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A Least-Squares-Based 2-D Filtering Scheme for Stereo Image Compression

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***Abstract*—A two-dimensional (2-D) least squares (LS)-based filtering scheme for high fidelity stereo image compression applications is introduced in this correspondence. This method removes the effects of mismatching in a stereo image pair by applying the left image as the reference input to a 2-D transversal filter while the right image is used as the desired output. The weights of the filter are computed using a block-based LS method. A reduced order filtering scheme is also introduced to find the optimum number of filter coefficients. The principal coefficients and the disparity vectors are used together with left image to reconstruct the right image at the receiver. The proposed schemes were examined on a real stereo image pair for 3DTV applications and the results were benchmarked against those of the block-matching method.**

***Index Terms*—Least squares, stereo image compression, 2-D adaptive filtering.**

I. Introduction

Three-dimensional (3-D) video imaging has found applications in numerous areas such as 3DTV, computer games, augmented reality and surgical environments due to its capability in providing stereoscopic pictures with high resolution and great sensation of reality [1]. The compression schemes for stereo image sequences generally utilize the characteristics that there are strong spatial correlations between the right and left images as well as between the current and previous frames. The former correlation is exploited to reproduce pictures by using either the right or left image and a small amount of information that corresponds to the binocular parallax. This operation, which is similar to motion compensation generally used to predict motion in a sequence of images, is known as disparity estimation [2]–[9]. The disparity (mostly limited to the horizontal direction) vector, which requires considerably shorter length codes, will then be encoded. The decoded disparity vector is then used in conjunction with one image to generate the other one at the receiver.

Traditionally, motion estimation algorithms have been applied for disparity estimation. However, the estimation of disparity vectors requires greater accuracy compared with the estimation of motion vectors, since human eyes can see still objects sharper than moving ones and have higher resolution with 3-D images than with two-dimensional (2-D) images. In addition, there are mismatching problems between the left and right images that are caused by reflectivity/illumination differences, object occlusion, deformation,and noise that need to be compensated for.

Block-matching method is used for both disparity estimation [2], [3] as well as motion estimation [10], [11] due to its simplicity and low encoding overhead requirements. However, for disparity estimation this method has several shortcomings including blocking artifacts and lack of compensation ability for the mismatched areas. Several block-based methods were proposed [4]–[9] to provide better compensation ability with accurate disparity and/or motion estimation. The generalized block-matching method [4], [5] provides models of rotations and deformations of blocks between two images by employing the generalized spatial transformations such as affine, perspective and bilinear coordinate transformations. The phase-based methods [6], [7] use the characteristic that the phase difference in the phase domain can be related to the displacement vector between two blocks or pixels. Unlike the generalized block-matching method, these schemes are relatively insensitive to changes in the intensity and can represent displacement vector by subpixel accuracy using continuous phase information. However, these methods can not compensate for the intensity mismatching between two blocks. Baysian method [8], [9] attempts to model motion or disparity map using Markov random fields with the smoothness assumption among neighboring displacement vectors. To take care of the discontinuity of displacement vector at the object boundaries and occlusion, this method needs some *a priori* knowledge about these regions. This method does not provide compensation ability for intensity differences and further the computational effort to detect the depth discontinuity is very high.

In this correspondence, a new scheme using 2-D filtering is proposed which can be viewed as a modified version of the block-matching scheme utilizing a 2-D transversal filter to represent the effects of mismatching in stereo image pairs prior to disparity estimation. To minimize the number of filter coefficients for reconstructing the blocks, a reduced order filtering scheme is also proposed. Simulation results are presented which attest to the effectiveness of the proposed scheme in compensating for the mismatching effects when compared with the results of the standard block matching method.

