure 1.2: Modified image change detection using DFrFT

1.6 Organization of Dissertation

This dissertation consists of 5 chapters which are organized as below:

Chapter 1: Introduction, this chapter will introduce important terminologies regarding dissertation, objectives, methodology used in the research work and organization of the dissertation.

Chapter 2: Literature review, in this chapter study the work which has been done regarding for designing various methods for image change detection. Along with it work related to fractional transform is also discussed in this chapter. The chapter also provides an overview of the gaps in study.

Chapter 3: Present work, this describes methodology used for image change detection, parameters used for analysis the results.

Chapter 4: Results and discussions, this chapter describes simulation performed for different image sets and comparison of results of presented method with other method.

Chapter 5: Conclusion and future scope, in this chapter whole work has been concluded, on the basis of observations and also future scope has been discussed.

Chapter 2
Literature Survey

This chapter overviews the work which has been done regarding image change detection and fractional transform along with their various design methods from time to time.

2.1 Image Change Detection

Image Change Detection plays a very paramount part role in modern infrastructure. The aim of change detection is to spot and characterize changes in images of the same scene taken at different times. Change dealing out on imagery data incorporates the detection of a set of pixels that have undergone a significant change relative in a previous data succession. These changes may arise due to object movement, addition, deletion, removal or distortion etc. The result of these changes is the variation in the spectral signatures at same pixel areas of two sets of images of the same scene.

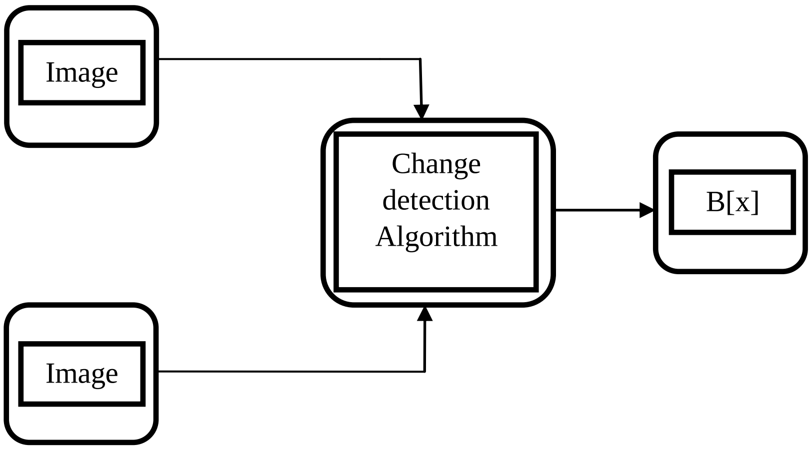


Figure 2.1: Block Diagram of Image Change Detection [55]

Generally, in the comparison process, two corresponding pixels belonging to the same position in an image pair are specified on the basis of a quantitative measure. If this measure rises above predefined threshold a change is labeled. In Figure 2.1 two images, captured at two different times of same area, have been taken then change detection algorithm is applied on both to detect change and B identifies the changed region. Two images or set of images is mandatory to identify change. Changes obtained are typically resulting from the appearance, disappearance, motion or change in the shape of a target object. There are wide range of applications in which change detection methods are used, like forest monitoring, agricultural surveys, urban studies and environmental monitoring.

Because of the advantages of repetitive data acquisition, its synoptic view, and digital format makes it appropriate for computer processing, remotely sensed data.

2.2 Change Detection Techniques

In the last few years, there has been a growing interest in the development of new change detection techniques for the analysis of multitemporal images. Although there are a number of methods, but these techniques can be broadly classified under three main approaches:

- Unsupervised Change Detection (no ground truth)
- Supervised Change Detection (ground truth)
- Semisupervised Change Detection

2.2.1 Unsupervised Change Detection

This approach performs change detection by transforming the two multispectral images, a single band or multiband image, in which the areas of land cover or land use; change can be successively detected. Here, changes obtained result in larger changes in radiance values than other factors. Classes of techniques/algorithm based classification:

- Algebra
- Transformation
- Clustering
- Other methods

Some of the above stated methods of Unsupervised Change Detection are explained as follow:

(a) Algebra based methods

Image math includes simple arithmetic functions are performed on images to get the change detected image. Some common techniques are Image differencing, Image rationing, Background subtraction etc. These methods are relatively simple and straightforward, but these cannot provide change matrix and type of transition. Details of these methods are given below:

(i) Image differencing

Image differencing involves images of the same area, obtained at two different periods of time, are subtracted pixelwise. The two images are compared pixel by pixel and pixels showing changed areas produce values noticeably different from those pixels associated to unchanged areas. The subtraction produces a third image in which positive and negative values of pixels showing area of change and zero values represent areas of no change. Mathematically, the difference image [39]

$$I_d(x,y) = I_2(\mathrm{x},\mathrm{y}) - I_1(x,y) \tag{2.1}$$

where I_1 and I_2 are the images taken at times t_1 and t_2 ($t_2 > t_1$) respectively, *(x, y)* are the coordinates of the pixels. The difference image I_d represents the pixel by pixel intensity difference of I_1 from I_2. The I_d is analyzed to acquire a change or no change classification by applying a threshold. Only the pixels having value above the threshold will correspond to a change at that location.

Image differencing is very simple and easy to implement, and its results can be easily interpret. However, it has the following shortcomings:

- It cannot provide a change matrix in detail and selection of thresholds is required.
- Differencing leads to lose information. In case, two differenced pixels can have the same value, but this shows nothing about the type of change that has occurred. For example, a change of 60 may be caused by differencing two pixels from 180 to 120 or from 110 to 50.

(ii) Image rationing

In this technique images are compared pixelwise as in case of image differencing. This method divides intensity values of pixels in one group by the intensity values of their corresponding pixels in another group to generate the output image. This method has a advantage as ratios reduce the illumination variations. Mathematically, the ratio image I_r [39] is

$$I_r(x,y) = \frac{I_1(x,y)}{I_2(x,y)} \tag{2.2}$$

Here I_r image takes values in the range [0,∞*)*. If the intensity values are equal, it takes the value 1. To normalize the value of I_r [40], we can benefit from the arctangent function as

$$I_r(x,y) = \arctan\frac{I_1(x,y)}{I_2(x,y)} - \frac{\pi}{4} \tag{2.3}$$

Now, ratio image takes values in the range [$-\pi/4$, $\pi/4$]. Normalization gives better results as compare to pixel by pixel division.

(iii) Image regression method

In this method a relationship between pixel values of two different dates is accomplished by using a regression function. Let the I_2 image (obtained from t_2) is assumed to be a linear function of the I_1 image (obtained from t_1). Under this assumption, we can find an estimate of $\widehat{I_2}$ by using least squares regression [39] as

$$\widehat{I_2}\ (x, y) = aI_1(\mathrm{x}, \mathrm{y}) + b \tag{2.4}$$

To estimate the parameters a and b [37],

$$a = \frac{n\sum_{n=1}^{N} I_1(x_n, y_n) I_2(x_n, y_n) - \sum_{n=1}^{N} I_2(x_n, y_n) \sum_{n=1}^{N} I_1(x_n, y_n)}{n\sum_{n=1}^{N} I_1(x_n, y_n)^2 - (\sum_{n=1}^{N} I_1(x_n, y_n))^2} \tag{2.5}$$

$$\mathrm{b} = \frac{\sum_{n=1}^{N} I_2(\mathrm{x_n}, \mathrm{y_n}) - a\sum_{n=1}^{N} I_1(x_n, y_n)}{\mathrm{N}} \tag{2.6}$$

We picked the observations (for n = 1. . . N) from I_1 and I_2 (from the unchanged areas). Change is detected after subtracting I_2 from $\widehat{I_2}$ as $I_d(x, y) = \widehat{I_2}\ (x, y) - I_2(x, y)$. It has advantages of reducing impact of atmospheric and environmental differences. But it does not provide change matrix.

(iv) Change Vector Analysis (CVA) method

In CVA, each pixel is referred to as a vector in M-dimensional space where M signifies the number of bands in the image. Then, for each couple of pixels, the change vector is obtained by the difference between the feature vectors at the two times. The statistical analysis of the magnitudes of the change vectors allows one to detect the presence of changes, while their directions help to distinguish among different kinds of transitions.

This method is demonstrated in Figure 2.2 using n-band example. From two n-band images, a change vector is obtained by subtracting the vectors of the image at time t_1 from the vectors of the image at time t_2.

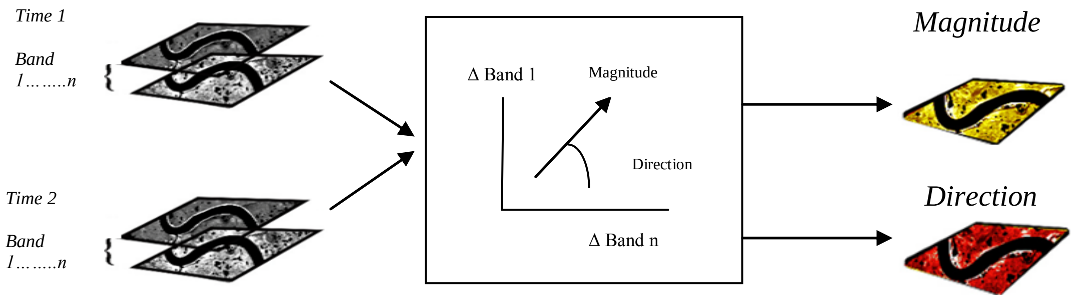
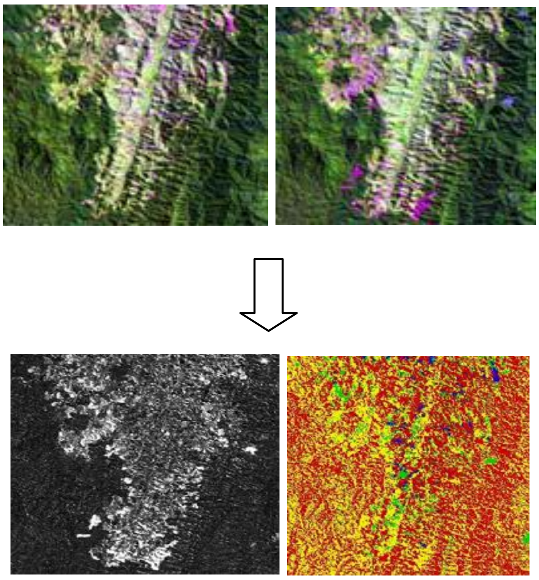


Figure 2.2: Formation of a change vector using two-n-band image vectors



Magnitude **Direction**

Figure 2.3: Image Change Detection Using Change Vector Analysis [55]

The automatic detection of longitudinal changes in brain images is valuable in the assessment of disease evolution and treatment efficacy. information about lesion evolution. R. Simoes *et al.* [50] presented an unsupervised 3D change detection method based on Change Vector Analysis. Automatically threshold was used to obtain a binary change map of the generalized likelihood ratio map. Histogram-based clustering was implemented to classify the change vectors. Kappa Index of 0.82 was obtained using various types of simulated lesions. The classification error was 2%. Finally, this method made us able to detect and discriminate both small changes and ventricle expansions in datasets from mild cognitive impairment patients.

