Image Change Detection using Discrete Fractional Fourier Transform along with Intensity Normalization and Thresholding

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ABSTRACT
This research paper describes an image change detection method based upon the Discrete Fractional Fourier transform (DFrFT) along with intensity normalization and thresholding. DFrFT is 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 artifacts like illumination variations, partial translation, large daylight change and shadowing effect etc. In this paper using precision as parameter of evaluation DFrFT along with intensity normalization and thresholding produces better results than 'DFrFT only' method**.**

Keywords
Image change detection, Discrete Fractional Fourier Transform, artifacts, intensity normalization, thresholding

1. INTRODUCTION
Change detection is a technique that is used in identifying any change occurring between two images that may result from various changing factors. These factors include appearance/disappearance of objects, changes in the shape or movement of objects and variations in colour or brightness of stationary objects. It is an important technique in finding out the change objects, which are the main region of interest, in the two images of the same scene taken at different times. Detecting regions of change find uses in a number of applications such as abnormalities detection in medical treatment, irregularities detection in factory examination, video surveillance and monitoring of damage assessment etc [1]. 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. The adaptive background subtraction technique is beneficial while dealing with images taken at a frequent rate where a series of previous frames is available [2]. However, in most situation image taken after long intervals are dealt with. In such cases simple techniques that work on image data directly such as simple image differencing, are not a suitable method, as these techniques are not able to remove artifacts such as illumination variations, shading, partial translation, large daylight changes and shadowing effect etc [3]. To improve reliability images are processed using information derived after segmentation or object classification. Different transformation techniques are available such as Discrete Cosine Transform (DCT) and Discrete Fourier Transform (DFT). Here Discrete Fractional Fourier Transform (DFrFT) is used to detect change [4]. The FrFT is a generalization of the simple Fourier transform (FT). FrFT was introduced by Victor Namias in 1980 [5] and its introduction causes other transforms to be fractionalized too [6]. Its refinement and mathematical explanation was explored by McBride and Keer in 1987 [7]. FrFT has gained popularity in analyzing time varying signals within a very short span of time [8]. In discrete domain, FrFT finds its use in the field of image processing as DFrFT [9]. When DFrFT alone is used [4] for change detection, it is not able to remove artifacts but here intensity normalization and thresholding is used along with DFrFT to detect change with removal of various artifacts.

The organization of paper is as follow: section 2 describes FrFT along with its discrete version DFrFT. Methodology of Image change detection using DFrFT along with intensity normalization and thresholding is presented in section 3. Section 4 presents the results and discussions and section 5 concludes the paper.

2. TRANSFORMATION DESCRIPTION
2.1 Fractional Fourier Transform
The FrFT is a generalization of ordinary FT with a tunable parameter 'a'. The a^{th} order FrFT operator is the a^{th} power of the ordinary FT operator mathematically. The FrFT with parameter $a = 1$ is the conventional FT and 0^{th} order transform is simply the function itself. From $0<a<1$ order transform is something in between function and it's Fourier Transform [10]]. The FrFT is defined as a linear integral transform with kernel $J_a(u,u')$ [11]]:

$$f_a(u) = F^a[g(u)] = \int J_a(u,u') g(u')\, du' \qquad (1)$$

here F^a is the a^{th} order fractional operator and $f_a(u)$ is the a^{th} order transform.

where the kernel $J_a(u,u')$ [11]] is

$$J_a(u,u') = \sqrt{1 - icot\phi}\, e^{i\pi\left[\left(cot(\phi u^2) - 2\, csc(\phi u u') + cot\left(\phi u'^2\right)\right]} \quad , \phi = \frac{a\pi}{2} \qquad (2)$$

There are four steps to compute FrFT of a signal (u) :

1. Multiplying the function with a chirp.

2. Obtaining its FT.

3. Again multiplying with a chirp.

4. Lastly multiplying with an amplitude factor.

2.2 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 [11]]. For that reason, to obtain the discrete version of the FrFT many attempts have been made [9]. In 1995, Santhanam claimed the first work on discrete fractional Fourier transform (DFrFT) [14].Now many researchers are trying to discretize this transform of linear integral but best method proposed by Candan et al. [13]. 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 [13]

