# A NEW ADAPTIVE LIFTING SCHEME TRANSFORM FOR ROBUST OBJECT DETECTION

*M. Amiri, H. R. Rabiee*

Digital Media Lab. (http://www.aictc.com/dml), Sharif University of Technology

**ABSTRACT**

This paper presents a new adaptive lifting scheme transform for detecting user-selected objects in a sequence of images. In our algorithm, we first select a set of object features in the wavelet transform domain and then build an adaptive transform by 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. It is shown that the presented algorithm is robust to the noisy environments with reasonable signal-to-noise ratio. We have verified our claims with experimental results on noisy 1-D signals and images.

## 1. INTRODUCTION

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, 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. This fact is already used to design optimal lifting wavelet filters for data compression [1].

In this paper for a given object of interest, we design an adaptive lifted wavelet transform so that the large coefficients in the high-pass component of the non-adaptive transform, vanish in the high-pass component of the adaptive transform. Both of the non-adaptive and the adaptive transform, are applied to any given test image. An algorithm is presented for detecting the object of interest by comparing the high-pass component coefficients of the non-adaptive and the adaptive wavelet transform.

Section 2 is devoted to a brief survey of the existing adaptive lifting scheme methods. Dual lifting wavelet transform is described in section 3. Our proposed detection algorithm is described in section 4 followed by experimental results in section 5. Finally, in section 6, the future works for increasing performance of the presented algorithm, are described.

## 2. ADAPTIVE LIFTING

Many adaptive approaches have been developed by various researchers. Best basis algorithm [2] 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 [3], provided 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. [4] 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. One will have to keep track of the chosen filters at each sample, to guarantee perfect reconstruction at the synthesis stage. They had to apply update stage first, in order to avoid sending information on chosen predictor for the reconstructor.

An update first strategy is also utilized by Piella and Heijmans [5]. Unlike Claypoole et. al., they choose a fixed predictor and take adaptiveness into the update stage in such a way that no bookkeeping is required.

Trappe and Liu [6] also adapt predict stage. They try to minimize the predicted detail signal by designing a data-dependent prediction filter. They present two different approaches. The first one is a 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 a local optimization criterion. Similar approaches had been earlier proposed by other researchers like Gerek and Çetin [7], Boulgouris et. al. [8], and Chan and Zhou [9].

## 3. DUAL LIFTING STEP

The fast lifted wavelet transform using a dual lifting step [10] has shown in Figure 1. Here, $\tilde{h}^{old}$ and $\tilde{g}^{old}$ 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 $\tilde{t}$ is applied to the low-pass component $\lambda$ and the output $\omega$ is subtracted from the old high-pass component $\gamma^{old}$, thus yielding the new high-pass component $\gamma$ as follows.

$$\omega = \left(x * \tilde{h}^{old}\right) * \tilde{t} \tag{1}$$

$$\gamma^{old} = x * \tilde{g}^{old} \tag{2}$$

$$\gamma = \gamma^{old} - \omega \tag{3}$$

where, $*$ denotes the convolution operator.

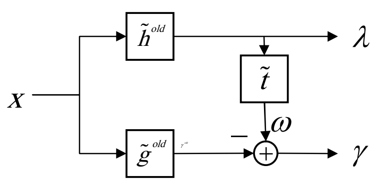


**Fig. 1.** The fast lifted wavelet transform using a dual lifting step.

## 4. DETECTION ALGORITHM

### 4.1. Prediction Filter in 1D Case

In this subsection we show how to find the coefficients of the prediction filter $\tilde{t}$, 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. Applying the non-adaptive wavelet transform to this signal will yield the following low-pass ($\lambda$) and high-pass ($\gamma^{old}$) components.

$$\lambda = s * \tilde{h}^{old} \Rightarrow \lambda_k = \sum_j s_j \tilde{h}^{old}_{k+1-j} \tag{4}$$

$$\gamma^{old} = s * \tilde{g}^{old} \Rightarrow \gamma^{old}_k = \sum_j s_j \tilde{g}^{old}_{k+1-j} \tag{5}$$

