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DETECTION OF OBJECTS USING SHADOW REMOVAL AND IMAGE RECONSTRUCTION

A. Abinaya and V. Ganesan
Department of Electronics and Telecommunication Engineering, Sathyabama University, Chennai, India
E-Mail: astrisha1@gmail.com

ABSTRACT

This project presents moving object detection based on background subtraction under complex wavelet transform domain for video surveillance system. The proposed approach has some advantages of background noise insensitiveness and invariant to varying illumination or lighting conditions. It also involves background updating model based on current frame and previous background frame pixels comparisons. The object detection also helps to track detected object using connected component analysis. The simulated result shows that used methodologies for effective object detection has better accuracy and with less processing time consumption rather than existing methods.

Keywords: image reconstruction, shadow removal, background subtraction, CWT domain.

1. INTRODUCTION

Background subtraction is the first step in the process of segmenting and tracking people. Distinguishing between foreground and background in a very dynamic and unconstrained outdoor environment over several hours is a challenging task. The background model is kept in the data storage and four individual modules do training of the model, updating of the model, foreground/background classification and post processing.

The first k video frames are used to train the background model to achieve a model that represents the variation in the background during this period. The following frames (from k + 1 and onwards) are each processed by the background subtraction module to produce a mask that describes the foreground regions identified by comparing the incoming frame with the background model. Information from frames k + 1 and onwards are used to update the background model either by the continuous update mechanism, the layered Updating, or both. The mask obtained from the background subtraction is processed further in the post processing module. which minimizes the effect of noise in the mask. Each of the modules will be described in detail in the following sections. The background model will be described first since it contains the fundamental model used in the other modules of the background subtraction process. Next the training of the model, which is the initialization of the model, is described. The foreground/background classification will be the third module to be described and after that the updating will be described. This order corresponds to the two modules in the actual background subtraction process.

2. DESCRIPTION OF PROPOSED SHADOW REMOVAL MODEL

a) System design

Background subtraction based on Effective moving object detection using, Complex wavelet transforms, and frame differencing and approximate median based background update.

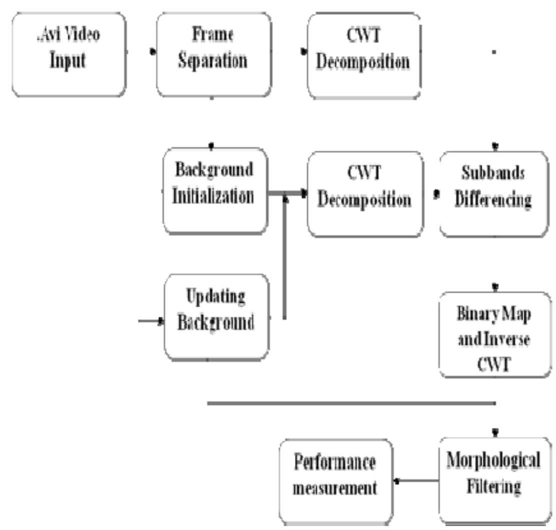

Figure-1. Block diagram of CWT domain.

b) Functional modules

1. Frame separation

An Input Video (.avi files) is converted into still images for processing it and to detect the moving objects. These sequences of images gathered from video files by finding the information about it through ‘aviinfo’ command. These frames are converted into images with help of the command ‘frame2im’Create the name to each images and this process will be continued for all the video frames. The following diagram represents the process flow of this separation.

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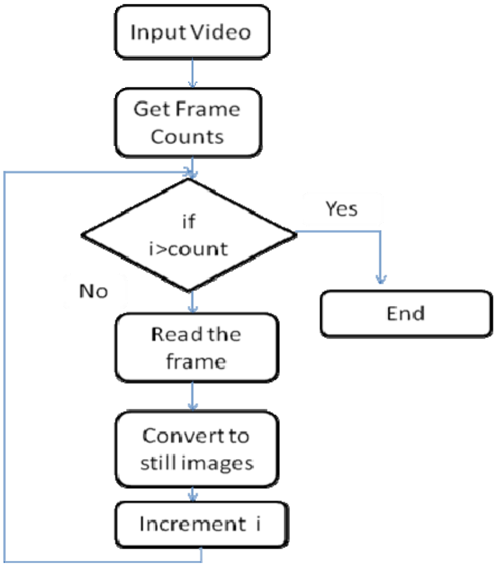

Figure-2. Process flow of frame separation.

c) Dual-tree complex wavelet transforms (DT-CWT).