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

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 [13] is

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

Note that as $m \to 0$ the difference equation following approximation [12]]

$$\frac{g(u+m)-2g(u)+g(u-m)}{m^2} + \frac{2(\cos(2\pi m u)-1)}{m^2} g(u) = \lambda g(u) \quad (5)$$

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 [13], denoted by *D*:

$$D = \begin{bmatrix} 2 & 1 & 0 & \cdots & 0 & 1 \\ 1 & 2\cos(2\pi/M) & 1 & \cdots & 0 & 0 \\ 0 & 1 & 2\cos(2\pi/M) & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 0 & 0 & \cdots & 1 & 2\cos(\frac{2\pi(n-1)}{M}) \end{bmatrix} \quad (6)$$

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 [13]:

$$F^a = \begin{cases} \sum_{k=0,k\neq M-1}^{M} u_k e^{-j\frac{\pi k a}{2}} u_k^T, & \text{when } M \text{ even} \\ \sum_{k=0,k\neq M}^{N} u_k e^{-j\frac{\pi k a}{2}} u_k^T, & \text{when } M \text{ odd} \end{cases} \quad (7)$$

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

The vital feature of DFrFT is its fractional orders. The 1D DFrFT is important in processing one dimensional signals such as speech waveforms. To find 2D DFrFT firstly 1D DFrFT is computed for each row and then for each column of the given matrix. The 2D DFrFT is important in analysis of two dimensional signals such as images. In 2D DFrFT two angle of rotation $\alpha=\pi/2$ and $\beta=\pi/2$ are considered. The 2D transformation kernel reduces to 1D transformation kernel if any one of these angles is zero. In image change detection process, DFrFT of flexible order (0-1) is applied to difference image to acquire its different versions.

3. METHODOLOGY OF IMAGE CHANGE DETECTION

Step 1: *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 [15].

$$\widehat{I_2}(x,y) = \frac{\sigma_1}{\sigma_2}(I_2(x,y) - \mu_2) + \mu_1 \quad (8)$$

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.

Step 2: *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 [15].

$$I_d(x,y) = \widehat{I_2}(x,y) - I_1(x,y) \quad (9)$$

Step 3: *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.

Step 4: *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 [4].

Step 5: *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.

Step 6: *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 [1]. Value of threshold vary according with the parameter '*a*'.

Step 7: *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.

Step 8: *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 [3]:

$$G_e = \min(Fx, Fy) \quad (10)$$

$$Fx = \frac{\sum(e_{1,x}(x) - \mu_{e_{1,x}})(e_{2,x}(x) - \mu_{e_{2,x}})}{\left(\max\left(\sigma_{e_{1,x}}, \sigma_{e_{2,x}}\right)\right)2} \quad (11)$$

$$Fy = \frac{\sum(e_{1,y}(y) - \mu_{e_{1,y}})(e_{2,y}(y) - \mu_{e_{2,y}})}{\left(\max\left(\sigma_{e_{1,y}}, \sigma_{e_{2,y}}\right)\right)2} \quad (12)$$

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 [3]:

$0.0 \le G_e \le 0.1$, 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.