(b) Transformation based methods

The transformation category includes PCA, fractional transform and wavelet transform etc. One benefit of these methods is in reducing data redundancy between bands and laying emphasis on different information in derived components. However, they cannot provide detailed change matrices and also require thresholds selection to recognize changed areas. Another disadvantage is the difficulty in interpreting and labeling the change information.

(i) Principal Component analysis (PCA)

Principal Component Analysis is a linear transformation technique and also the most common of these techniques. PCA is based on the eigenvectors of the variance-covariance matrix of the merged dataset. These eigenvectors are linearly transformed to obtain the eigen structure which indicates the type of information content in dataset. Change detection can be performed by applying the PC transformation separately to the feature space at single time or to the merged feature space at two times. Figure 2.4 illustrates the progression of this method.

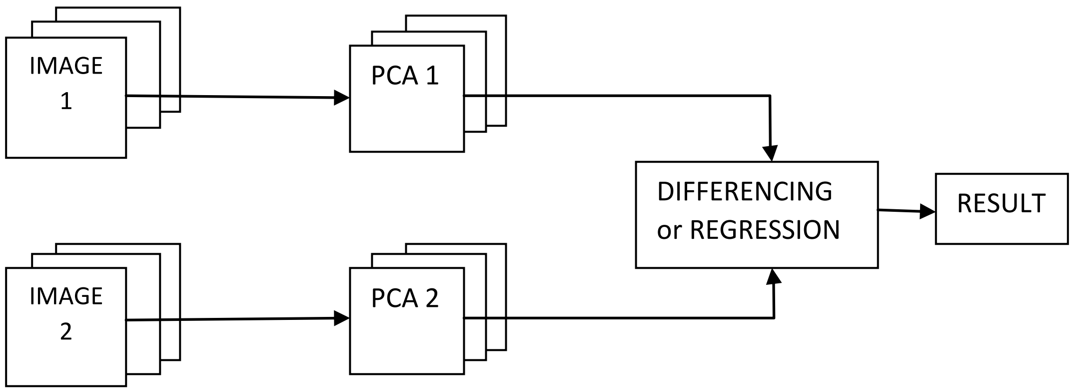


Figure 2.4: Principal components analysis with band-by-band differencing [44]

(ii) Fractional transform based method

Image change detection using fractional transform has been given by S. Singh *et al.* [54]. DFrFT provides a flexible approach by varying its fractional parameters so as to get the best possible results. Change regions were marked on difference image depending upon a particular size limit that may vary according to image dimensions. Further, a gradient correlation filtering technique was used for categorization of these obtained regions. This method gave out improved results, in terms of precision and recall parameters, as compare to DCT and JHT methods.

(iii) Wavelet transform based method

A multiscale contextual unsupervised change-detection method for optical images has been presented by G. Moser *et al.* [15]. It was based on discrete wavelet transforms and Markov random fields. Wavelets were applied to the difference image to extract multiscale features, and markovian data fusion was used to integrate both these features and the spatial context in the change-detection process. Expectation–maximization and Besag's algorithms were used to estimate the model parameters. The selection of the optimal wavelet-transform operator within a predefined dictionary was automated by a minimum-energy criterion. Experiments on real optical images point out the effectiveness of this method as compared with state-of-the-art techniques.

T. Celik *et al.* [56] presented an unsupervised change-detection method for multitemporal satellite images using dual-tree complex wavelet transform (DT-CWT). The algorithm exploited the inherent multiscale structure of DT-CWT to individually decompose each input image into one low-pass subband and six directional high-pass subbands at each scale. A binary decision has been based on an unsupervised thresholding derived from a mixture statistical model, with a goal of minimizing the total error probability of change detection. Extensive simulation results clearly showed that the presented algorithm consistently performed quite well on both objective and subjective change-detection performance evaluation under either noise-free or speckle noise interference cases.

(iv) Adaptive polar transform based method

Motivated by LPT (Log Polar Transform), another new registration algorithm that talks the issues of the conventional LPT, while keeping up the strength to scale and turn, was presented by R. Matungka *et al.* [46] that familiarized a novel adaptive polar transform (APT) technique that evenly and effectively sampled the image in the Cartesian coordinates. Translation among the registered images was recuperated with the new inquiry plan utilizing Gabor feature extraction to accelerate the localization procedure. Also an image comparison scheme was planned for locating the area where the image pairs differ.

(c) Clustering based methods

An unsupervised change detection technique using k-means clustering on the combined difference image has been given by Y. Zheng *et al.* [66]. The motivation of this method was to use the local consistency and edge information of the difference image after using the mean filter and median filter respectively for better difference image representation. Experiments were performed on four real SAR image data sets that had demonstrated the effectiveness of the presented method.

W. Luo *et al.* [61] gave a new change detection method for unregistered multitemporal satellite images using the combinatorial clustering method. To obtain the change detection map, firstly, the method of over segmentation was employed for the input images to reduce the computational cost. Secondly, the combinatorial clustering method was applied, which integrates the methods of bottom-up unsupervised clustering and the top-down discriminative clustering, to obtain the segmentation score for the result of over segmentation. Finally, the change detection map has been obtained by thresholding the score. Experimental evaluation on the multitemporal satellite images demonstrated that the presented method has good performance on the unregistered images.

(d) Other methods

Y. Q. Cheng *et al.* [65] presented an improved algorithm of unsupervised change detection technique by taking the same low-order FrFT on multitemporal images acquired on the same geographical area but at different time instances, then generates the difference image by the absolute log-ratio operator. In order to acquire the eigenvector space, PCA was performed on m × m nonoverlapping difference image blocks. The feature vectors were extracted using m × m data blocks projection onto eigenvector space. The change detection map is generated by clustering the feature vectors using *k*-means algorithm into two disjoint classes: changed and unchanged. The experimental results demonstrated the effectiveness.

F. Baselice *et al.* [13] gave an novel technique for change detection in urban areas using very high resolution synthetic aperture radar multichannel stacks. Instead of using the amplitude image the presented technique used the full complex image in a Markovian framework. The presented algorithm estimated, first, two hyperparameter maps on given data sets and after that compared the similarity between them. The statistical distribution of the hyperparameter maps would change when changes occurred. An index of changes was obtained by maximum distance between the two obtained statistical distributions.

J. Tian *et al.* [24] presented a buliding change detection method based on stereo imagery and digital surface models (DSMs). With the help of stereo matching methodology, both stereo imagery and DSMs were generated. Kullback–Leibler divergence and Dempster–Shafer fusion theory were used to improve the accuracy of change detection.

Y. Pu *et al*. [64] discussed a novel unsupervised change detection approach based on cross-correlation coefficient. The cross-correlation coefficient is a measure of the similitude between two variables. The change detection issue could be seen as the procedure to partition two input images into two distinct regions, specifically "changed" and "unchanged", as indicated by binary change detection mask. Each region in the pair of the images of the corresponding position was considered as two sets of variables, whose cross-correlation coefficient was figured so as to give an ideal segment of the changed and unchanged regions. In the optimal partition, it is obvious that the cross -correlation coefficient of the set of the unchanged variables should be the maximum, while the absolute -value of that of the changed variables should be the minimum, because the corresponding unchanged regions are similar while the changed regions are quite different. Genetic Algorithm was used to get the ideal non-ruled result as the change detection using cross-correlation coefficient was a multi-objective optimization issue. The simulation experiment demonstrates that the result utilizing the new method was effective and robust to radiometric difference.

M. Hao *et al.* [38] gave a novel unsupervised change detection approach based on expectation-maximization based level set method (EMLS). Two new energy terms, signifying contrasts in the middle of pixels and the means of changed and unaltered pixels, were included into the starting level set to reinforce the correctness of the created change maps. The experiments were performed on Landsat and QuickBird images and the results showed that EMLS produces the most accurate change maps compared with those of LSII, MRSFE, DRLSE, CV, MLS, and MLSK.

An unsupervised method for change detection from remote sensing images using hybrid genetic FCM has been presented by K. K. Singh *et al.* [26]. PCA was used on combined image of three difference images to extract change information. Three difference images were used to improve the overall accuracy of the algorithm. Clustering of change maps, into changed and unchanged, were created by using Hybrid Genetic FCM clustering algorithm. The results of the presented algorithm were quiet accurately compared with some of the existing methods.

H. Sahbi [20] discussed an alternative and semi-automatic change detection method based on relevance feedback. This calculation was focused around a question and response demonstrate that asks the user the most informative inquiries regarding the pertinence of his focused on changes, and as per these responses redesigned change detection results. Then the algorithm consequently learnt a choice rule in order to upgrade change detection results. Analyses directed show that surely the presented methodology was effective.

An unsupervised change detection method based on 2-D fuzzy entropy has been projected by W. Sun *et al.* [62]. This method made full utilization of spatial information of difference image and grouping distributing information of 2-D histogram. Furthermore, the system performed change detection on the entire gray level. So it can actualize ideal change detection. It should be recognized that the means could distinguish edge pixels or noises well, so the detection result was superior to conventional algorithms.

S. Liu *et al.* [53] gave a complete methodology for land cover change detection by fusing change information found from multiple difference images. Measurement and decision level fusion techniques were used to pool multiple difference images, and support vector machine (SVM) was chosen to detect the changes. Multi-temporal CBERS images acquired in 2002 and 2008 were used to detect land cover changes and urban expansion in Shanghai, and experimental results affirmed the handiness of the presented approach. Utilizing additional change information, both the omission error and commission error could be made less.

A motion detection system was employed by A. Ansari *et al.* [1] to detect the motion in a video stream environment and this is a thought to verify that the observing frameworks not just energetically have impact in ceasing the wrongdoing, yet do so while the wrongdoing is occurring. Thus, a system was utilized to recognize any movement in a live streaming video and when movement has been identified in the live stream, the software will enact a cautioning framework and catch the live streaming video.

A robust method for geometric co registration, and a faultless change detection technique focused around statistical method for multi-temporal high-resolution satellite imagery was given by M. Abdelrehman *et al.* [35] in which scale-invariant feature transform (SIFT) was utilized to achieve a set of correspondence points in a pair, or numerous pairs, of images that were taken at different times and under distinctive circumstances, then Random Sample Consensus (RANSAC) was utilized to wipe out the outlier set. The resulting inliers matched points was an accurate correspondences which was utilized to register the given images. Changes in registered images were perceived utilizing statistical analysis of image differences. Finally, Markov-Gibbs Random Field (MGRF) was used to model the spatial-context oriented data encased in the resulting change mask. Experiments with generated synthetic multiband images, and LANDSAT5 Images, approved the correctness of the presented algorithm.

R. J. Radke *et al.* [45] introduced an orderly overview of the common processing steps and core decision rules in current change detection algorithms, including significance and hypothesis testing, predictive models, the shading model, and background modeling. Also discussing important preprocessing methods, methodologies to authorizing the consistency of the change mask, and principles for assessing and looking at the execution of change detection algorithms.

