Detection of Changes in Images with Two Dimensional Moments

Fikret ARI, Ziya TELATAR

Ankara University, Faculty of Science, Department of Electronic Engineering
06100, Besevler Ankara TURKEY
fari@science.ankara.edu.tr
telatar@science.ankara.edu.tr

Abstract
In this paper, a new algorithm based on two dimensional discrete moment transforms is presented for the detection of abrupt changes in images. The developed algorithm was tested under disturbances such as noise and illumination variations. The performance of the algorithm was evaluated and the results were compared to the existing methods. Our algorithm outperforms the existing methods in terms of computation time by reducing the number of features required for difference metric.

Keywords: Change detection, Feature extraction, Two dimensional moments.

1. Introduction

Change detection has an important role in image processing. The problem of detecting and estimating the location of change points in images is fundamental to many areas of image processing applications such as wide area surveillance [1], monitoring systems [2] and machine vision applications [3]. The benefit of detecting changes before any further processing is the reduction of the amount of raw image data to be processed [4].

One of the important feature of a change detection system is its robustness to disturbances like noise and illumination variations [5]. Another aspect is the amount of computation time that may be critical for some special applications.

Contents of most image sequences changes dynamically. This change may occur in various ways. An unknown object may appear in the scene or moving around the scene or vice versa. Many of image processing systems use this information for their purposes. For example, detection of these changes in sequential image frames may be the first and most important step for recognition.

Change detection can be thought as a feature extraction problem. Basically, the system designed takes two input images and calculates various features as desired. Calculations may be pixel based or region based. The selected features are compared if there is a significant change at that location. Calculated features must be distinct for different input images. They must be robust against all disturbances encountered as far as possible. For example if there is illumination change in the scene, in order to detect changes successfully, selected features must not to be affected by this effect. Calculations of the number of features depends on the requirement.

Disturbances faced with for change detection problem are illumination changes and noise effects. In order to overcome these influences, effects on images must be decreased [6]. If this is not possible, features less sensitive to these effects must be selected.

Many change detection algorithms have been reported in literature. Skistad and Jain suggested a method for change detection in varying illumination case [7]. Another method suggested by Liu, Fu and Chang depends on the circular shift moments [5]. Carlotto purposed another approach for change detection [1], his algorithm for detection depends on the use of specific patterns of change instead of local image properties. Li and Zhou used edge contours as local image features in their image segmentation algorithm [8].

In this paper, we investigated the above methods which depends on local variances and circular shift moments, examined their performances for disturbances explained. Then, we carried out two dimensional moments [9], as features in our algorithm and used them for experiments. Next sections explain some previously published methods and our algorithm in detail.

2. Related Works and Proposed Method

The simplest method for change detection is differencing the images followed by thresholding. In this method, selected features are intensity levels of the images. This is the least complex method from all others. Changes can be computed easily because of the less number of operations. But this method may crash easily owing to the nature of effective disturbances. Detected changes may be caused by actual object changes or it may be caused by other effects like noise. Decision rule is given as follows.

$$d(x,y) = f_1(x,y) - f_2(x,y) \qquad (1)$$

$$c(x,y) = \begin{cases} 1 & ,\text{if } d(x,y) > T \\ 0 & ,\text{otherwise} \end{cases} \qquad (2)$$

Where $f_1(x,y)$ and $f_2(x,y)$ denotes input intensity images, $d(x,y)$ denotes difference metric, T denotes predetermined threshold and $c(x,y)$ denotes output image with changes. This is the usual method for change detection process except that selected features may change.

Skistad and Jain's method [7] was the solution for change detection in varying illumination case. Their method named 'shading model method' depends on modeling the structure of the image intensities. They used Prong's shading model which says basically that 'for a given point P, intensity of P is multiply of illumination and points shading coefficient'. They used this information to eliminate effects of illumination changes. For this purpose they divided input images, later they computed local variances to generate difference metric as given in equation (3).

$$E\{\sigma_i^2\} = E\left\{ \frac{1}{MN} \sum_{x,y\in A_i} \left(\frac{f_1(x,y)}{f_2(x,y)} - \mu_i \right)^2 \right\} \qquad (3)$$

Where $E\{\}$ denotes expection operator, M-N denotes size of the region of interest (A_i), μ_i denotes mean value of input intensity ratios in A_i and σ_i denote second central moment (variance) of A_i. This method overcome illumination changes, but at the same time it is very susceptible to noise because of the natural characteristics.