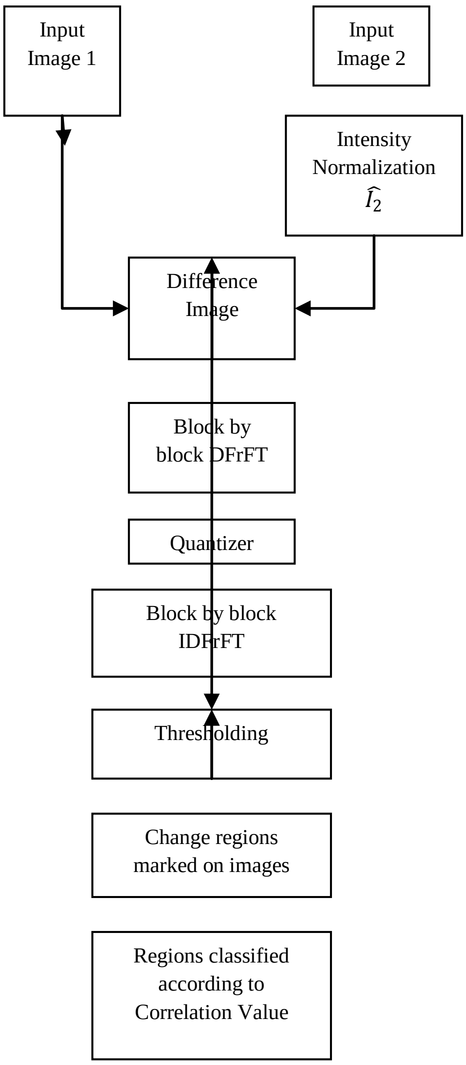


Fig 1: The flowchart of the discussed approach

4. EXPERIMENTAL RESULTS

Change has been detected by performing simulation for three different sets of images. Here Images with different level of shadow have been taken for simulation. There may be different kind of changes including artifacts like shadowing, large daylight change and partial translation etc but main focus is on appearance and disappearance of objects [3].

After detecting changed regions in the images, the correct detected objects (C), false detected regions (F) have been categorized and results are obtained for two parameters precision and recall.

Recall: Recall is a measure of quantity or completeness [4]. Mathematically recall is given by:

$$\text{Recall, } Re = \frac{C}{(C+M)} \tag{13}$$

where, C = No. of correctly detected object

M = No. of Missed Regions

Precision: Precision is a measure of correctness or quality [4]. Mathematically it is defined as:

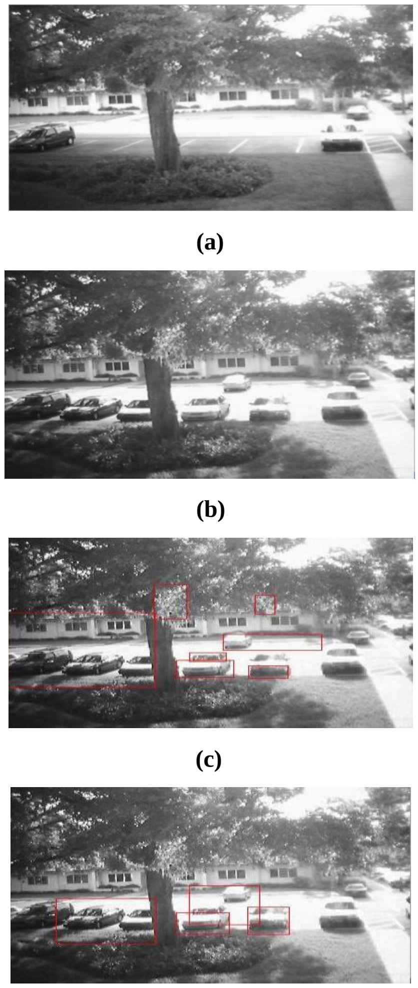
$$\text{Precision,} Pr = \frac{C}{(C+F)} \tag{14}$$

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.

4.1 Robustness against large daylight change



(a)

(b)

(c)

(d)

Fig 2: (a), (b) Original image sets to be change detected [3] of size 641 x 480. (c) Change region using DFrFT [4]. (d) Change regions using discussed method with a=0.85 and threshold value=0.11.

Table 1. Change-Detection Result for Fig 2

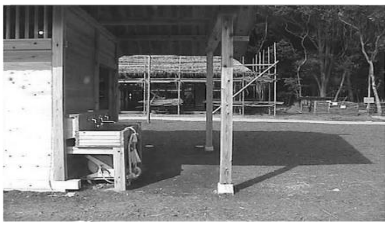
Method	T_a	T_d	C	F	M	Pr	Re
DFrFT [4]	5	7	5	3	0	0.625	1
DFrFT along with intensity normalization and thresholding	5	4	5	0	0	1	1

where, T_a = Number of objects to be detected

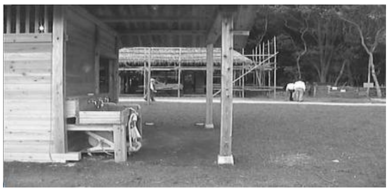
T_d = Total detected regions

Fig 2(a) and 2(b) provide a typical example in which two images of the same parking lot taken at 9:00 PM and at 10:00 AM, respectively [3]. Fig 2(c) represents changed region detected using DFrFT [4]. 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 [3]. 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 2(d). In above figure 2(d), we 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. In this case, precision value for proposed method is increased by 60% than previous method, but recall value is same for both methods. Results showing that no false and missed regions are detected with proposed method.