G. Xue *et al.* [16] presented a novel foundation demonstrating strategy by trusting on factual models which utilize pixel stage rather than intensities. They initially uprooted the phase feature of the pixel utilizing Gabor filters. Then, each one stage peculiarity was demonstrated freely by a mixture of Gaussian models and upgraded with a novel plan. Since frontal area pixels were scattered in the preparatory detection result, distance transform was employed on the binary image which converts the image into a separation map. Sectioning the distance image with a threshold created the last come about.

The work introduced by D. Crispell *et al.* [9] summed up past probabilistic 3-D models in such a route, to the point that different requests of size reserve funds away were conceivable, making high-resolution change detection of substantial scale scenes from high-resolution aerial and satellite imagery possible. Decisively, the natural reliance on a discrete cluster of consistently estimated voxels was evacuated through the induction of a probabilistic model which represented uncertain geometry as a density field, permitting executions to proficiently inspect the volume in a non-uniform style.

A new scene change detection method using multiple histograms was presented by S. J. Kang *et al.* [52]. For successive frames, this method produced multiple histograms of split blocks. Then, optimal threshold value was calculated using automatic thresholding based on the Otsu method and chose whether the scene change occurred or not using the difference between threshold values in consecutive frames. In the experiments for the subjective evaluation, this method rightly recognized the scene change, thereby preventing artifacts. The presented method enhanced the accuracy of the scene change detection by up to 0.461 compared with the benchmark methods.

A novel Personal Rapid Transit (PRT) framework was right away being composed by Advanced Transport Systems Ltd (ATS) characteristics. Image change detection for a particular rapid transit application by A. Peters *et al.* [4] described two strategies that utilize changes in the visual image of inside to anticipate the likelihood of left objects and remaining people. The first method was based on identifying structural differences. The second utilized a shading model method. A variation of the shading model with information from the color channels is also described. The conclusions demonstrated that the modified shading model approach gives the best performance.

2.2.2 Supervised Image Change Detection

In order to overcome the shortcomings of an unsupervised approach, one can use supervised classification methods to multitemporal images. It generates a change detection map where changed areas are identified and the transition type can also be recognized.

Various techniques are discussed as follows:

(a) Post Classification Comparison (PCC) method

PCC is the simplest method of this category. It performs change detection by comparing the classification maps obtained by classifying separately two images of the same area acquired at different times. In this way, it is possible to detect changes and to recognize the types of transitions that have taken place. Furthermore, the classification of multitemporal images avoids the need to normalize for atmospheric conditions, solar angle, between the acquisitions. However, the performances of the PCC technique depends on the accuracies of the classification maps. In particular, the final change detection map exhibits an correctness close to the product of the accuracies got at the two times. Figure 2.6 illustrates the technique. Similar classes from both images are subtracted to create change classes which are then merged into one result.

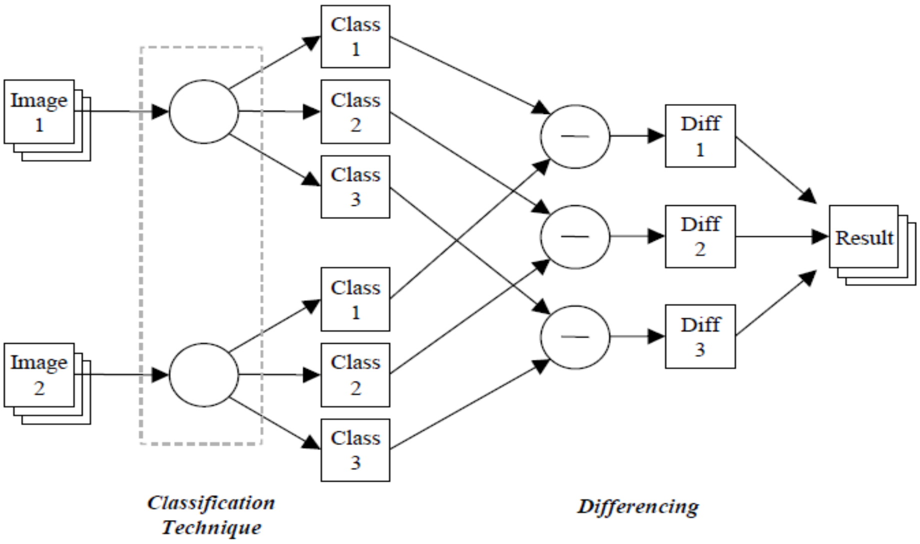


Figure 2.5: A flow diagram illustrating post classification [55]

Accurate registration is not an issue in case where classes generally represent larger areas. It is probably; however, that registration would become more of an issue while making an attempt to observe smaller targets like tanks and trucks.

(b) Direct Multidate Classification (DMC) method

In this method, pixels are characterized by a vector obtained by stacked feature vectors related to the images obtained at two times. Each transition is considered as a class to produce change detection and by training a classifier to recognize the transitions. Suitable training sets are required: the training pixels at the two times should be linked to the same points on the ground and should represent precisely the proportions of all the transitions in the whole images.

PCC does not take into account the dependence existing between multitemporal, while DMC is able to overcome this problem.

(c) Iterative approach

M. Roy *et al.* [40] presented a neural approach under active learning mode for change detection in remotely sensed Images. Here, radial basis function neural networks and a multilayer perceptron were used as learners. The network was iteratively trained with label patterns. The most informative set of labeled patterns can be iteratively generated by querying, like uncertainty sampling and query-by-committee. From results, it has been found that this approach is better than semi-supervised method.

2.2.3 Semisupervised Image Change Detection

Semisupervised image change detection is new approach taking account of combination of unsupervised and supervised approach. As unsupervised methods do not need prior knowledge of images, whereas, supervised learning methods will outperform unsupervised ones by utilizing labeled samples to obtain a more exhaustive description of the changes. However, when a few labeled samples are available, their performance is poor [12]. Fortunately, the issue can be dealt with by exploiting the information of unlabeled samples in a semisupervised way.

(a) Kernel based method

L. Jia *et al.* [33] discussed a semisupervised cluster-neighborhood (CN) kernel method for SAR image change detection. The method has illustrated the wealth of the CN kernel to SAR images. The presented CN kernel, which uses both labeled and unlabeled samples, can extract the intrinsic characteristics of SAR images in a more complete manner. As a result, the discrimination and the noise immunity of the CN kernel method are improved. Experimental results on real SAR image change detection prove that the CN kernel method gives more precise results and exhibits stronger robustness against speckle noise compared with the composite ratio kernel method.

(b) PCA based method

J. S. Deng *et al.* [23] presented a new method using multitemporal and multisensor data to detect land-use changes in an urban environment based on PCA and hybrid classification methods. After geometric correction and radiometric normalization, PCA was used to enhance the change information from stacked multisensor data. Then, a hybrid classifier combining unsupervised and supervised classification was performed to identify and quantify land-use changes. This method shows satisfying results with an overall accuracy to be 89.54% and 0.88 for the kappa coefficient. When compared with the post-classification method, PCA-based change detection also showed a better accuracy in terms of overall, producer's, and user's accuracy and kappa index.

2.3 Fractional Transforms

During the last two decades, the process of going from the whole of an entity to fractions of it underlies several interesting applications such as fractal objects, fuzzy logic and fractional signal processing [27]. The fourth power of 8 may be defined as 7^4= 7x7x7x7, but it is not apparent to define $7^{3.5}$ in a similar way. It must have taken sometime before the common definition $7^{3.5} = 7^{7/2} = \sqrt{7}^7$ emerged.

The first and second derivatives of the function $f(x)$ are commonly denoted by:

$$\frac{df(x)}{dx} \text{ and } \frac{d^2 f(x)}{dx} = \frac{d}{dx}\left[\frac{df(x)}{dx}\right] = \frac{d[df(x)/dx]}{dx} = \left(\frac{d}{dx}\right)^2 f(x) \text{ respectively.}$$

And higher order derivatives are defined similarly. But it is not obvious that what will be 0.9^{th} order derivative using above definition. We know that by using differentiation property of Fourier Transform (FT), the a^{th} derivative of $f(x)$ i.e. $\frac{d^a f(x)}{dx^a}$ is equivalent to the inverse Fourier transform of $(i2\pi\mu_a)^a$ F (μ_a) where F (μ_a) is the FT (of real order 'a') of the function $f(x)$. FT is widely used in many areas of science and engineering like optics, physics, acoustics, statistics, heat conduction and diffusion, electrical engineering, antenna and array processing etc. FT is a linear transform used to solve linear system problems. However, the FT is unable to solve certain classes of ordinary and partial differential equations of optics, signal processing and quantum mechanics [47]. Looking into the applicability of FT the concept of fraction was introduced in the FT in the year 1929 [41] and lead to the development of fractional Fourier transform (FrFT). If we go on to map the history of fractional thought it is found that in 17th century, Bernoulli (1695) formulated a question about the meaning of a non-integer order derivative. This was the start of the fractional calculus which is the base of the continuous time fractional systems described by the fractional differential equations. Since then, the concept of fractional calculus has evolved in pure mathematics and developed by famous mathematicians [27]. In spite of the advancement in pure mathematics this concept had been applied in applied sciences only in 1920's. Furthermore, it is only in the last three decades that the applications of fractional calculus have emerged in engineering field which lead to a significant impact in several areas and attracted the scientific and technical community to the fractional objects [27].

(a) Fractional Fourier Transform

The Fourier Transform (FT) is undoubtedly one of the most appreciated and frequently used tools in signal processing and analysis. Little need be said of the prominence and ubiquity of the ordinary Fourier transform in many areas of science and engineering. The FrFT, which is a generalization of the simple Fourier transform, was introduced 75 years ago but only in the last two decades, it has gained prominence in signal processing, optics and quantum mechanics.

V. Namias [60] first introduced the Fractional order of Fourier Transform in 1980. Here the indispensable showing of this transform has been utilized for the development of fractional order Fourier transform. A generalized operational analytics was built, paralleling the familiar one for the ordinary transform Its requisition offers helpful methodology for illuminating the certain class of ordinary and partial differential equations which arise in quantum mechanics from classical quadratic Hamiltonians. Essentially the method has been applied in quantum mechanics for portraying quantum mechanical dynamics of electrons in time varying magnetic field.

Several decades later L. B. Almedia translated this fractional Fourier transform as rotation operator that rotates the signal in time-frequency plane relying upon the value of a parameter alpha. Before publication in [29] the FrFT stayed as new to Signal Processing Community. Almedia acclimated a few properties of the FrFT and additionally related this Fractional Fourier Transform with other time-frequency representations as Wigner distribution, the short time Fourier transform, ambiguity function, and the spectrogram. In this publication examples of FrFT of some simple signals were specified. He also explained the application, demonstrating that how the utilization of FrFT allowed a treatment of swept-frequency filters that is like classical treatment of shift-invariant filter with the Fourier transform. The Fourier transform and Fractional Fourier transform are related by the A. I. Zayed in [3] for comprehension properties and to find its use in the areas where the conventional Fourier transform have been utilized.

