# Robust and Efficient Change Detection Algorithm

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**Abstract.** Change detection in temporally related image sequences is a primary tool for extraction and detection of activities in background scene with vast and wide range of applications ranging from security and surveillance to fault detection and power savings. The prevalent methods for change detection are derived from the difference extraction where differences in the gray-level of values of the pixels between the two or more image sequences are used for the estimation and prediction of these changes. However this approach and its derived modifications are largely dependent and reliant on the application of value thresholds to provide significance to the differences, in order to compensate for the vulnerability of these methods to illumination variability and noise. A frequency domain approach to change detection is proposed that eliminates the need for thresholds and provides comparatively superior performance to the existing algorithms.

## 1 Introduction

Detection of changes in a scene in order to trigger an action or track an event or mark the beginning of a timeline is a very important tool in computer vision, digital image and video processing, it provides a veritable platform for the selective prioritization of camera feed for human monitoring and control in security and surveillance applications, it is also used in applications that track and detect activities, errors, abnormal trends and outliers in several applications use cases for optimal extraction of changes.

Several methods exists for the extraction of the image scene changes, One of the prominent, earliest and basic method for change detection is the signed difference of the two input image sequences, in this method the difference of two temporally related images is used for the analysis of the changes. However the major pitfall of this approach is its strong vulnerability to variation in lighting of the scene as the pixel values return considerable changes due to this variation, in addition noise in the captured image effectively reduces the reliability of the method as it is incapable to detecting, compensating or eliminating its presence. An additional and required supplement to this method is the application of a defined threshold to the resulting difference, in order to eliminate noise and match the sensitivity requirement of the specific application use case.

Other related approach to the signed difference is the change vector analysis [1], which uses the modulus difference of the feature vectors (representing the magnitude and direction of change) of the image sequences to detect change. The method also

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adopts a threshold application approach for the several use cases. Image ratio-ing [2] [3] is another technique that uses intensity ratios rather than differences to detect changes. Different applications of principal component analysis (PCA) [4] [5] have also been proposed and used to extract changes across images, with several methods of selecting the principal components that represent the changed parts of the image. Multiple variants and hybrids of these techniques have been proposed in literature for generic and specific application use cases. However most of the existing techniques rely heavily on the application of threshold for the performance tuning, but the task of estimating a global threshold for every possible application is completely arduous if not elusive, hence the development of thresholds for specific set of image scenes with known characteristics and application requirements, more so the methods [6] of the evaluating the appropriate threshold for each use case are mostly experimental devoid of any objective validation and mathematical rigor. This could result in sub-optimal implementations with no guarantee of performance as the spectral dynamics of the input images may not be reliably and deterministically predicted for each use case. More so thresholds are largely inadequate solution to the problem of illumination variation and noise; hence the development additional pre-processing techniques like intensity normalization [7], background modeling [8] [9], illumination modeling [10] and image averaging.

The proposed method models the problem as the extraction of the differences across fine-grained spectral structures of an image sequence, the correlation of the spectral content within a defined spatial boundary is used as the evaluation factor for change classification. The proposition has been iteratively refined and optimized to produce the presented simple and efficient implementation that embodies the complete functionality of the method. The technique completely eliminates the need for threshold and provides a platform for change detection across wide application areas, with improved performance in comparison to existing generic or application specific methods. The paper is presented in the following layout, section one is this introduction while section two contains details of the proposed method, the experimental analysis is presented in the third section with conclusion and insight for future work in the fourth.

## 2 Change Detection Algorithm

The problem of change detection is modeled as the determination of the change mask across image sequence I1…N, where N = 2. The proposed change detection algorithm pre-supposes the alignment of the image sequence in the same co-ordinate system. In an ideal scenario the difference in the image pair can be extracted from the simple signed difference, but the problem of noise and illumination distorts this status, hence mechanisms for the compensation of the two factors is implemented.

### 2.1 Noise

To eliminate the impact of noise, the spectral content generated from redundant discrete wavelet transform of the image pair, which provides the space-frequency information is used, the choice of wavelet is predicated upon the core requirement for high spatial resolution, this yields wavelet coefficients influenced by large amount of neighbor pixels, and this reduces the effects of noise to minimal deviations in co-efficient values across the image pair.

$$W_s f(x) = f(x) * \left( s \frac{d\theta_s(x)}{dx} \right) = s \frac{d}{dx} (f * \theta_s)(x) \tag{1}$$

where $\theta_s(x) = \frac{1}{s} \theta\left(\frac{x}{s}\right)$ is a smooth function integrates to 1 and converges to zero at infinity, Wsf(x) is single step decomposition using redundant discrete wavelet transform (see Figure 1).

## 2.2 Illumination Variance

The output of the first step for the input frames is temporally filtered using the Haar integer reversible high pass wavelet filter, as shown in Figure 2 below, by doing which, the illumination variance will be mostly removed.