II. Two-Dimensional Filtering Scheme for Disparity Estimation

The block diagram of the proposed system is shown in Fig. 1. In this scheme, the right image is considered as the desired image and the left image as the input image, X, to the 2-D transversal filter. The function of the filter is to represent the effects of mismatching between

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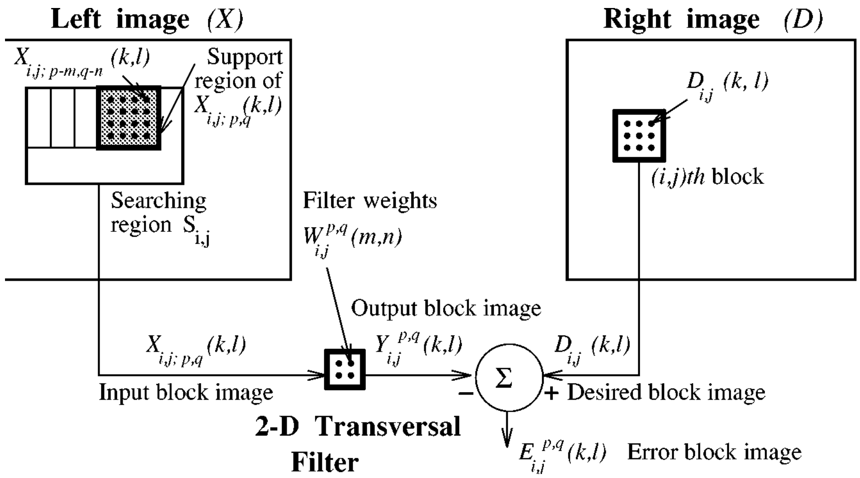


Fig. 1. Two-dimensional filtering scheme for disparity estimation (block size: 3 × 3, filter order: 2 × 2).

the right and left images prior to disparity estimation. This guarantees a better match for the right image within the search region of the left image. This is accomplished by finding the optimum filter weights to minimize the sum squared error between the right and the left filtered images. The estimated disparity and some of the filter weights are then used in conjunction with the encoded left image to reconstruct the right image. As can be observed, this scheme is inherently similar to the block matching method with the added compensation ability for the mismatching areas.

Let us assume that the right image is partitioned into nonoverlapping blocks of size K by L and the same displacement vector is assumed for all the pixels within a block. The (k,l)th pixel of the (i,j)th right image block is represented by $D_{i,j}(k,l) = D(iK+k, jL+l)$ and the corresponding pixel in the left image relatively displaced by (p,q) from $D_{i,j}(k,l)$ by $X_{i,j;p,q}(k,l) = X(iK+p+k, jL+q+l)$. The relative displacement, (p,q), is limited to the search region, i.e., $(p,q) \in S_{i,j}$. Note that the blocks in the right image move block-wise, i.e., no overlapping, while the blocks within the search region in the left image move pixel-wise, i.e., overlapping. Thus, the (i,j)th block in the right image can be expressed by $\{D_{i,j}(k,l); k \in [0, K-1], l \in [0, L-1]\}, \forall i,j$ and the candidate blocks in the search region of the left image by $\{X_{i,j;p,q}(k,l); k \in [0,K-1], l \in [0, L-1], (p,q) \in S_{i,j}\}, \forall i,j$. Now, let $W_{i,j}^{p,q}(m,n)$ and $Y_{i,j}^{p,q}(k,l)$ be the weights and output of the 2-D transversal filter, respectively, as shown in Fig. 1. Then, the filter output block can be represented by

$$Y_{i,j}^{p,q}(k,l) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} W_{i,j}^{p,q}(m,n) X_{i,j;p-m,q-n}(k,l), \quad k \in [0, K-1], \quad l \in [0, L-1] \tag{1}$$

where the filter support region of size $(K+M-1) \times (L+N-1)$ is defined by $R_{i,j;p,q} = X(r,s), r \in [iK+p-M+1, iK+p+K-1], s \in [jL+q-N+1, jL+q+L-1]$. The disparity vector is now estimated by searching the spatial location, $(p,q) \in S_{i,j}$, which minimizes the sum squared error or matching criterion

$$\hat{d}_{i,j} = \arg \min_{(p,q)\in S_{i,j}} \sum_{k=0}^{K-1}\sum_{l=0}^{L-1} \left[D_{i,j}(k,l) - Y_{i,j}^{p,q}(k,l)\right]^2. \tag{2}$$

At $\hat{d}_{i,j} = (\hat{p}, \hat{q})$ for which the minimum is attained $\hat{D}_{i,j}(k,l) = Y_{i,j}^{\hat{p},\hat{q}}(k,l), k \in [0, K-1], l \in [0, L-1], (\hat{p},\hat{q}) \in S_{i,j}$.