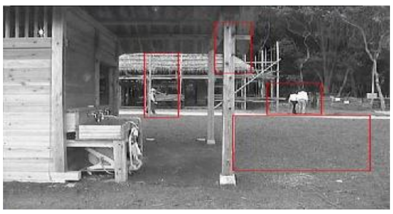
4.2 Robustness against large shadow appearance



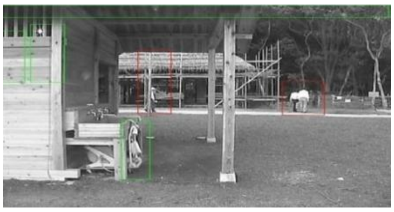
(a)



(b)



(c)



(d)

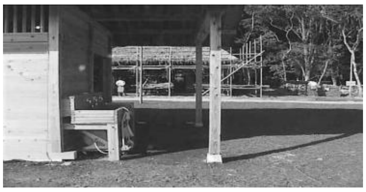
Fig 3: (a), (b) Original image sets to be change detected [3] of size 500 x 500. (c) Change region using DFrFT [4]. (d) Change regions using discussed method with a=0.85 and threshold value=0.097.

Fig 3(a) and 3(b) were captured with a five minute interval between images [3]. These images provide an example of a rapid change in daylight that causes difficulty with respect to change detection. Fig 3(c) shows change detected region using DFrFT [4]. Intensity changes due to the appearance of shadows can be observed in difference image. But with the help of discussed method we detect only significant changes i.e. objects removing insignificant changes, occurring due to shadowing. Through the gradient correlation processes, the appearances of people are detected, as indicated by red blocks. In this case, precision value for proposed method is increased by 50% than previous method, but recall value is same for both methods.

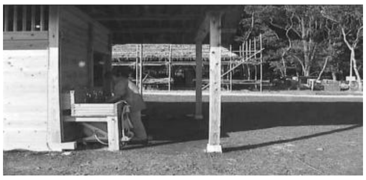
Table 2. Change-Detection Result for Fig 3

Method	T_a	T_d	C	F	M	Pr	Re
DFrFT [4]	2	4	2	2	0	0.5	1
DFrFT along with intensity normalization and thresholding	2	6	2	0	0	1	1

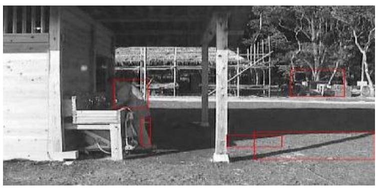
4.3 Robustness against partial translation



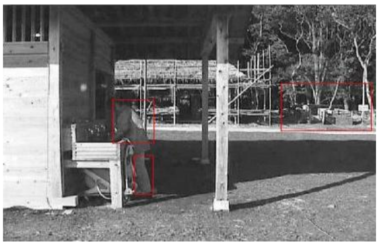
(a)



(b)



(c)



(d)

Fig 4: (a), (b) Original image sets to be change detected [3] of size 630 x 481. (c) Change region using DFrFT [4]. (d) Change regions using discussed method with a=0.85 and threshold value=0.092.

Fig 4(a) and 4(b) are images taken at 14:32 PM and 14:42 PM respectively [3]. Between taken images, the shadows moved according to the movement of the sun. Fig 4(c) shows changed region obtained using DFrFT. With the help of discussed 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 Fig 4(d). Results showing that no false and missed regions are detected with proposed method.

Table 3. Change-Detection Result for Fig 4

Method	T_a	T_d	*C*	*F*	*M*	*Pr*	*Re*
DFrFT [4]	2	5	2	2	0	0.5	1
DFrFT along with intensity normalization and thresholding	2	3	2	0	0	1	1

5. CONCLUSION

In this paper using DFrFT along with intensity normalization and thresholding 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 application like remote sensing, video surveillance and civil infrastructure etc. 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 is 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 are performed for three sets of images and change detection results were analyzed using precision and recall parameters values. Recall value is 1 for all image sets using both methods, it shows that desired objects are detected, However, precision value for proposed method is 60-100% more as compared to 'DFrFT only' method which means artifacts are removed.

For future scope, manual thresholding technique can be replaced with automatic thresholding technique to have better results. This modification may also helpful to make algorithm 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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