Object Detection Using Dual Lifting

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Abstract

This paper is an approach to extend the functionality and application fields of adaptive lifting. An adaptive lifting scheme is used for detecting user-selected objects in a sequence of images. In this algorithm, first a set of object features in the wavelet transform domain is selected and then an adaptive transform is built using the selected features. The adaptive transform is constructed based on adaptive prediction in a lifting scheme procedure. Adaptive prediction is performed such that, the large coefficients in the high-pass component of the non-adaptive transform vanishes in the high-pass component of the adaptive transform. Finally, both the non-adaptive and adaptive transforms are applied to a given test image and the transform domain coefficients are compared for detecting the object of interest.

Keywords : Dual Lifting, Adaptive Lifting, Object Detection

1. Introduction

Two important sub problems of the computer vision are the detection and recognition of 2D objects in images. The goal of the object detection is to locate object in an image. The basic understanding of the object detection found some basic techniques that could be used for detecting objects in an image. Template matching is a technique in object detection for finding small parts of an image, which match a template image.

There are different approaches in accomplishing template matching. Some perform better than other, and some find better matches. Template matching is to loop through all pixels in the search image and compare them to the pattern. While this method is simple to implement and understand, it is one of the slowest methods.

Feature Extraction involves simplifying the amount of resources required to describe a large set of data accurately. The performance analysis of complex data which stems from the number of variables involved is one of the major problems. Analysis with a large number of variables generally requires a large amount of memory and computation power or classification algorithm, which over fits the training sample and generalizes poorly to new samples.

In the past few years, wavelet-based methods for detection and enhancement tasks have received considerable attention within the image processing community. The Discrete Wavelet Transform (DWT) has properties that makes it an ideal transform for the processing of images encountered in image understanding applications, including efficient representation of abrupt changes and precise spatial information, ability to adapt to high background noise,

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ability to adapt to uncertainty about object properties, ability to adapt to changing local image statistics, and existence of the fast processing algorithms.Inherent ability for the efficient approximation of smooth signals is one of the prominent reasons for the success of wavelets in various applications like compression. But real-world signals are not always as smooth as classical wavelet transform approaches request. Adaptive approaches are required to overcome discontinuities encountered in real-world signals. For the smooth input signals, most of the coefficients in the high-pass component of the wavelet transform are zero. One may conclude that the remaining coefficients in the high-pass component, which have large magnitude, may be considered as the features of the input signal.

Section 2 discusses the basics of lifting scheme and steps to obtain the lifting. Section 3 is devoted to a brief survey of the Adaptive lifting scheme. Dual lifting Transform is discussed in Section 4. Detection Algorithm is described in Section 5 followed by results in section 6. Finally in section 7, conclusions and future works for increasing performance of the presented algorithm, are described.

2. Lifting Scheme

The lifting scheme is a new approach to construct the so-called second-generation wavelets, i.e., wavelets which are not necessarily translations and dilations of one function. The basic lifting scheme for wavelet transform of discrete-time signal consists of three steps.

Split: The signal is split into even and odd sub arrays. The splitting into even and odd is called the lazy wavelet transform.

Predict: The filtered even array is used to predict the odd array. Then the odd array is redefined as the difference between the existing array and the predicted one. If the predictor is correctly chosen then this step decorrelates the signal and reveals its high- frequency component.

Update: To estimate aliasing, which appears while down sampling the original signal, and to obtain the low-frequency component of the signal, the even array is updated using the filtered new odd array.

The newly produced even and odd sub arrays are the coefficients from the single decomposition step of the wavelet transform.