Given the prediction filter $\tilde{t}$, high pass component of the adaptive lifted wavelet transform ($\gamma$) is obtained as follows.

$$\omega = \lambda * \tilde{t} \Rightarrow \omega_k = \sum_j \lambda_j \tilde{t}_{k+1-j} \tag{6}$$

$$\gamma_k = \gamma^{old}_k - \omega_k \tag{7}$$

If we consider a coefficient in the old high-pass component $\gamma^{old}$, with index $k'$, which has large magnitude and try to vanish its corresponding coefficient in the high-pass component $\gamma$, based on eq. (7), we would have

$$\gamma_{k'} = 0 \Rightarrow \omega_{k'} = \gamma^{old}_{k'} \tag{8}$$

and by substituting $\omega$ from eq. (6), we obtain

$$\sum_j \lambda_j \tilde{t}_{k'+1-j} = \gamma^{old}_{k'} \tag{9}$$

In the other hand, it is known that, the high-pass analysis filter for the adaptive lifted wavelet transform is given by the following equation [10].

$$\tilde{g}^{new}(z) = \tilde{g}^{old}(z) + \tilde{h}^{old}(z)\tilde{t}(z^2) \tag{10}$$

Clearly, the summation of the filter coefficients is zero,

$$\sum_k \tilde{g}^{new}_k = 0 \tag{11}$$

which is equivalent to

$$\sum_k \tilde{t}_k = 0 \tag{12}$$

Let $p$ be the length of the prediction filter $\tilde{t}$. Now if we let $v$ be the number of selected large coefficients of the old high-pass component with indices $k'_1, k'_2, \ldots, k'_v$ and try to vanish their corresponding coefficients in the new high-pass component. Considering eq. (9) and eq. (12), the system of equations in (13) is formed.

When $v+1 = p$, eq. (13) could be solved by the Gaussian elimination algorithm. When $v+1 > p$, Gauss-Newton method may be used to solve eq. (13) in order to obtain the coefficients of the prediction filter $\tilde{t}$.

$$\begin{bmatrix} \lambda_{k'_1} & \lambda_{k'_1-1} & \cdots & \lambda_{k'_1-p+1} \\ \lambda_{k'_2} & \lambda_{k'_2-1} & \cdots & \lambda_{k'_2-p+1} \\ \vdots & \vdots & \ddots & \cdots \\ \lambda_{k'_v} & \lambda_{k'_v-1} & \cdots & \lambda_{k'_v-p+1} \\ 1 & 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} \tilde{t}_1 \\ \tilde{t}_2 \\ \vdots \\ \tilde{t}_p \end{bmatrix} = \begin{bmatrix} \gamma^{old}_{k'_1} \\ \gamma^{old}_{k'_2} \\ \vdots \\ \gamma^{old}_{k'_v} \\ 0 \end{bmatrix} \tag{13}$$

### 4.2. Detection Algorithm, 1D Case

After finding the desired prediction filter, the following algorithm could be used for detecting the 1D signal of interest, for any given test signal.

1. The signal of interest $s$ and the test signal $x$ are assumed to be the input arguments.
2. Select a non-adaptive wavelet transform, and values of the parameters $p$ and $v \geq p-1$.
3. Find the desired prediction filter $\tilde{t}$, as described in section 4.1.
4. Apply the non-adaptive and the adaptive lifted wavelet transforms to the test signal $x$ and find the high-pass components $\gamma^{old}$ and $\gamma$.
5. Construct an empty vector $D$ with the same length as $\gamma^{old}$ and $\gamma$.
6. Compare each coefficient of $\gamma^{old}$ with the corresponding coefficient in $\gamma$ and if it is decreased, find the vanishing percentage (VP) and write it in vector $D$.
7. Sweep vector $D$ with a window of the same length as signal $s$, and find sum of the VPs for each windowed location. The location of the maximum value for this sum, could be considered as the location of the signal $s$, in the test signal $x$.