Mathematically, the a^{th} order FrFT operator is the a^{th} power of the conventional FT operator. The fractional Fourier transform with parameter $a = 1$ corresponds to the orthodox Fourier transform. It is noticeable to bring in mind that the ordinary Fourier transform is a special case of a continuum of fractional Fourier domains. Essentially, the a^{th} order FrFT is an intermediate between any function x(t) and its FT X(u). The 0^{th} order transform is merely the function itself, whereas the 1^{st} order transform is its Fourier transform. In all the time–frequency representations, one typically uses a plane with two orthogonal axes that usually are time and frequency. If we consider a signal x(t) to be represented along the time axis and its ordinary FT X(u) to be represented along the frequency axis, then the Fourier transform operator (denoted by F) can be visualized as a change in representation of the signal corresponding to a counter clockwise rotation of the axis by an angle π/2. This is reliable with some of the pragmatic properties of the Fourier transform (FT).

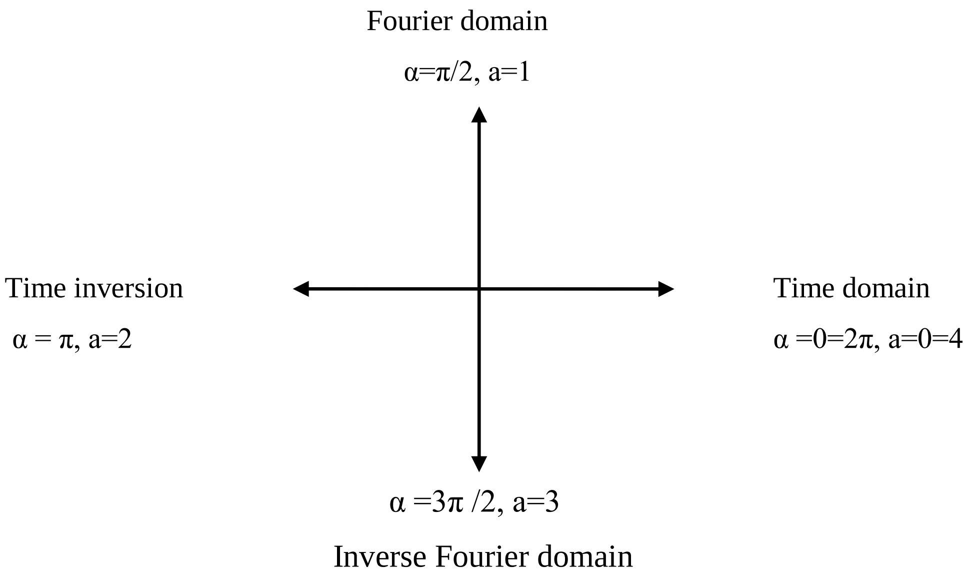


Figure 2.6: FrFT domain in time-frequency plane

The Figure 2.7 shows the FrFT domain in Time-frequency plain. The FrFT is a linear operator that corresponds to the rotation of the signal through an angle which is not a multiple of π/2, i.e. it is the representation of the signal along the axis making an angle α with the time axis. Some important cases of the FRFT operator for $\alpha = a\frac{\pi}{2}$ are listed below:

- For $\alpha = 0$ or 4; i.e. $a = 0$ or 2π, one acquires the identify operator: $F^0 = F^4 = I$ (Identity Operator)
- For $\alpha = \frac{\pi}{2}$; i.e. $a = 1$,one gets the Fourier operator: $F^1 = F$ (Fourier Operator)
- For $\alpha = \pi$; i.e. $a = 2$, one achieves the reflection operator: $F^2 = FF = I -$ (Reflection Operator shown by time inversion).
- For $\alpha = \frac{3\pi}{2}$; i.e. a=3, one gets the inverse Fourier operator $F^3 = FF^2 = F^{-1}$ (Inverse Fourier Operator)

So for an angle from 0 to 2 π, we have the values of 'a' from 0 to 4 and it can be shown that the transform kernel is periodic with a period 4. The FrFT is further explained by following definition.

The transform is defined as a linear integral transform with kernel $K_a(u, u')$ [54]:

$$X_\alpha(u) = F^{a}\left[f(u)\right] = \int K_a\left(u, u'\right) x\left(u'\right) du' \tag{2.7}$$

where $\mathcal{F}^a$ is the a^{th} order fractional operator and $X_\alpha(u)$ is the a^{th} order transform.
where the kernel $K_a(u, u')$ [55] is

$$K_a\left(u, u'\right) = \sqrt{1 - i\cot\phi}\, e^{i\pi\left[\left(\cot\cot\left(\phi u^2\right) - 2\csc\csc\left(\phi uu'\right) + \cot\cot\left(\phi u'^2\right)\right)\right]}, \phi = \frac{a\pi}{2} \tag{2.8}$$

The FrFT of a signal x(t) as can be computed by four steps process [30]:

1. Multiplying the function with a chirp,
2. Taking its Fourier transform,
3. Again multiplying with a chirp, and
4. Then multiplication with an amplitude factor.

It is found that the FrFT of a signal x (t) exists under the same conditions in which its Fourier transform exists.

Table 2.1: Properties of FrFT [29]

Sr. No.	**Operation**	**Signal, *x*(*t*)**	**Fractional Fourier Transform, $X_\alpha(u)$**
1.	Time shifting	$x(t-\tau)$	$e^{j\left(\frac{\tau^2}{2}\right)\sin\alpha\cos\alpha - ju\tau\sin\alpha} X_\alpha(u-\cos\alpha)$
2.	Modulation	$x(t)\, e^{jvt}$	$e^{-jv^2(\sin\alpha\cos\alpha)/2 + juv\cos\alpha} X_\alpha(u-\sin\alpha)$
3.	Scaling of time axis	$x(ct)$	$\sqrt{\frac{1-j\cot\alpha}{c^2-j\cot\alpha}}\, e^{j\,u^2/2\cot\alpha(1-(cos^2\beta/cos^2\alpha))}$
4.	Differentiation	$X'(t)$	$X_a'(u)\cos\alpha + ju\sin\alpha\, X_a(u)$
5.	Integration	$\int_a^t x(t')dt'$	$\sec\alpha\, e^{-j(u^2/2)\tan\alpha}\int_a^u X_a(z)e^{j(z^2/2)\tan\alpha}\, dz$ If α- π / 2 is not a multiple of π
6.	Multiplication with ramp	$tx(t)$	$u\cos\alpha\, X_a(u) + j\sin\alpha\, X_a'(u)$

7.	Convolution	*x(t) *g(t)*	$F^{-a}[(F^a x)(F^a g)]$

There are mainly two types of fractional fourier transform: continuous fractional Fourier transform (FrFT) and discrete fractional Fourier transform (DFrFT).

The above discussed fractional fourier transform is of continuous type. Though FrFT has a number of applications in the areas of signal and image processing applications as signal detectors, correlation, pattern recognition, time variant filtering, multiplexing and image encryption etc, yet there was always a need to discretize the fractional transform application. The sampled or the discrete version is quite handy for the tenacity in the current signal processing environment. The real time implementation of fractional transforms is essential requirement for all above mentioned applications of FrFT. Particularly to implement a versatile device for all above real time applications, the real time computation of FrFT can be accomplished by implementing its discrete form known as Discrete Fractional Fourier transform.

(b) Discrete Fractional Fourier transform (DFrFT)

A discrete edition of a transform is equivalent to the continuous edition of transform. In the last few years, the FrFT has gained immense importance as a signal processing tool [18, 37]. For that reason, to obtain the discrete version of the FrFT many attempts have been made [7, 19]. In 1995 [6], Santhanam claimed the first work on DFrFT. In this work the angular parameter values of 0^0 and 360^0 as identity operation, and 90^0 as DFT operation were exhibited by him. He depicted the DFrFT signal as equivalent to mixture of signal, its DFT, time inversion of the signal and it's DFT.

A discrete version of FrFT had already been created yet its results did not match with those of continuous version. But in 1996, S. C. Pei *et al.* [50] presented another form of DFrFT. This new DFrFT conveys comparable transforms as those of continuous FrFT and likewise secure the rotation properties.

In 1998, S. C. Pei *et al.* [51] developed a 2D-DFrFT which preserved the rotation properties and gave comparable results to continuous FrFT. DFrFT basically involves rotation of a discrete signal by an angle α in the time-frequency plane. But for analysis of 2D signals such as images, a two dimensional version of DFrFT is required. For an M x N matrix, the 2D DFrFT is computed in an unpretentious way. The 1D DFrFT is applied to each row of given matrix and then same is applied to each column of the result matrix. Thus, the generalization of the DFrFT to 2D is given by taking the DFrFT of the rows of the matrix i.e. image in a fractional domain and then taking the DFrFT of the subsequent column wise. In case of 2D DFrFT, two angles of rotation $\alpha=\pi/2$ and $\beta=\pi/2$ have to be taken.

In 2000, C. Candan *et al.* [7] introduced a definition of the DFrFT that generalizes the discrete Fourier transform (DFT) in the comparative sense that the continuous fractional Fourier transform generalizes the continuous ordinary Fourier transform (FT). This definition is demonstrated utilizing a specific set of eigenvectors of the DFT matrix, which constitutes the discrete equivalent of the set of Hermite-Gaussian functions. The definition is unitary, index additive, and reduces to the DFT for unit order. This method is consider as best method to discretize FrFT.

In this concept of Eigen vectors is used. Eigen vectors are discrete version of the continuous Hermite Gaussian functions. This definition fulfills all the fundamental properties such as unitary, index additive, reduction to DFT when order is equal to unity and approximation of continuous FrFT. If F^a be the $M \times M$ matrix representing the DFrFT, this definition can be stated as follows [7]:

$$F^a = \sum_{p=0}^{3} e^{j\frac{3\pi}{4}(p-a)} \frac{\sin \pi(p-a)}{4\sin \frac{\pi}{4}(p-a)} F^p \tag{2.9}$$

where, F^p is the pth (integer) power of the DFT matrix. Now the importance would be on finding an eigenvector of the DFT matrix that can provide as discrete versions of the Hermite–Gaussian functions. The Hermite–Gaussian generating differential equation [7] is

$$\frac{d^2 g(t)}{dt^2} - 4\pi t^2 g(t) = \lambda g(t) \tag{2.10}$$

Note that as $m \to 0$ the difference equation following approximation [7]

$$\frac{g(u+m) - 2g(u) + g(u-m)}{m^2} + \frac{2(\cos\cos(2\pi m u) - 1)}{m^2} g(u) = \lambda g(u) \tag{2.11}$$

When $m = \frac{1}{\sqrt{M}}$, periodic coefficients have been obtained from difference equation (4). Hence, the solutions of the difference equation are periodic and can be jotted down as the eigenvectors of the following matrix [7], denoted by *D*:

$$D = \begin{bmatrix} 2 & 1 & 0 & \dots & 0 & 1 \\ 1 & 2\cos(2\pi/M) & 1 & \dots & 0 & 0 \\ 0 & 1 & 2\cos(2\pi/M) & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 0 & 0 & \dots & 1 & 2\cos(2\pi(n-1)/M) \\ & & & & & \end{bmatrix} \tag{2.12}$$

Hence, difference equation can be written as $Dg = \lambda g$. It can also be shown that D commutes with DFT matrix. After getting eigenvectors set, now the DFrFT matrix can be defined as follows [7]:

$$F^a = \begin{cases} \sum_{k=0, k\neq M-1}^{M} u_k e^{-j\frac{\pi ka}{2}} u_k^T, \text{when } M \text{ even} \\ \sum_{k=0, k\neq M}^{N} u_k e^{-j\frac{\pi ka}{2}} u_k^T, \text{when } M \text{ odd} \end{cases} \tag{2.13}$$

here, u_k corresponds to the *D* matrix eigenvectors with k zero-crossings.