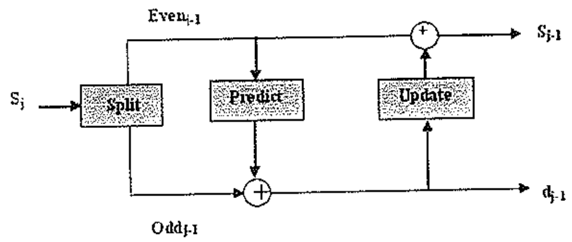


Figure.2.1 Forward Lifting Scheme

The inverse transform is implemented in a reverse order. The transform generates bi-orthogonal wavelets basis for the signal space. The specifics of the transform and its generated wavelets are determined by the choice of the predicting and updating filters. An odd sample is predicted from a polynomial interpolation of neighboring even samples. Various kinds of splines are used as predicting and updating aggregates in the lifting scheme.

3. Adaptive Lifting

Many adaptive approaches have been developed by various researchers. Best basis algorithm is a good example of a common adaptive approach where we choose a wavelet basis which depends on the input signal. The basis is selected by minimizing a cost function such as entropy in the wavelet packet transform tree. But it is a global adaptive approach and the chosen basis is fixed for the entire block of data. Lifting scheme, presented by Sweldens provide a good structure for creating adaptive wavelet transforms. Lifting scheme presents a means for decomposing wavelet transform into predict and update stages.

One may adapt prediction or update stage filters to the local signal properties and build desired adaptive wavelet transforms.

Claypoole et. Al. proposed an adaptive lifting scheme for image compression and denoising applications. They switch between different linear predictors at the predict stage. Higher order predictors where the image is locally smooth and lower order predictors near edges to avoid prediction across discontinuities.

An update first strategy is also utilized by Piella and Heijmans. Unlike Claypoole et. Al they have chosen a fixed predictor and took adaptive ness into the update stage in such a way that no bookkeeping is required. Trappe and Liu also adapt predict stage. They tried to minimize the predicted detail signal by designing a data-dependent prediction filter. They have presented different approaches. The first one is global adaptivity and its goal is to minimize norm of the entire detail signal. In the second approach, the coefficients of the prediction filter vary over time based on local optimization.

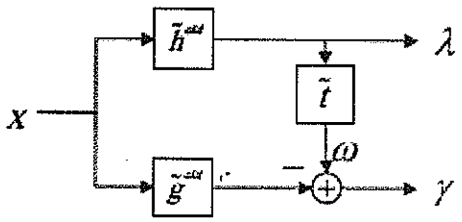
4. Dual Lifting

The fast lifted wavelet transform using a dual lifting step is shown in Figure 4.1. Here h^{old} and g^{old} are the low-pass and high-pass analysis filters of the non adaptive wavelet transform that are applied to the input signal X, respectively. The Prediction filter t is applied to the low-pass component and the output is subtracted from the old high-pass component γ^{old}, thus yielding the new high-pass component as follows.

$$\omega = (x * h^{old}) * t \qquad (4.1)$$

$$\gamma^{old} = x * g^{old} \qquad (4.2)$$

$$\gamma = \gamma^{old} - \omega \qquad (4.3)$$



where, * denotes the convolution operator.

Figure 4.1. The Dual Lifting Scheme

5. Detection Algotithm

5.1 Choosing the Prediction Filter

In this subsection we show how to find the coefficients of the prediction filter t such that large coefficients of the non-adaptive wavelet transform's high-pass component, vanish in the high-pass component of the adaptive lifted wavelet transform. Let *s* be the signal of interest.

$$\lambda = s*h^{old} = \lambda_k = \sum s_j h^{old}_{K+1-j} \qquad (5.1)$$

$$\gamma^{old} = s*g^{old} = \gamma_k^{old} = s_j g^{old}_{K+1-j} \qquad (5.2)$$

Given the prediction filter *t*, high pass component of the adaptive lifted wavelet transform (γ) is obtained as follows.

$$\omega = \lambda * t = \sum \lambda_j t_{K+1-j} \qquad (5.3)$$

$$\gamma_k = \gamma_k^{old} - \omega_k \qquad (5.4)$$

If we consider a coefficient in the old high-pass component, with index k', which has large magnitude and try to vanish its corresponding coefficient in the high-pass component.