### 4.3. Detection Algorithm, 2D Case

Our detection algorithm for 1D signals, could be expanded to the 2D case for detecting an object of interest in a given test image. We may consider the 2D object as a set of separable 1D signals corresponding to rows and columns of the 2D object. The algorithm for 2D case is as follows.

1. Choose a reference block $O_{(n\times m)}$ which encompasses the object of interest and test image $T_{(N\times M)}$ as the input arguments.
2. Consider row $i_o$ of the object $O$ as the 1D 'signal of interest' and find prediction filter $\tilde{t}^{r}_{i_o}$ as described in section 4.1. Repeat this for $i_o = 1,\ldots,n$.
3. Consider column $j_o$ of the object $O$ as the 1D 'signal of interest' and find prediction filter $\tilde{t}^{c}_{j_o}$ as described in section 4.1. Repeat this for $j_o = 1,\ldots,m$.
4. Sweep test image $T$ with a 2D window of the same size as object $O$.
5. Apply non-adaptive and adaptive lifted wavelet transforms to the rows and columns of the windowed image. Compare corresponding coefficients similar to the 1D case and find sum of the VPs. The location of the maximum value for this sum, could be considered as the 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 VPs.

- 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.

## 5. EXPERIMENTAL RESULTS

In the first example, we have created a random test signal including a signal of interest in the middle part shown in Figure 1.a. Biorthogonal wavelet (bior2.2) with 2 vanishing moments for analysis and synthesis filters, were chosen for the non-adaptive wavelet transform. Parameter $v$ and prediction filter length, $p$, both were set to 10. Resulted windowed sum of the VPs from 1D signal detection algorithm are plotted in Figure 2.b and Sum of the Squared Error (SSE) values of the classic template matching are plotted in Figure 2.c. The results of these algorithms for the noisy case (by adding white Gaussian noise) with 3dB SNR, are also plotted in Figure 2.d and Figure 2.e, respectively. Maximum value in the windowed sum of VPs points to the correct location in both of the cases while minimum value of SSE do not occur in the middle part of the test signal for the noisy case.

In the second example, we have chosen a 512 by 512 synthesized image shown in Figure 3, from our database of comprehensive experiments. Test image is generated by adding 3dB white Gaussian noise to the original synthesized image. Reference block in the first image, Figure 3.a, and its 3 true matches in the test image, Figure 3.b, are shown by illuminated boxes around the blocks. Biorthogonal wavelet (bior2.2), were chosen for the non-adaptive wavelet transform. Parameter $v$ was set to 15 and $p$ was set to 16. The array that holds sum of the VPs, is plotted in Figure 3.c. The high peaks truly represents the location of the reference block in the test image.

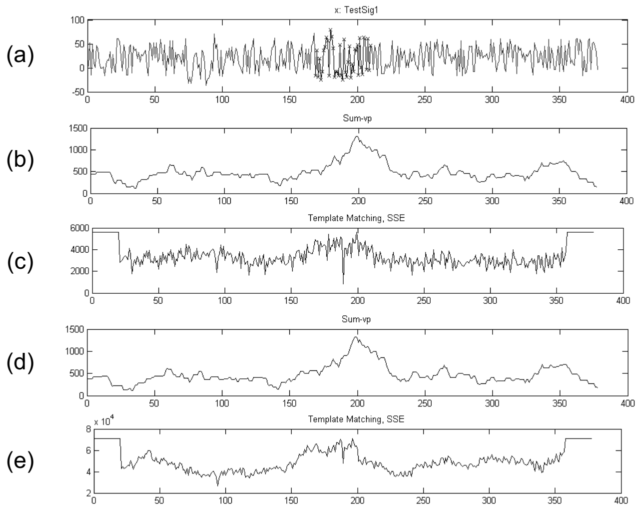


**Fig. 2.** a) Test signal, b) Windowed sum of VPs, c) Template matching, d) Windowed sum of VPs for noisy test signal, e) Template matching for noisy test signal.