The dual-tree complex wavelet transform (CWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. It achieves this with a redundancy factor of only 2d for d-dimensional signals, which is substantially lower than the UN decimated DWT. The multidimensional (M-D) dual-tree CWT is non separable but is based on a computationally efficient, separable filter bank (FB). The theory behind the dual-tree transforms shows how complex wavelets with good properties can be designed, and illustrates a range of applications in signal and image processing.

In the neighborhood of an edge, the real DWT produces both large and small wavelet coefficients. In contrast, the (approximately) analytic CWT produces coefficients whose magnitudes are more directly related to their proximity to the edge. Here, the test signal is a step edge at n = no, x(n) = u(n − no). The figure shows the value of the wavelet coefficient d (0, 8) (the eighth coefficient at stage 3 in "Real-Valued Discrete Wavelet Transform and Filter Banks, as a function of no. In the top panel, the real coefficient d(0,8) is computed using the conventional real DWT. In the lower panel, the complex coefficient d (0, 8) is computed using the dual-tree CWT.

d) Complex wavelets

First, the magnitude of the Fourier transform does not oscillate positive and negative but rather provides a smooth positive envelope in the Fourier domain. Second, the magnitude of the Fourier transform is perfectly shifting invariant, with a simple linear phase offset encoding the shift. Third, the Fourier coefficients are not aliased and do not rely on a complicated aliasing cancellation property to reconstruct the signal and fourth, the sinusoids of the M-D Fourier basis are highly directional plane waves. The DWT, which is based on real-valued oscillating wavelets, the Fourier transform is based on complex-valued oscillating sinusoids.

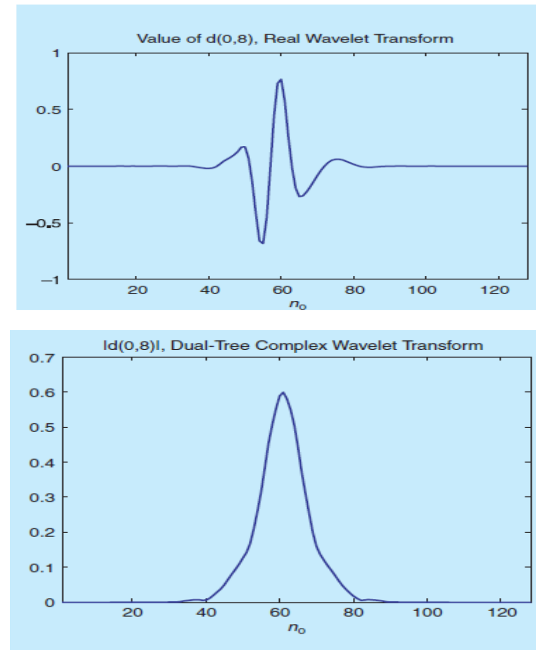

Figure-3. The value of the wavelet coefficient in "Real-valued discrete wavelet transform and filter banks.

$$e^{j\Omega t} = \cos(\Omega t) + j\ \sin(\Omega t)$$

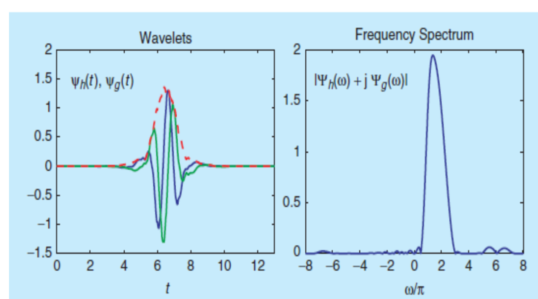

Figure-4. A q-shift complex wavelet corresponding to a set of orthonormal dual-tree filters of length.