In contrast to the block-matching method where the original left block image, $X_{i,j;p,q}(k,l)$, is directly used in the matching process, in this scheme the filter output, $Y_{i,j}^{p,q}(k,l)$, is compared to the desired block, $D_{i,j}(k,l)$, hence providing better matching and more accurate disparity estimation.

A. 2-D Optimum Block Filter

The minimum for the matching criterion is typically found by performing pixel-by-pixel search of all the possible candidate blocks within the search region and using (1) and (2) operations. This is a very tedious and computationally demanding task. In order to decrease the computational load of this so-called full-search algorithm, fast search methods such as the three-step search [12] and cross-search [13] may be used. In this section, a block-based filtering method using the block implementation scheme [14] is devised, which estimates the disparity vector using the criterion in (2), by computing the filter weights once per block instead of once per pixel. In this method, the optimal filter weights and the filter output are computed and all the possible filter output blocks are compared to the desired block and the relative displacement vector, (p,q), at which the filter output satisfies the matching criterion is chosen as the disparity vector estimate.

Using the block implementation of 2-D transversal filters [14], a matrix form of (1) can be achieved by arranging $Y_{i,j}^{p,q}(k,l)$s and the associated $W_{i,j}^{p,q}(m,n)$s in a row-ordered vector form to yield $\mathbf{y}_{i,j}^{p,q}$ of size $KL \times 1$ and $\mathbf{w}_{i,j}^{p,q}$ of size $MN \times 1$, respectively, i.e.,

$$\mathbf{y}_{i,j}^{p,q} = \left[\hat{\mathbf{y}}_{i,j}^{p,q}(0) \quad \hat{\mathbf{y}}_{i,j}^{p,q}(1) \quad \cdots \quad \hat{\mathbf{y}}_{i,j}^{p,q}(K-1)\right]^T \tag{3a}$$

where

$$\hat{\mathbf{y}}_{i,j}^{p,q}(r) = \left[Y_{i,j}^{p,q}(r,0) \quad Y_{i,j}^{p,q}(r,1) \quad \cdots \quad Y_{i,j}^{p,q}(r,L-1)\right], \quad r \in [0, K-1] \tag{3b}$$

and

$$\mathbf{w}_{i,j}^{p,q} = \left[\hat{\mathbf{w}}_{i,j}^{p,q}(0) \quad \hat{\mathbf{w}}_{i,j}^{p,q}(1) \quad \cdots \quad \hat{\mathbf{w}}_{i,j}^{p,q}(M-1)\right]^T \tag{4a}$$

where (see (4b) at the bottom of the page).

$$\hat{\mathbf{w}}_{i,j}^{p,q}(r) = \left[W_{i,j}^{p,q}(r,0) \quad W_{i,j}^{p,q}(r,1) \quad \cdots \quad W_{i,j}^{p,q}(r,N-1)\right], \quad r \in [0, M-1]. \tag{4b}$$

Additionally, $X_{i,j;p,q}(k,l)$'s is arranged in a matrix form, $\mathbf{X}_{i,j;p,q}$ of size $KL \times MN$, i.e.,

$$\mathbf{X}_{i,j;p,q} = \begin{bmatrix} \hat{\mathbf{X}}_{iK+p,} & \hat{\mathbf{X}}_{iK+p-1} & \cdots & \hat{\mathbf{X}}_{iK+p-M+1} \\ \hat{\mathbf{X}}_{iK+p+1} & \hat{\mathbf{X}}_{iK+p} & \cdots & \hat{\mathbf{X}}_{iK+p-M+2} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \hat{\mathbf{X}}_{iK+p+K-1} & \hat{\mathbf{X}}_{iK+p+K-2} & \cdots & \hat{\mathbf{X}}_{iK+p-M+K} \end{bmatrix} \quad \text{(5a)}$$

where (see (5b) shown at the bottom of the page) and $r \in [iK+p-M+1, iK+p+K-1]$. Using this arrangement, (1) becomes

$$\mathbf{y}_{i,j}^{p,q} = \mathbf{X}_{i,j;p,q}\mathbf{w}_{i,j}^{p,q}. \quad (6)$$