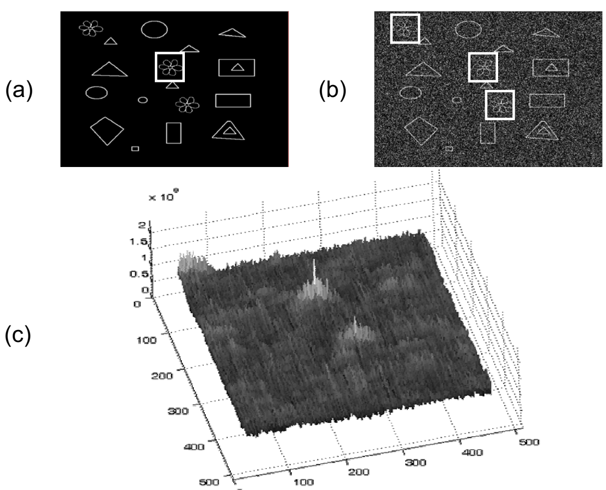


**Fig. 3.** a) Sample photo including illuminated reference block, b) Test image, c) Mesh plot of the array that holds sum of the VPs.

## 6. CONCLUSIONS

In this paper, we have presented a new adaptive lifted wavelet transform based algorithm for detecting an object of interest in a given test image. We have only examined the potential of the new adaptive lifted transform for object detection. Many variations on the presented detection algorithm could be designed to improve its performance for detecting noisy and degraded forms of the desired object. For example, one may consider deeper levels of the wavelet packet transform tree for detecting dilated and condensed objects. Moreover, one may use several different image instances of the desired object for designing prediction filter of the adaptive transform. This would make the algorithm more robust to the slight object deformations in the test image. We are currently investigating the robustness properties of our detection algorithm and comparing it with several existing object detection schemes.

## 7. REFERENCES

[1] K. Kuzume and K. Niijima, "Design of Optimal Lifting Wavelet Filters for Data Compression," *Proc. IEEE-SP International Symposium on Time-Frequency and Time-Scale Analysis*, Pittsburgh, pp. 337-340, 1998.

[2] S. G. Mallat, *A Wavelet Tour of Signal Processing*, San Diego, CA: Academic, 1998.

[3] W. Sweldens, "The lifting scheme: A construction of second generation wavelets," *SIAM Journal on Mathematical Analysis*, Vol. 29, No. 2, pp. 511-546, 1997.

[4] R. L. Claypoole, G. M. Davis, W. Sweldens, and R. G. Baraniuk, "Nonlinear wavelet transforms for image coding via lifting," *IEEE Transactions on Image Processing*, Vol. 12, No. 12, pp. 1449-1459, Dec. 2003.

[5] G. Piella and H. J. A. M. Heijmans, "Adaptive lifting schemes with perfect reconstruction," *IEEE Transactions on Signal Processing*, Vol. 50, No. 7, pp. 1620-1630, Jul. 2002.

[6] W. Trappe and K. J. R. Liu, "Adaptivity in the lifting scheme," *Proc. 33rd Conference on Information, Sciences and Systems*, Baltimore, MD, pp. 950-955, Mar. 1999.

[7] O. N. Gerek and A. E. Cetin, "Adaptive polyphase subband decomposition structures for image compression," *IEEE Trans. on Image Processing*, Vol. 9, No. 10, pp. 1649-1660, 2000.

[8] N. V. Boulgouris, D. Tzovaras, and M. G. Strintzis, "Lossless image compression based on optimal prediction, adaptive lifting, and conditional arithmetic coding," *IEEE Transactions on Image Processing*, Vol. 10, No. 1, pp. 1-14, Jan. 2001.

[9] T. F. Chan and H. M. Zhou, "Adaptive ENO-wavelet transforms for discontinuous functions," *Computational and Applied Mathematics Technical Report 99-21*, UCLA, 1999.

[10] I. Daubechies and W. Sweldens, "Factoring wavelet transforms into lifting steps," *Journal of Fourier Analysis and Applications*, Vol. 4, No. 3, pp. 245-267, 1998.