Table 2.2: Properties of DFrFT [55]

Sr. No.	Property	Description
1.	Inverse	$(F^a)^{-1} \Leftrightarrow F^{-a}$
2.	Unitary	$(F^a)^{-1} \Leftrightarrow (F^a)^H$
3.	Commutative	$F^{a2} F^{a1} \Leftrightarrow F^{a1} F^{a2}$
4.	Index Additive	$F^{a1} F^{a2} \Leftrightarrow F^{a1+a2}$
5.	Associative	$F^{a3}(F^{a1} F^{a2}) \Leftrightarrow (F^{a3} F^{a2}) F^{a1}$
6.	Periodicity	$F^{a+2\pi} \Leftrightarrow F^a$

It has been recently observed that DFrFT can be used in the field of image processing. The vital feature of Discrete Fractional Fourier domain Image compression aids from its extra degree of freedom that is provided by its fractional orders.

2.4 Gaps in Study

The following gaps have been observed during study:

- A key issue is that the change mask should *not* contain “unimportant” or “nuisance” forms of change, such as those induced by camera motion, sensor noise, illumination variation, non-uniform attenuation, or atmospheric absorption.
- The most common techniques for change detection are: Image differencing, image rationing, PCA, Post-classification comparison. There is still no conclusion on which technique is best suited for a particular application.
- There are no major works in the frequency domain for image change detection.
- Detection of appearance/disappearance of objects from satellite images is generally very difficult since background pixels also change their intensity values owing to various factors.
- Although Image Differencing method takes advantage of straightforward as well as rapid calculation, its accuracy is based on high quality of the images and precise geometric calibration. Also the threshold value is critical, since too low a value will cause false alarm while too high a value will mark some changed pixels as unchanged ones.

2.5 Summary

Change detection analysis remains an active research topic and new techniques keep on being created. For a new change detection technique, it is imperative to have the capacity to execute it effectively and for it to give accurate change detection results associated with change trajectories. In spite of the fact that a variety of change detection techniques have been developed, it is still hard to select a suitable method to implement accurate change detection for a specific research purpose or study area. Selection of a suitable change detection method requires cautious consideration of major impact factors. In practice, several change detection techniques are often used to implement change detection, whose results are then compared to recognize the best product through visual assessment or quantitative accurate assessment. Regardless of numerous factors influencing the choice of suitable change detection methods, image differencing, PCA and post-classification are, in practice, the most commonly used. In recent years, LSMA, FrFT, GS, ANN and GIS have become important techniques to enhance change detection accuracy.

Transforms play vital roles in the analysis of signal processing. Transforms help in discovering the hidden properties of a signal, which are unrecognizable from the time domain representation of the signal. The choice of the transform depends on the type of the signal and the application. Due to significant applications of FT, concept of fraction was introduced to it resulting in the development of FrFT. A need to discretize FrFT, so as to bring it into a digitally processed form, lead to introduction of DFrFT. DFrFT has been widely used in various applications like optical, image and other signal processing applications.

Chapter 3
Present Work

3.1 Introduction

In this dissertation, modified image change detection method based on DFrFT. A previously implemented technique based on DFrFT [54] has been taken as reference to develop the presented image change detection method. Actually the presented method is modified version of method in [54]. Two new blocks, intensity normalization and thresholding, are added in previous method as shown in Figure 3.1. Firstly, two images are taken at different time of same scene then intensity normalization is applied on second image to make its mean and variance compatible with the first image. After doing an initial differencing step, the main blocks incorporating fractional functions are the applications of fractional and inverse fractional block with a varying value of fractional parameter. The quantizer selects only appropriate coefficients and round off other to zero.

3.2 Methodology Used

The presented method of image change detection shown in Figure 3.1 consists of following steps:

- Intensity Normalization: This technique is applied to Image 2 to overcome illumination variation artifact and make I_2 compatible with I_1 in term of brightness etc. The values of pixel intensity in I_2 are normalized to have same variance and mean as of I_1 [39].

$$\widehat{I_2}(\mathrm{x},\mathrm{y}) = \frac{\sigma_1}{\sigma_2}(I_2(x,y) - \mu_2) + \mu_1 \tag{3.1}$$

where $\widehat{I_2}$ is the normalized form of I_2 and (x,y) are pixel coordinates. μ_1, σ_1 and μ_2, σ_2 are the mean and standard deviation of I_1 and I_2 respectively. After normalization, difference image will have zero mean.

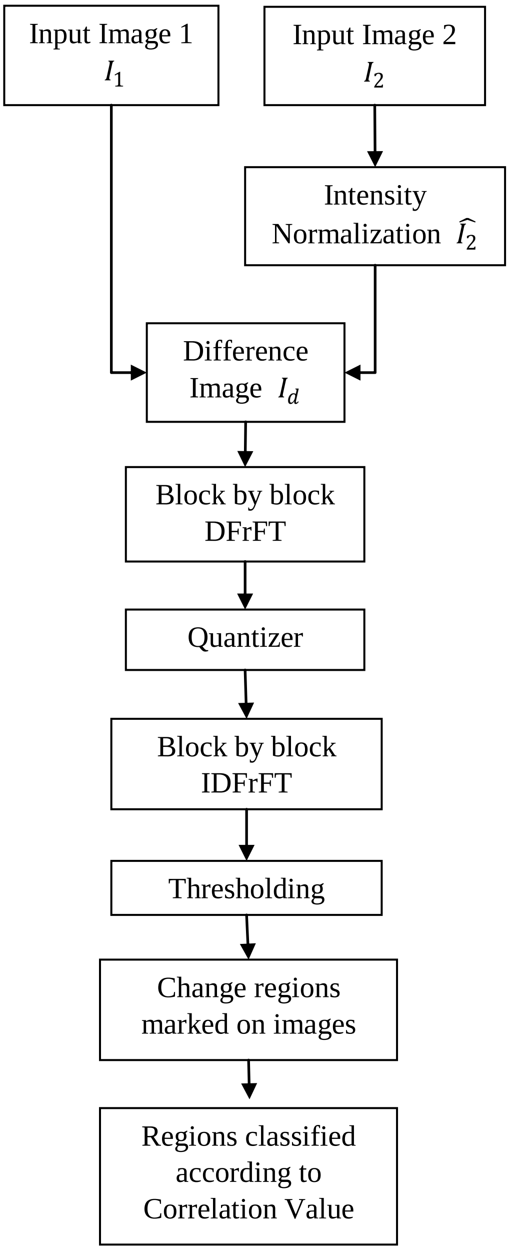


Figure 3.1: Overview of presented method

- Differencing: This is the basic step to obtain change mask. In this technique I_1 is subtracted from $\widehat{I_2}$ pixelwise to obtain difference image I_d.The resultant I_d is a raw changed image which is to be used for further processing [39].

$$I_d(x, y) = \widehat{I_2}(\mathrm{x}, \mathrm{y}) - I_1(x, y) \tag{3.2}$$

- Transformation: Then Discrete fractionally Fourier transform is applied on I_d block by block to get different fractions in the frequency domain by varying parameter ‘a’ for both rows and columns.

- Quantization: After transformation, a quantizer is applied on equivalent transform matrix. It selects only desired coefficients of matrix and round off other to zero. Quantization helps thresholding to obtain desire change [54].

- Inverse transformation: IDFrFT is applied to retrieve the change image with parameter *‘a’= -a*. There should be appropriate number of coefficients in transform matrix after quantizer to retrieve the change image otherwise we wouldn’t get desire results.

- Thresholding: The various artifacts can be removed using this block of thresholding. Threshold is applied to classify pixels as changed or unchanged. Whichever pixel exceeds a threshold value, a decision is made in favor of change [46]. Value of threshold vary according with the parameter ‘*a*’.

- Region marking on the image: The changed regions are detected and then a particular region size is selected according to image size for the categorization of the detected regions. Hence estimation of changed regions is done properly. These changed regions are highlighted using red rectangles.

- Final classification of regions using the correlation coefficient value: Gradient correlation checking is adopted as an filtering process for further discrimination of significant change regions. A gradient measure of similarity, G_e or correlation is given by [59]:

$$G_e = min\ (Fx, Fy) \tag{3.3}$$

$$Fx = \frac{\sum (e_{1,x}(x) - \mu_{e_{1,x}})(e_{2,x}(x) - \mu_{e_{2,x}})}{\left(\max\left(\sigma_{e_{1,x}}, \sigma_{e_{2,x}}\right)\right)2} \tag{3.4}$$

$$Fy = \frac{\sum (e_{1,y}(y) - \mu_{e_{1,y}})(e_{2,y}(y) - \mu_{e_{2,y}})}{\left(\max\left(\sigma_{e_{1,y}}, \sigma_{e_{2,y}}\right)\right)2} \tag{3.5}$$

where $e_{i,k}(k)$, $\mu_{e_{i,k}}$ and $\sigma_{e_{i,k}}$ represent the pixel value of input images ,average and standard distribution of the gradient image in the kth direction of image in a candidate region respectively and Fx and Fy are the gradient similarity measures of the input images in the candidate regions in the X and Y directions respectively.

There are three classes for candidate region according to G_e [63] :

- $0.0 \le G_e \le 0.1$, change with high certainty represented by red square
- $0.1 < G_e \le 0.3$, change with low certainty represented by yellow square
- $0.3 < G_e \le 1.0$, no change with represented by green square .

3.3 Parameters Used for Analysis

In any image change technique, there are certain parameters should be discussed in result to understand whether changed regions correctly detected or not. Algorithm should able to identify false region, missed region and corrected region. Parameters like recall and precision are used to judge the level of change detection. These parameters are discussed below:

Recall: Recall is a measure of quantity or completeness [54]. Mathematically recall is given by:

$$\text{Recall, } Re = \frac{C}{(C+M)} \tag{3.6}$$

where, C= No. of correctly detected object

M= No. of missed regions

Precision: Precision is a measure of correctness or quality [54]. Mathematically it is defined as:

$$\text{Precision, Pr} = \frac{C}{(C+F)} \tag{3.7}$$

where, C= No. of correctly detected object

F= No. of false detected change regions

For e.g. let suppose a scene change contains 10 objects. If the algorithm identifies 6 objects and among them 4 are correct, then the Pr is 4/6 and Re is 4/10.

More the value of above parameters, more accurate will be the results.

3.4 Summary

In this chapter modified image change detection based on DFrFT has been presented. It provides a flexible approach by varying its fractional parameters so as to get the best possible results. Intensity normalization makes mean of multitemporal images equal and helps in removal of illumination variation effect. Thresholding helps to classify pixels as changed or unchanged. Change regions were marked using a gradient correlation filtering technique. Parameters like recall and precision will be used to judge the level of change detection.