Another method suggested by Liu, Fu and Chang [5], depends on the circular shift moments as image features. This method was less susceptible to noise because features used were weighted sum of the columns (or rows) in the related A_i.

$$m_{x,k}^{j} = \frac{\sum_{x=1}^{M} \left[(x'-j)_{\bmod M} \sum_{y=1}^{N} f_k(x,y) \right]}{\sum_{x=1}^{M}\sum_{y=1}^{N} f_k(x,y)} \qquad (4)$$

In this equation $m^j_{x,k}$ denotes jth circular shift moment of A_i in kth image frame along x direction, x' term denotes actual pixel coordinates in whole image, $(x'\text{-}j)_{\text{modM}}$ term denotes remainder of $(x'\text{-}j)$ divided by M except that result is M if $(x'\text{-}j)$ is a multiple of M. As can be seen that $(x\text{-}j)_{\text{mod}M}$ term is a weighting function. Similar equation can be written for y direction.

As described in the previous section, distinct features must be calculated for change detection. For this purpose we proposed to use two dimensional general integral transform to generate image feature.

$$g_k(u,v,...) = \iint_{x,y} f_k(x,y) w(x,y,u,v,...) dxdy \quad (5)$$

Discrete formula can be written in the same manner. Function $w(x,y,u,v,...)$ in equation (5) forms kernel of the transform. Its construction affects result and depends on requirement. For example, if it is selected as given in equation (6), it results axial moment of the function $f_k(x,y)$ along h direction.

$$w(x,y,h) = \left| x \sin\left(\frac{h\pi}{n}\right) + y \cos\left(\frac{h\pi}{n}\right) \right| \qquad (6)$$

and,

$$m_k(h) = \sum_x \sum_y f_k(x,y) w(x,y,h) \qquad (7)$$

Equation (7) is the discrete form of equation (5) for this example. With $m_k(h)$, another feature of the image which is symmetry transform of $f_k(x,y)$, can be calculated [9]. Another example is two dimensional fourier transform, where $w(x,y,w_1,w_2)=e^{jw1x}e^{jw2y}$.

In our algorithm, we used two dimensional moments to describe local image properties according to equation (5) and (7) as given,

$$m_{p,q} = \sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y) x^p y^q \qquad (8)$$

Equation (8) describes p,qth discrete moment in the region of interest, A_i. It can be shown as extended version of one dimensional circular shift moments except a few detail. First, sum of the A_i, which is the denominator of the equation is only a scaling factor for calculation. Also, it can be used to estimate discrete two dimensional moments described as given in equation (9).

$$m_{p,q} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y) x^p y^q}{\sum_{x=1}^{M}\sum_{y=1}^{N} f_k(x,y)} \qquad (9)$$

Second, it doesn't contain shift coefficient j, however calculated circular shift moments for various shift coefficients don't have any additional information about image. Specially, this equation contains information about each direction.

3. Experimental Results

Some results are presented in this section with a 256x256 pixel grayscale blood image taken from Matlab still image gallery. This image is given in figure 1a. Some small objects have been added to image in order to obtain a modified version of this experiment is shown in figure 1b. Block size was 8x8 in all tests and we selected p=q=0.5 for moment calculations. Figure 2a, b and c shows the results of detecting changes between figure 1a and b with algorithms 'shading model', 'circular shift moments' and 'two dimensional moments' in noise free case. It can clearly be seen that there is no significant difference between results for this example. Next experiment results in figure 3a and figure 4a shows shading model method crashes in detection because selected features for detection are local image variances. Other results shown in figure 3b ,c ,figure 4b and c are identical except number of features used for detection. Our method outperforms circular shift moments method, as it has less mathematical complexity and computation time. Table (1) shows error rates for algorithms with various noise variances and number of features calculated.

Error Rate (%)	Shading Model	Circular Shift Moments	2-D Moments
Noise free	0.292	0.097	0.292
Noisy case σ^2=0.0459	6.835	0.097	0.292
Noisy case σ^2=0.0892	22.070	0.781	0.781
Number Of features	1	16	1

Table 1.) Error rates for various noise variances and number of features

4. Conclusion

This work describes a new approach to change detection based on two dimensional discrete moment transform. Two different previous methods are investigated in this work in order to compare performances with our method for both noise free and noisy cases. Advantage of our algorithm is to decrease computation time and computational complexity. This is due to less number of features needed for same results.