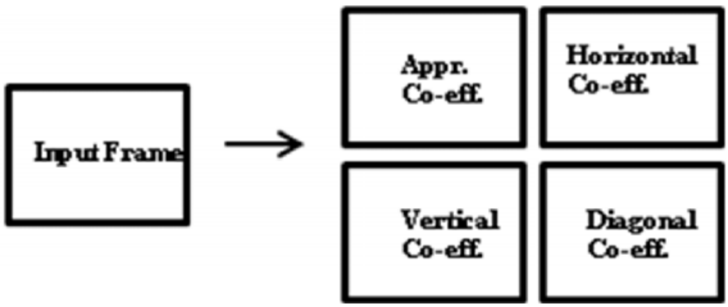


**Fig. 1.** Redundant discrete wavelet transform

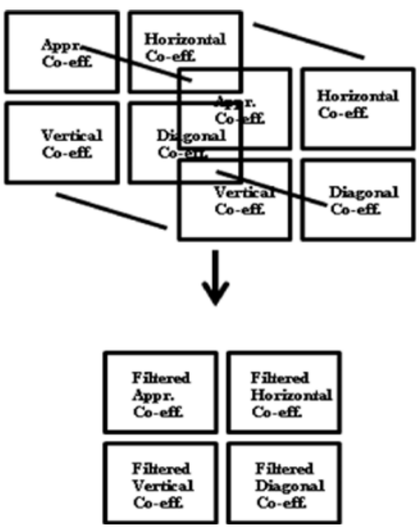


**Fig. 2.** Temporal filtering of the wavelet sub bands, derived from the two input frames

### 2.3 Noise – Illumination Compensation

The application of threshold classification to the temporally filtered coefficients, is used to eliminate the near zero values. The hard magnitude threshold is applied to the output.

## 3 Implementation

Inverse discrete wavelet transform of the output of step 3 above, and the output an inverse discrete wavelet with the filtered approximation coefficients replaced with zero values is summed up to produce the motion profile of the two frames, all non zero values in the motion profile are areas of relative motion across the frames, this is shown in Figure 3.

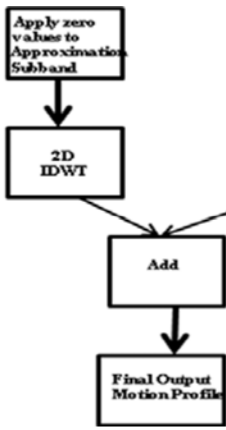


**Fig. 3.** Generation of the changes across two input frames

In Figure 3, the motion profile is used for deterministic search and matching across the input frames for estimation of the displacement vectors.

The estimation of differences and displacement vectors across the input frames is restricted to the areas of changes across the frames, as defined by the motion profile. The objective criteria and the shape and size of the matching units (regions or blocks) used are user defined, any method can be implemented. An example is shown in Figure 4 below:

**Fig. 4.** An example of estimation of areas of changes across two input frames

# 4 Experimental Analysis, Test and Results

The experimental evaluation of the change detection algorithm was performed in four categories of tests and presented in the following subsections. The categories are:

## 4.1 Simple Image Scene

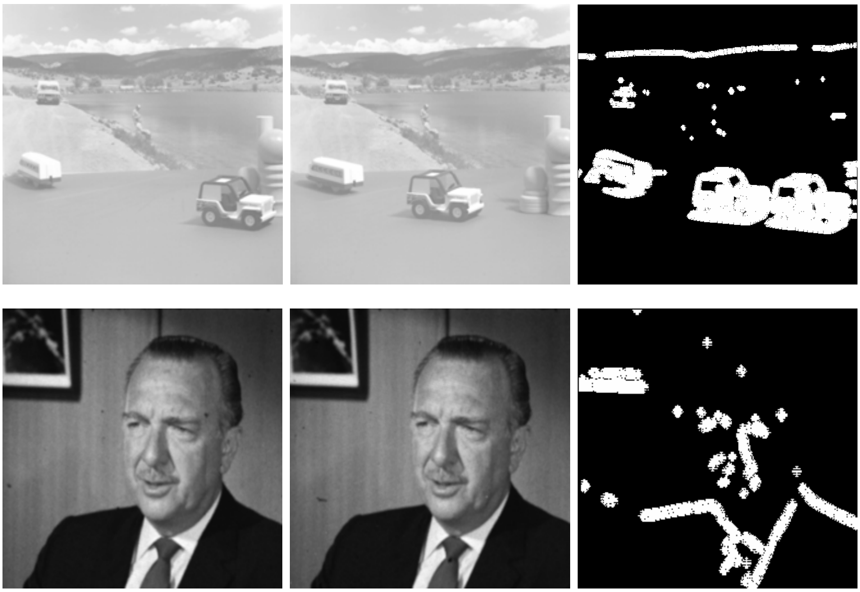

**Fig. 5.** Output estimation of areas of changes across two simple input frames. (Top: sequences 1, Bottom: sequences 2).

## 4.2 Complex Image Scene

**Fig. 6.** Output estimation of areas of changes across two complex input frames. (Top: sequences 3, Bottom: sequences 4).

**Fig. 6.** (*Continued*)

### 4.3 Variable Lighting (Alpha Value)

**Fig. 7.** Output estimation of areas of changes across two input frames with variable lighting

### 4.4 Noise (3 % Gaussian noise)

**Fig. 8.** Output estimation of areas of changes across two input frames with 3% Gaussian noise in one of them

## 5 Conclusion

The proposed change detection method provides robust and efficient approach to the problem of image change extraction that eliminates the need and use of the experimentally determined value thresholds. The implementation results in the generation of an image of the differences between two input image frames with sub-pixel accuracy.

This approach results in a technique that transcends specific application boundaries and the limitations of variations caused by noise and illumination. Future work on the extension of the method to motion estimation and temporal super resolution is currently evaluated.

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