Chapter 4
Results and Discussions

4.1 Artifacts Removal Process

In image change detection process, the main goal is to estimate the 'change mask', comprising of set of pixels in the current image that are 'significantly different' from the previous image. Significant changes such as appearance/disappearance of objects, changes in the shape or movement of objects and variations in colour or brightness of stationary objects should be detected properly for better image change detection. A key issue in estimating the change mask is that it should include only significant changes not the insignificant due to artifacts like, illumination variation, partial translation, large daylight changes and shadowing effect etc [45].

Due to these artifacts it is difficult to implement perfect change detection in particular application. So it is necessary to removal of these artifacts in change detection process. In next topic, we will try to remove discussed artifacts using presented method.

4.2 Simulation Results

Different test image sets have been chosen for the experimental resolutions. Test image sets have different artifacts like large daylight change, large shadow appearance and partial translations. The partial movement of objects, such as waving trees, often occurs between images, and the detection of such movement is undesirable. The simulations have been performed in MATLAB software and following results have been obtained. Each artifact has been encountered one by one using presented work.

4.2.1 Robustness against Large Daylight Change

Three different image sets under large daylight change have been taken for analysis by using three different methods namely image change detection using DCT, image change detection using DFrFT and image change detection using presented method.

a) Image set 1

Figure 4.1 (a) and 4.1 (b) provide a typical example in which two images of the same parking lot were taken at 9:00 pm and at 10:00 pm respectively [63]. These pictures include objects of various materials, such as a building, cars, trees and roads. Various intensity changes are induced by changes in daylight. Change detection is very difficult in this case [63].

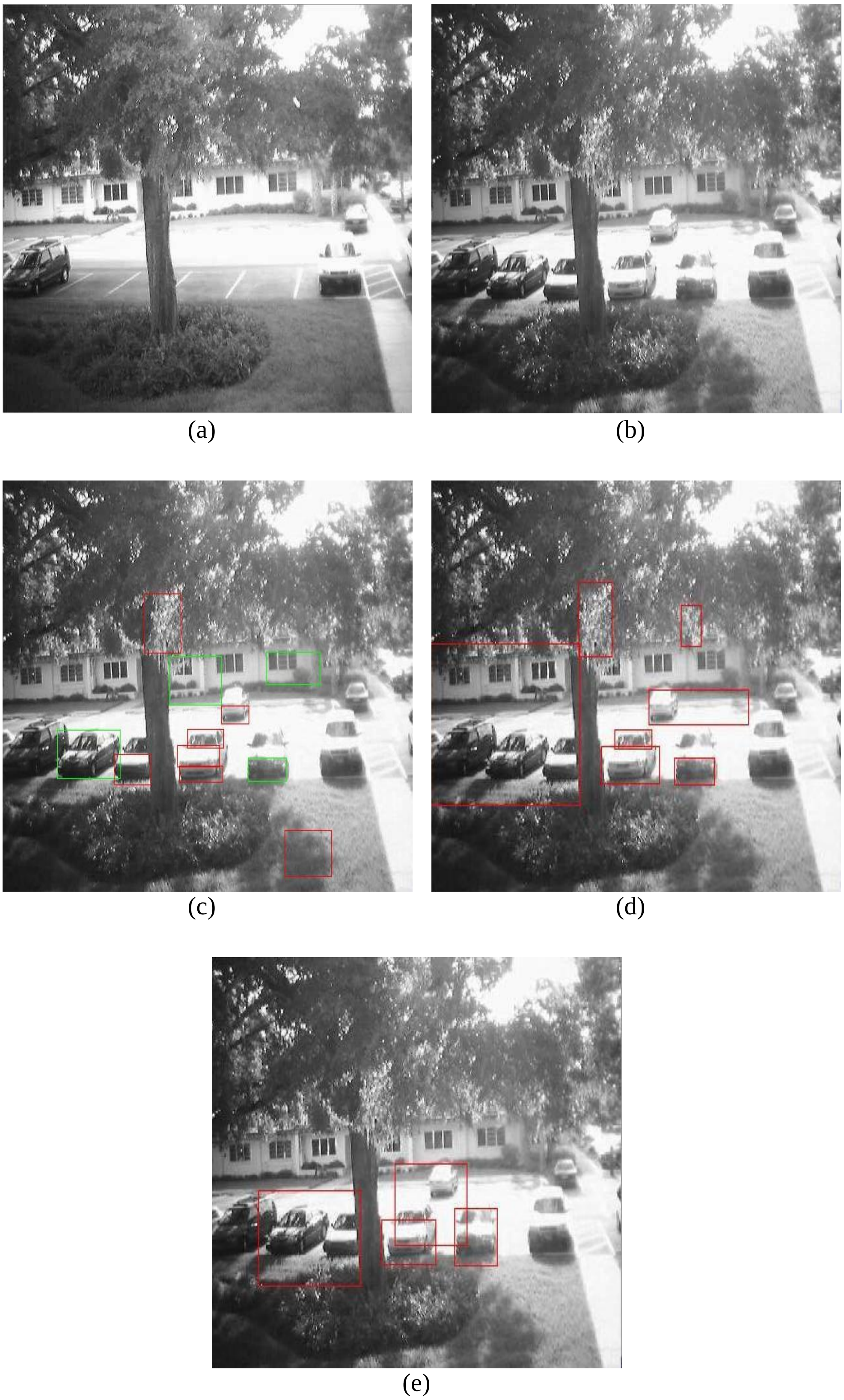


Figure 4.1: (a), (b) Original image sets to be change detected [63] of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.11.

In [63], a few regions were also detected undesirably. The reason for this is that, in this case, many background pixels appear as small clusters on the joint histogram and their clusters were not selected. As a result, pixels corresponding to newly appearing cars were not extracted separately [63]. Figure 4.1 (c) and Figure 4.1 (d) represent changed region detected, using DCT and using DFrFT [54] respectively. Figure 4.1 (e) shows changed region detected using presented method. But this method managed to extract most of appearances/disappearances of cars. Change Detection between these two images using with a threshold of 0.11 and with a region size of area greater than 200 pixels is carried out and the result is shown in Figure 4.1 (e). Change regions are classified regions as main change region (red rectangles), low certainty change regions (yellow rectangle), and no change or non-significant regions (green rectangle) if any.

b) Image set 2


(a)


(b)


(c)


(d)

(e)

Figure 4.2: (a), (b) Original image sets to be change detected of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.1.

Figure 4.2 (a) and 4.2 (b) show two images of the same balcony were taken at 2:00 PM and at 4:00 PM respectively. These pictures include objects such as a bucket, football, wooden stick and a plume. Various intensity changes are induced by changes in daylight. Figure 4.2 (c) and Figure 4.2 (d) represent changed region detected, using DCT and using DFrFT, respectively. Figure 4.2 (e) shows changed region detected using presented method. This method, using '*a*' = 0.85 and threshold of 0.1, managed to extract most of appearances/disappearances of objects.

c) Image set 3

(a)

(b)

(c) (d)

(e)

Figure 4.3: (a), (b) Original image sets to be change detected of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.09.

Figure 4.3 (a) and 4.3 (b) show images that were captured at 6:00 AM and at 12:00 PM respectively. These pictures show appearance or disappearance of objects such as cars and persons. Various intensity changes are induced by changes in daylight. Figure 4.3 (c) and Figure 4.3 (d) represent changed region detected, using DCT and using DFrFT, respectively. Figure 4.3 (e) shows changed region detected using presented method. The presented method, using '*a*' = 0.85 and threshold of 0.09, managed to extract most of appearances/disappearances of objects.

TABLE 4.1: Change Detection Result under Large Daylight Change Artifact

	Method	T_a	T_d	C	F	M	Pr	Re
Image set 1 Figure 4.1	DCT [55]	5	11	3	2	1	0.6	0.75
	DFrFT [54]	5	7	5	3	0	0.62	1
	Presented Method	5	4	5	0	0	1	1
Image set 2 Figure 4.2	DCT [55]	4	14	2	4	2	0.5	0.33
	DFrFT [54]	4	10	3	1	1	0.75	0.75
	Presented Method	4	5	4	1	0	0.8	1
Image set 3 Figure 4.3	DCT [55]	10	11	4	1	6	0.8	0.4
	DFrFT [54]	10	15	8	3	2	0.72	0.8
	Presented Method	10	7	10	1	0	0.91	1

where, T_a = Number of objects to be detected

T_d = Total detected regions

C = No. of correctly detected object

M = No. of missed regions

F = No. of false detected change regions

Re = Recall value

Pr = Precision value

For Image set 1, the precision value for presented method is improved by 61.2% to other methods and recall value for presented method is same as DFrFT method but improved by 33.33% to DCT method. For Image set 2, the precision value for presented method is improved by 6.6% to DFrFT method and 60% to DCT method, and recall value for presented method is improved by 33.33% to DFrFT method and 203.03% to DCT method. For Image set 3, the precision value for presented method is improved by 26.3% to DFrFT method and 13.7% to DCT method, and recall value for presented method is improved by 25% to DFrFT method and 150% to DCT method.

The presented method improves precision value by 6-62 % and recall value by 0-25% to previous DFrFT method [54].

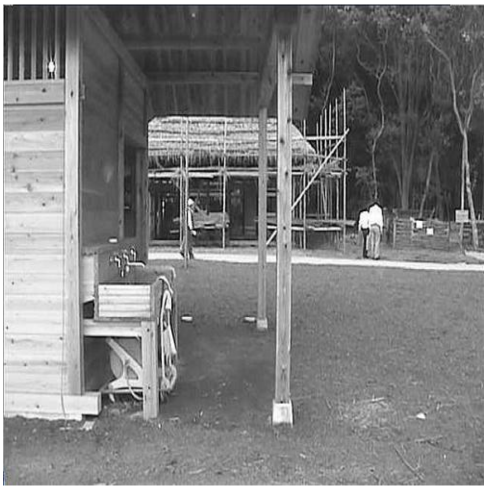
4.2.2 Robustness against Large Shadow Appearance

Three different image sets under large shadow appearance have been taken for analysis by using three different methods namely; image change detection, using DCT, using DFrFT and using presented method.

a) Image set 1

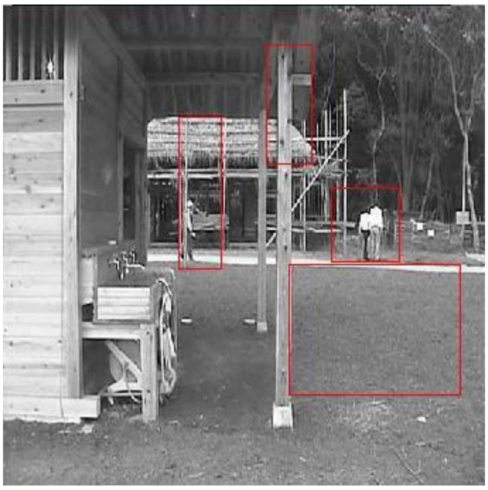
Figure 4.4 (a) and 4.4 (b) show images that were captured with a five minute interval between images [63]. These pictures show appearance or disappearance of objects such as persons, and shadowing is also there.