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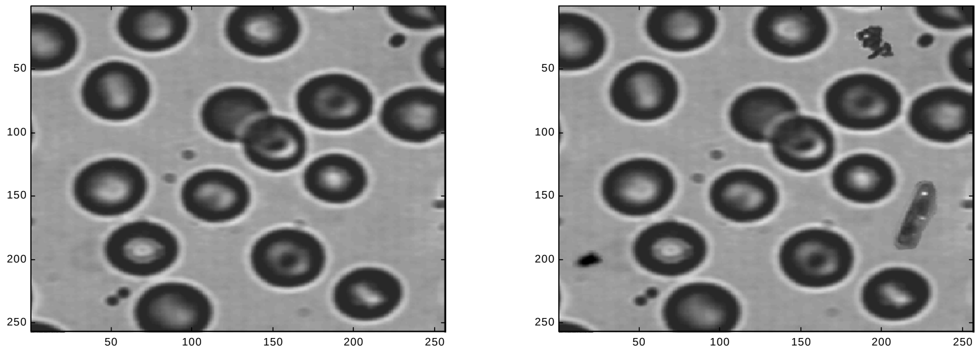
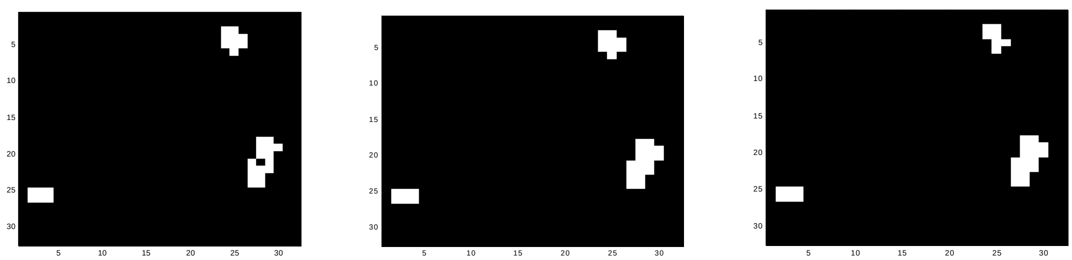


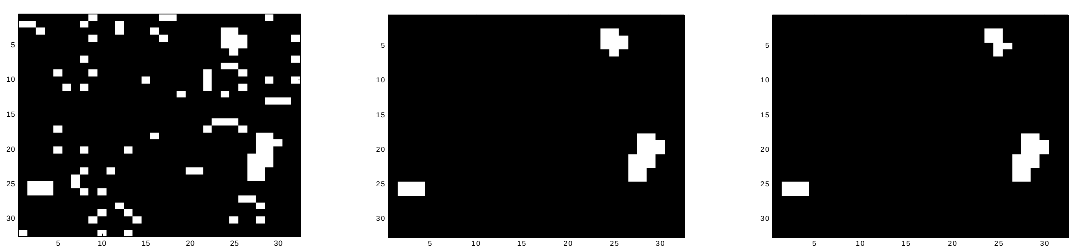
(a) (b)

Figure 1.) a.) Original test image b.) Test image with added small objects



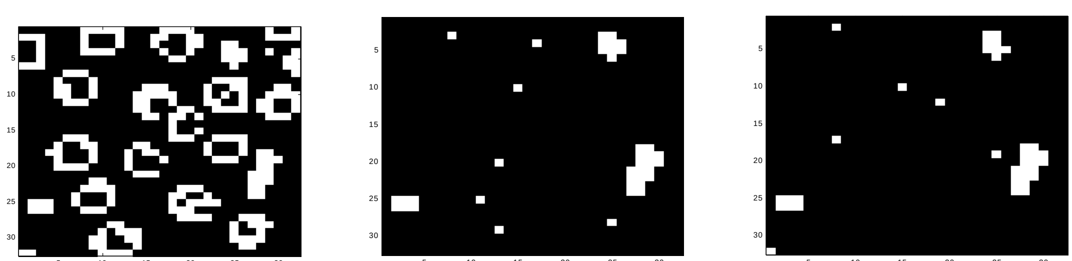
(a) (b) (c)

Figure 2.) Change detection results from figure 1 in noise free case a.) Shading model method b.) Circular shift moments method c.) Two dimensional moments method



(a) (b) (c)

Figure 3.) Change detection results from figure 1 in noisy case with noise variance 0.0459 a.) Shading model method b.) Circular shift moments method c.) Two dimensional moments method



(a) (b) (c)

Figure 4.) Change detection results from figure 1 in noisy case with noise variance 0.0892 a.) Shading model method b.) Circular shift moments method c.) Two dimensional moments method