$$\gamma_k = 0 = \gamma_k^{old} \qquad (5.5)$$

and by substituting ω from eqn. (5.3), we obtain

$$\Sigma\lambda_j t_{K+1-j} = \gamma_k^{old} \quad (5.6)$$

Let p be the length of the prediction filter t. Now if we let v be the number of selected large coefficients of the old high-pass component with indices $k'_1, k'_2, , , k'_v$ and try to vanish their corresponding coefficients in the new high-pass component When$v+1=p$, eq (5.7) could be solved by the Gaussian elimination algorithm in order to obtain the coefficients of the prediction filter t. eq.5.7 is as follows.

$$\begin{bmatrix} \lambda_{k'_1} & \lambda_{k'_1-1} & \cdots & \lambda_{k'_1-p+1} \\ \lambda_{k'_2} & \lambda_{k'_2-1} & \cdots & \lambda_{k'_2-p+1} \\ \vdots & \vdots & \ddots & \cdots \\ \lambda_{k'_v} & \lambda_{k'_v-1} & \cdots & \lambda_{k'_v-p+1} \\ 1 & 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} \tilde{t}_1 \\ \tilde{t}_2 \\ \vdots \\ \tilde{t}_p \end{bmatrix} = \begin{bmatrix} \gamma_{k'_1}^{old} \\ \gamma_{k'_2}^{old} \\ \vdots \\ \gamma_{k'_v}^{old} \\ 0 \end{bmatrix}$$

5.2 Algorithm For Detection

Choose a reference block O $_{(n*m)}$ which encompasses the object of interest and test image T $_{(N*M)}$ × as the input arguments.

Consider row i_o of the object o as the 'signal of interest' and find prediction filter t as described (i_o=1....n).

Consider Column i_o of the object O as the 'signal of interest' and find prediction filter t as described (j_o=1....m).

Sweep test image T with a 2D window of the same size as object O .Apply non-adaptive and adaptive lifted wavelet transforms to the rows and columns of the windowed Image. Find sum of the vanishing percentage. The location of the maximum value for this sum could be considered as location of the reference block in the test image T.

Finding prediction filter for each row and column of the reference block could be a time consuming task. But in many applications, like image retrieval, we only need to compute the prediction filters once, and use the same filters for detecting object of interest in any chosen test image from the database.

Due to the following reasons, noise or slight deformations in the object of interest, would not have considerable impact on the resulted vanishing percentage.

Most of the large values in the high-pass component remain among large values in the noisy signals as well. Both of the non-adaptive and the adaptive transforms are applied to the same noisy signal, therefore vanishing Percentage values will not experience a considerable change.

6. Results

The prescribed algorithm for detection is tested for various samples and the algorithm worked successfully.And it is tested by including various noises.Even in noisy environment it can be able to detect output.Samples are shown in Figure 6.1. Table 1 show PSNR values after adding noises.We have compared original output with the noise added sample images detected output.