(a)

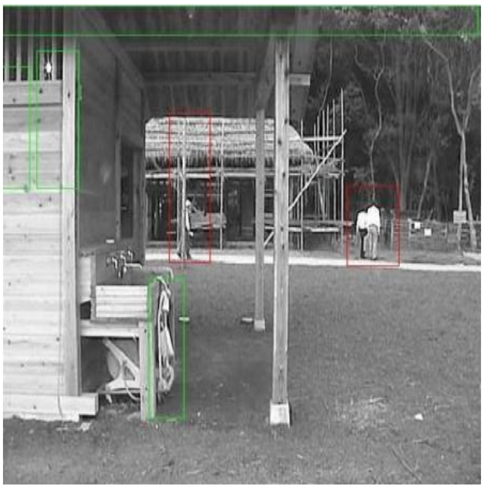


(b)

(c)



(d)



(e)

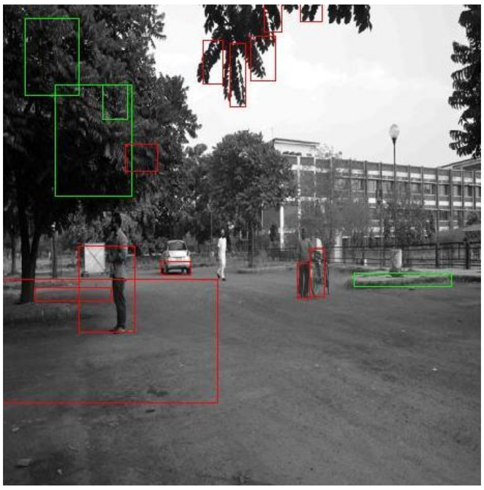
Figure 4.4: (a), (b) Original image sets to be change detected [63] of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.097.

In [63], two objects were detected successfully but third object was detected as low certainty change region. Figure 4.4 (c) and Figure 4.4 (d) represent changed region detected, using DCT and using DFrFT, respectively. Figure 4.4 (e) shows changed region detected using presented method. The presented method, using '*a'* = 0.85 and threshold of 0.097, managed to extract significant changes without detected shadowing in images. Change regions are classified regions as main change region (red rectangles), low certainty change regions (yellow rectangle), and no change or non-significant regions (green rectangle) if any.

b) Image set 2

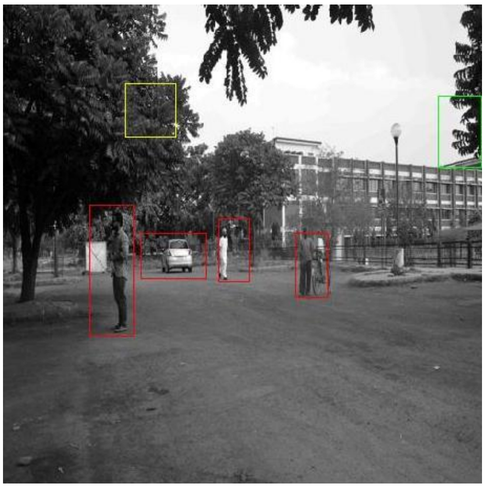
(a)

(b)



(c)

(d)



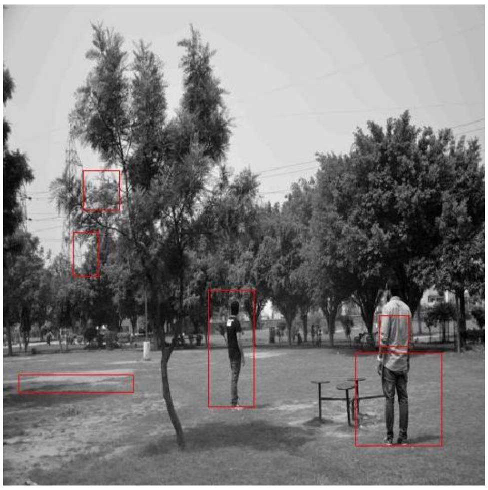
(e)

Figure 4.5: (a), (b) Original image sets to be change detected of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.073.

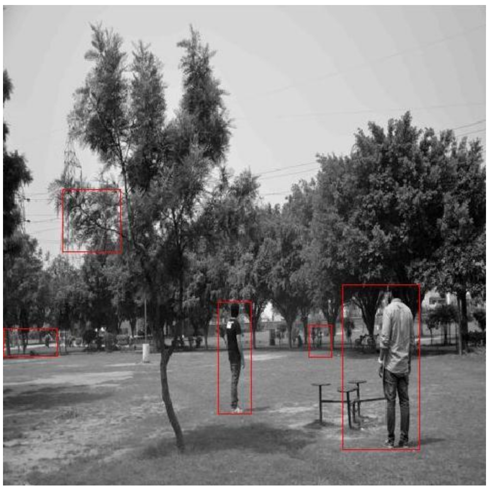
Figure 4.5(a) and 4.5 (b) show images that were taken at 5:00 PM and at 7:00 PM respectively. Here main objects to be detected are persons, a car and a bicycle. Figure 4.5 (c) and Figure 4.5 (d) represent changed region detected, using DCT and using DFrFT, respectively. Figure 4.5 (e) shows changed region detected using presented method at '*a*' = 0.85 and threshold of 0.073. The presented method has obtained more significant changes than other methods. Change regions are classified regions as main change region (red rectangles), low certainty change regions (yellow rectangle), and no change or non-significant regions (green rectangle) if any.

c) Image set 3


(a) (b)




(c) (d)



(e)

Figure 4.6: (a), (b) Original image sets to be change detected of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.09.

Figure 4.6 (a) and 4.6 (b) show images that were captured at 1.00 PM and 1.05 PM respectively. These pictures show appearance or disappearance of objects such as persons, and shadowing is also there. Figure 4.6 (c) and Figure 4.6 (d) represent changed region detected, using DCT and using DFrFT, respectively. Figure 4.6 (e) shows changed region detected using presented method at '*a*' = 0.85 and threshold of 0.09. The presented method managed to extract significant changes without detected shadowing in images. Change regions are classified regions as main change region (red rectangles), low certainty change regions (yellow rectangle), and no change or non-significant regions (green rectangle) if any.

TABLE 4.2: Change Detection Result under Large Shadow Appearance Artifact

	Method	T_a	T_d	*C*	*F*	*M*	*Pr*	*Re*
Image set 1 Figure 4.4	DCT [55]	3	8	3	5	0	0.37	1
	DFrFT [54]	3	4	3	2	0	0.6	1
	Presented Method	3	6	3	0	0	1	1
Image set 2 Figure 4.5	DCT [55]	5	15	3	8	2	0.27	0.6
	DFrFT [54]	5	16	5	5	0	0.5	1
	Presented Method	5	6	5	1	0	0.83	1
Image set 3 Figure 4.6	DCT [55]	7	6	2	3	4	0.4	0.33
	DFrFT [54]	7	5	2	1	4	0.67	0.33
	Presented Method	7	5	6	1	1	0.86	0.86

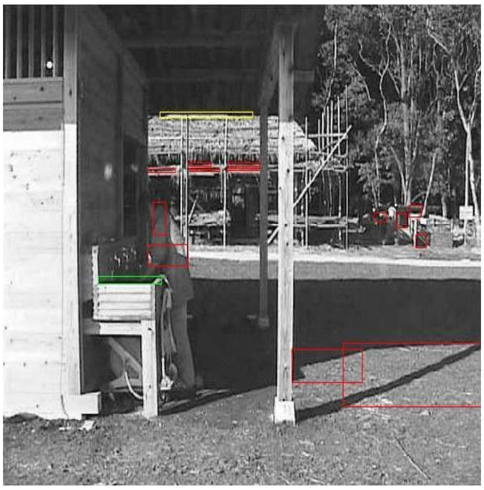
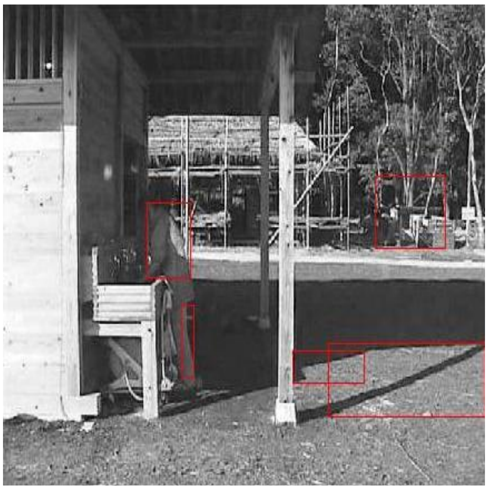
For Image set 1, the precision value for presented method is improved by 66.67% to DFrFT method and 167% to DCT method, and recall value for presented method is as same as other methods. For Image set 2, the precision value for presented method is improved by 66% to DFrFT method and 207.4% to DCT method, and recall value for presented method is as same as DFrFT method but improved by 66.6% to DCT method. For Image set 3, the precision value for presented method is improved by 28.3% to DFrFT method and 115% to DCT method, and recall value for presented method is improved by 160.6% to other methods.

4.2.3 Robustness against Partial Translation

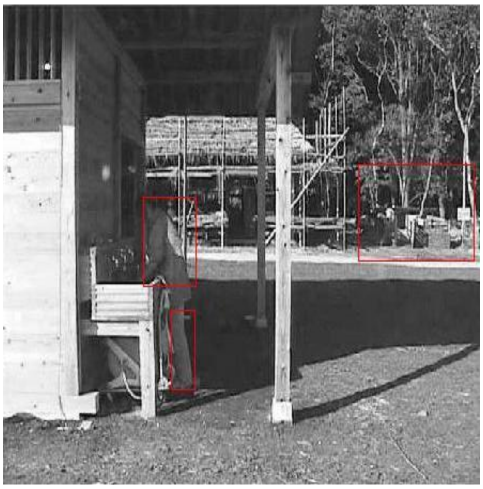
Three different image sets under large shadow appearance have been taken for analysis.

a) Image set 1


(a) (b)

(c) (d)