The oscillating cosine and sine components (the real and imaginary parts, respectively) form a Hilbert transform pair; i.e., they are 90◦ out of phase with each other. Together they constitute an analytic signal e j_t that is supported on only one-half of the frequency axis (_ >0).The oscillating cosine and sine components (the real and imaginary parts, respectively) form a Hilbert transform pair; i.e., they are 90◦ out of phase with each other. Together they constitute an analytic signal e j_t that is supported on only one-half of the frequency axis (_ >0).

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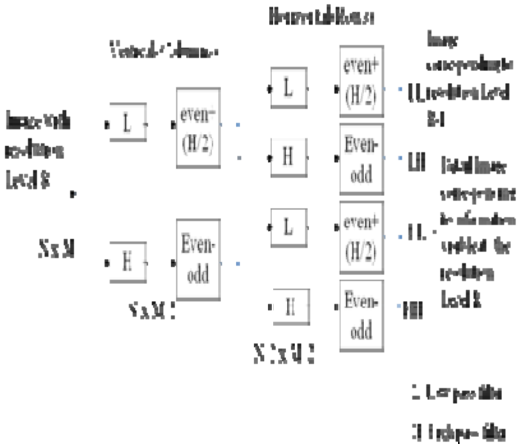

Figure-5. Flow diagram of complex wavelets.

e) Morphological filtering

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to grey scale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

- Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test whether it "hits" or intersects the neighbourhood:
- An excellent Cast shadow Removal writers is given by Liu [3].

3. SIMULATION RESULTS

A wave is an oscillating function of time or space that is periodic. The wave is an infinite length continuous function in time or space. In contrast, wavelets are localized waves. A wavelet is a waveform of an effectively limited duration that has an average value of zero.

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts).
An excellent Background Reconstruction writers is given by Ngai Ming Kwok [4].

A function $\psi(x)$ can be called a wavelet if it possesses the following properties:

a) The function integrates to zero, or equivalently, its Fourier transform is denoted as $\psi(\omega)$ is zero at the origin:

$$\int_{-\infty}^{\infty} \psi \; (x) \, dx = 0$$

b) It is square integral, or equivalently, has finite energy:

$$\int_{-\infty}^{\infty} | \psi \; (x) |\wedge 2 \, dx < \infty$$

c) The Fourier transform $\psi(x)$ must satisfy the admissibility condition given by

$$C = \int_{-\infty}^{\infty} \frac{|\psi\omega)|^2}{\omega} d\omega < \infty$$

(a)

(b)

(c)

(d)

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(e)

(f)

Figure-6. (a)input image (b)median filter (c)morphology filter (d)median-morphology filter (e)output image (f)color mask.

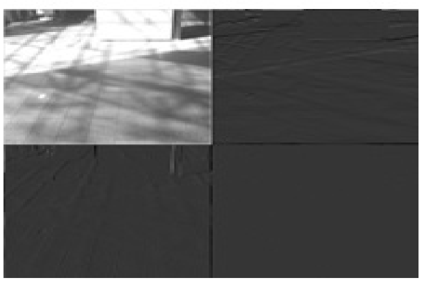

Figure-7. Sub band images of background in complex wavelet transform.

Table-1. Comparison of filters and wavelet transform.

Method	RMSE	PSNR (db)	Accuracy
Median Filter	0.364309	52.5161	80.5378
Morphology Filter	0.28477	53.5859	86.125
Median-Morphology Filter	0.269162	53.8307	87.3125
Wavelet	0.107892	57.8009	92.776

Complex Wavelet Transform is used to separate the Approximation and Detailed Coefficients from the time domain images. CWT decomposes the image into different sub band images, namely, LL, LH, HL, and HH for embedding the messages in the pixel coefficients of sub bands. Complex scheme is a technique to convert DWT coefficients to Integer coefficients without losing information. LL sub bands contain the significant part of the spatial domain image. High-frequency sub band contains the edge information and noise component of input image. The sub-band filtering process is done after the CWT of background frame and the foreground frames.

4. CONCLUSIONS AND FUTURE WORK

The project presents moving object detection based on background subtraction under complex wavelet transform. The simulated result shows that used methodologies for effective object detection has better accuracy and with less processing time consumption rather than existing methods.

Our future work will focus on other feature like Cross Wavelet and Wavelet Coherence. This is extremely difficult and time consuming process in background Reconstruction.

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