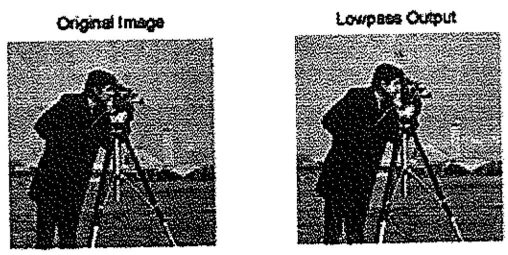


Figure 6.1 Sample Image and Detected Desired Object

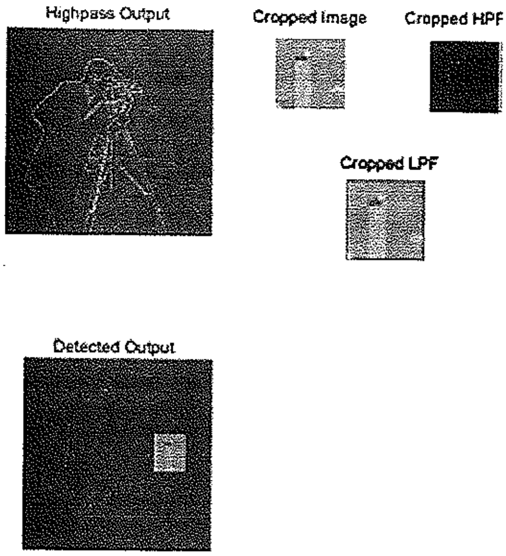
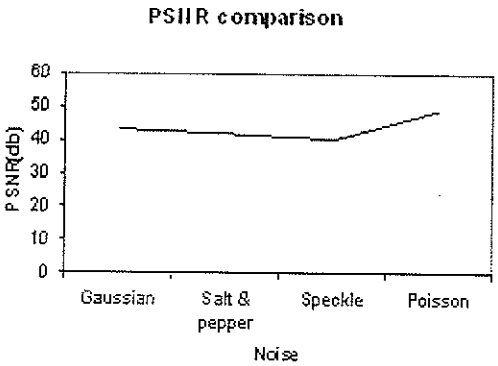


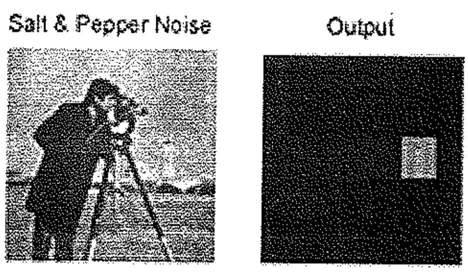
Table 1 PSNR VALUE

Sample image: Cameraman

Noise type	PSNR
Gaussian	43.2905
Salt & pepper	42.0142
Speckle	40.1562
Poisson	49.2740

Graph1:PSNR for different type of noises





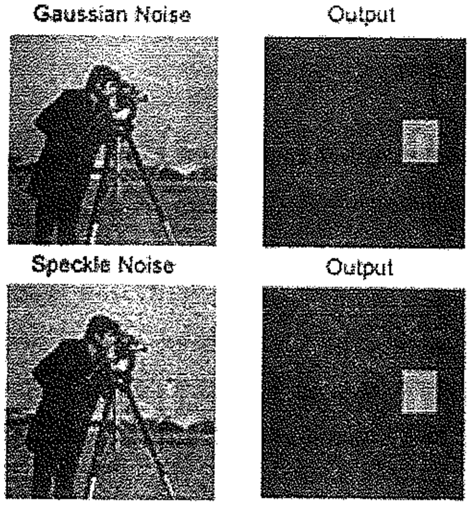
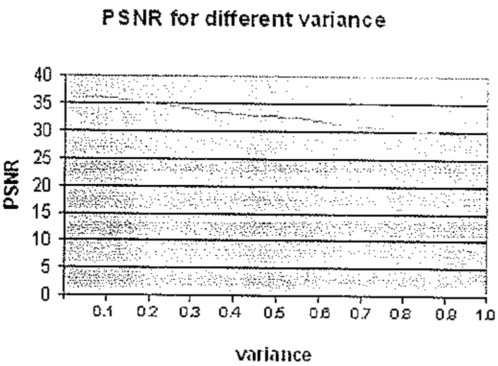


Table2 : PSNR for different variance :

Noise type : Speckle noise

Variance	PSNR
0.1	36.1314
0.2	35.3255
0.3	34.3051
0.4	33.0817
0.5	32.1419
0.6	32.0012
0.7	30.5975
0.8	29.7110
0.9	29.1022
1.0	28.5657

Graph2 : PSNR for different variance ranges



Conclusions And Future Work

We have only examined the potential of the adaptive lifted transform for object detection. Many variations on the presented algorithm could be designed to improve its performance for detecting noisy and degraded forms of the desired object. Moreover one may use several different image instances of the desired object for designing prediction filter of the adaptive lifted transform. This would make the algorithm more robust to the slight deformations in the test image. We are currently in process of applying this algorithm in medical images to detect tumor cells.

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