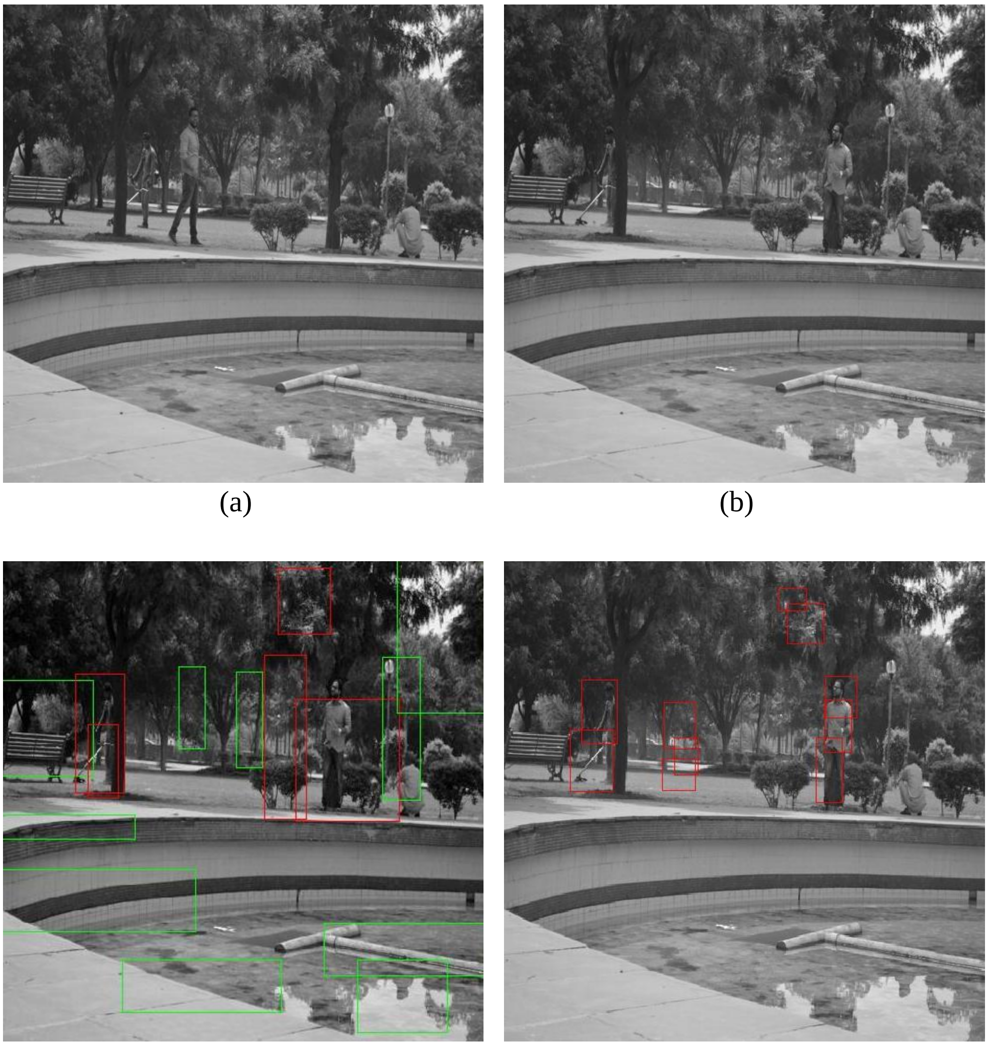


(e)

Figure 4.7: (a), (b) Original image sets to be change detected of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.092.

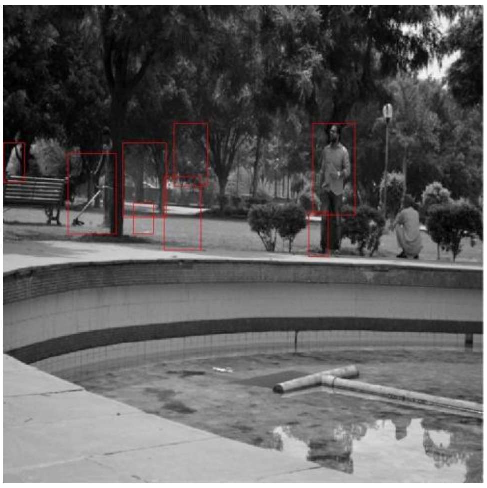
Figure 4.7 (a) and 4.7 (b) are images taken at 14:32 PM and 14:42 PM respectively [63]. In [63], change due to movement of sun was detected, which is undesirable, marked by yellow region. Between taken images, the shadows moved according to the movement of the sun. Figure 4.7 (c) and Figure 4.7 (d) represent changed region detected, using DCT and using DFrFT, respectively. With the help of presented method, using '*a'* = 0.85 and threshold of 0.092, only the disappearance/appearance of people were correctly detected, as indicated by the red squares in Figure 4.7 (e).

b) Image set 2



(a) (b)

(c) (d)



(e)

Figure 4.8: (a), (b) Original image sets to be change detected of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.071.

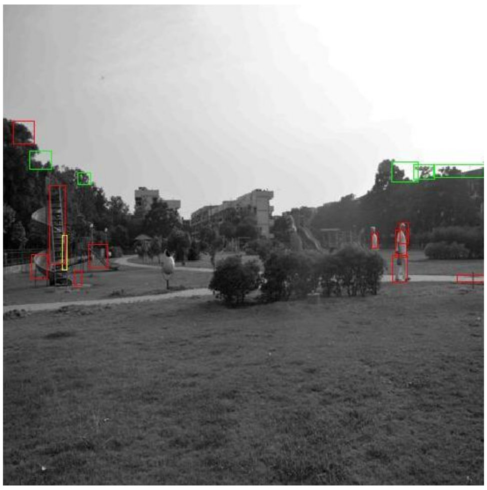
Figure 4.8 (a) and 4.8 (b) show images that were taken at 1:30 PM and at 1:31 PM respectively. Here main objects to be detected are persons. But due to wind, movement of branches of trees was also captured, which is insignificant change. Figure 4.8 (c) and Figure 4.8 (d) represent changed region detected, using DCT and using DFrFT, respectively. Figure 4.8 (e) shows changed region detected using presented method at using '*a'* = 0.85 and threshold of 0.071. More significant changes have been obtained by presented method than other methods as shown in Figure 4.8 (e).

c) Image set 3

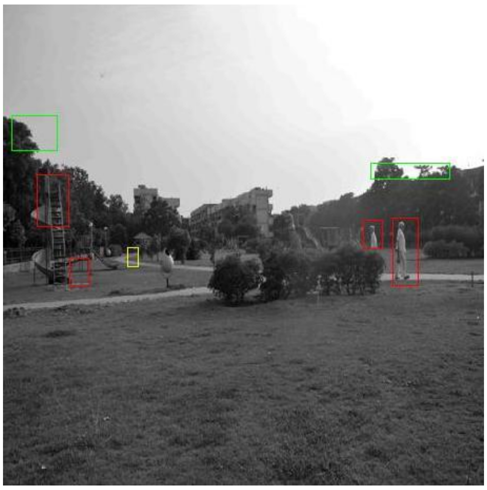
(a)

(b)

(c)



(d)



(e)

Figure 4.9: (a), (b) Original image sets to be change detected of size 500 x 500. (c) Change region using DCT. (d) Change region using DFrFT. (e) Change regions using presented method with a=0.85 and threshold value=0.066.

Figure 4.9 (a) and 4.9 (b) show images that were captured at 6:00 PM and at 6:15 PM respectively. Here main objects to be detected are persons with removal of movement of leafs. Figure 4.9 (c) and Figure 4.9 (d) represent changed region detected, using DCT and using DFrFT, respectively. Figure 4.9 (e) shows changed region detected using presented method at using '*a*' = 0.85 and threshold of 0.066. More significant changes have been obtained by presented method than other methods.

TABLE 4.3: Change-Detection Result under Partial Translation Artifact

	Method	T_a	T_d	C	F	M	Pr	Re
Image set 1 Figure 4.7	DCT [55]	4	15	3	8	1	0.27	0.75
	DFrFT [54]	4	5	4	2	0	0.67	1
	Presented Method	4	3	4	0	0	1	1
Image set 2 Figure 4.8	DCT [55]	4	15	2	3	1	0.4	0.67
	DFrFT [54]	4	10	3	2	1	0.6	0.75
	Presented Method	4	8	4	1	0	0.8	1
Image set 3 Figure 4.9	DCT [55]	5	6	3	1	2	0.75	0.6
	DFrFT [54]	5	16	4	5	1	0.44	0.8
	Presented Method	5	7	4	1	1	0.8	0.8

For Image set 1, the precision value for presented method is improved by 49.2% to DFrFT method and 270.3% to DCT method, and recall value for presented method is as same as DFrFT method but improved by 33.33% to DCT method. For Image set 2, the precision value for presented method is improved by 33.33% to DFrFT method and 100% to DCT method, and recall value for presented method is improved by 33.33% to DFrFT method and 49.25% to DCT method. For Image set 3, the precision value for presented method is improved by 81.81% to DFrFT method and 6.6% to DCT method, and recall value for presented method is as same as DFrFT method and improved by 33.33% to other methods.

4.3 Summary

In this chapter, various artifacts like, illumination variation, partial translation, large daylight changes and shadowing effect have been encountered. It is necessary to removal of these artifacts due to these artifacts it is difficult to implement perfect change detection in particular application. So it is necessary to removal of these artifacts in change detection process. The simulations have been performed for different sets of test images. Change detection results have been analyzed, using precision and recall parameters values, by using three methods namely, DCT, DFrFT and presented method. Results have shown that DCT method is poorest among DFrFT and presented method. By calculation, very large values of recall value have been obtained for all image sets using presented method, it shows that desired objects are detected. The overall improvement in recall value is 0-34% to DFrFT method [54]. However, precision value for presented method is 6-82% more as compared to DFrFT method which means very small numbers of false regions have been detected.

Chapter 5
Conclusion and Future Scope

5.1 Conclusion

The capability to detect regions of change in images is a powerful tool that can be used in a diverse kind of applications. Changes obtained are typically resulting from the appearance/disappearance, motion or change in the shape of a target object. There are wide range of applications in which change detection methods are used, like agricultural surveys, urban studies, environmental monitoring, video surveillance, remote sensing, medical diagnosis and treatment, civil infrastructure, forest monitoring, underwater sensing and driver assistance systems. For instance, timely and accurate change detection of Earth's surface features is extremely important for understanding relationships and interactions between human and natural phenomena in order to promote better decision making. In medical analysis, detection of missing part of organs and comparative analysis of scans become easy with image change detection.

There are various image change detection methods, but their applicability is restrained by the limitation of the information they are evaluated upon, the type of image acquisition available, need of information to be retrieved after change detection etc. The main methods that have been used for image change detection are Image math (image differencing, image subtraction and image rationing), PCA, PCC, CVA and ANN etc.

The current research work used DFrFT based image change detection method. The presented method helps in removing artifacts like illumination variations, partial translation, large daylight change and shadowing effects etc. The removal of these artifacts helps in implementing this image change detection system in various applications, like remote sensing, video surveillance and civil infrastructure etc, more accurately. Intensity normalization helps in making mean of mutitemporal images equal. As a result of which illumination variation effect is removed. Thresholding is applied to classify pixels as changed or unchanged. A decision has been made in favor of change whenever pixel exceeds a threshold value. Change regions are marked on second image using a gradient correlation filtering technique. The simulations have been performed for different sets of test images. Change detection results have been analyzed, using precision and recall parameters values, by using three methods namely, DCT, DFrFT and presented method. Results have shown that DCT method is poorest among DFrFT and presented method. By calculation, very large values of recall value have been obtained for all image sets using presented method, it shows that desired objects are detected. The overall improvement in recall value is 0-34% to DFrFT method [54]. However, precision value for presented method is 6-82% more as compared to DFrFT method which means very small numbers of false regions have been detected.

5.2 Future Scope

As image change detection technique is widely used in different application area such as, video surveillance, remote sensing, medical diagnosis and treatment etc. It is necessary to have best results that detect exact change in multitemporal image. In this work manual thresholding technique is used to detect change, this can be replaced with automatic thresholding technique to have better results. This modification may also helpful to make algorithm more simpler. In this work unsupervised approach has been used, results can be enhanced by using supervised approach with different techniques or algorithm.

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