The error vector, $\mathbf{e}_{i,j}^{p,q}$, of size $KL \times 1$ can be represented by

$$\mathbf{e}_{i,j}^{p,q} = \mathbf{d}_{i,j} - \mathbf{y}_{i,j}^{p,q} = \mathbf{d}_{i,j} - \mathbf{X}_{i,j;p,q}\mathbf{w}_{i,j}^{p,q} \quad (7)$$

where $\mathbf{d}_{i,j}$ is the desired output vector of size $KL \times 1$ defined by

$$\mathbf{d}_{i,j} = \left[\hat{\mathbf{d}}_{i,j}(0) \quad \hat{\mathbf{d}}_{i,j}(1) \quad \cdots \quad \hat{\mathbf{d}}_{i,j}(K-1)\right]^T \quad \text{(8a)}$$

where

$$\hat{\mathbf{d}}_{i,j}(r) = [D_{i,j}(r,0) \quad D_{i,j}(r,1) \quad \cdots \quad D_{i,j}(r,L-1)], \quad r \in [0, K-1]. \quad \text{(8b)}$$

Then, (2) can be represented in matrix form as

$$\hat{d}_{i,j} = \arg \min_{(p,q)\in S_{i,j}} \varepsilon_{i,j}^{p,q} \quad (9)$$

where the sum squared error is $\varepsilon_{i,j}^{p,q} = (\mathbf{e}_{i,j}^{p,q})^T \mathbf{e}_{i,j}^{p,q}$. In this block-based formulation, the relative displacement vector, (p,q), in the input data matrix can be shifted by the filter size, i.e., M rows and/or N columns instead of pixel-by-pixel, since the support region of input data matrix contains MN blocks of size $(K+M-1)\times(L+N-1)$ and the filter is applied to all the pixels inside that area. In this case, the displacement vector, (p,q), is represented by integer multiples of M and N, respectively. Note that in stereo image compression, much smaller filter order than the block size, i.e., $M \ll K$ and $N \ll L$ is required. This is different from the other image filtering applications such as image smoothing and enhancement [14].

Having formulated the 2-D linear filter equations in matrix form, the optimal filter weight vector, $\mathbf{w}_{i,j}^{p,q*}$, for the input data matrix, $\mathbf{X}_{i,j;p,q}$, and the desired output vector, $\mathbf{d}_{i,j}$, using the LS solution [15] is given by

$$\mathbf{w}_{i,j}^{p,q*} = \mathbf{\Phi}_{i,j;p,q}^{-1}\theta_{i,j}^{p,q} \quad (10)$$

where $\theta_{i,j}^{p,q}$ is the cross-correlation vector between the desired and input blocks, i.e., $\theta_{i,j}^{p,q} = \mathbf{X}_{i,j;p,q}^T\mathbf{d}_{i,j}$ and $\mathbf{\Phi}_{i,j;p,q}$ is the input data auto-correlation matrix given by $\mathbf{\Phi}_{i,j;p,q} = \mathbf{X}_{i,j;p,q}^T\mathbf{X}_{i,j;p,q}$.

To reconstruct the (i,j)th right image block at the receiver, the disparity vector estimate, $\hat{d}_{i,j} = (\hat{p},\hat{q})$, and the optimal filter weight vector, $\mathbf{w}_{i,j}^* = \mathbf{w}_{i,j}^{\hat{p},\hat{q}*}$, need to be encoded and transmitted. Note that the representative disparity vector can be defined by the filter lag at which the maximum value of weight $\mathbf{w}_{i,j}^*$ occurs. This scheme which allocates the same filter order to each block will be referred to as the "full-order" LS-based filtering scheme. Obviously, encoding several filter weights for each block is not efficient in practice. The following section describes a reduced order LS-based filtering scheme which uses minimal number of weights in each block depending on the type of the compensation needed.

B. Reduced Order Filtering Scheme

It is interesting to note that a large number of blocks in the right image can be reconstructed by the representative disparity vector and using the encoded reference left image without the need to use the filter weights, $\mathbf{w}_{i,j}^*$, at all. This is due to the fact that these blocks are related by simple translation. However, to remove the mismatching effects some principal filter weights in $\mathbf{w}_{i,j}^*$ should also be used for reconstruction of certain blocks. To determine these principal weights allocated in each block and to reduce the number of filter weights needed for reconstruction, a reduced order filtering scheme is introduced. A threshold value representing the quality of the reconstructed image blocks is chosen to be the block peak signal-to-noise ratio $(\mathrm{PSNR_{block}})$, i.e.,

$$\begin{aligned} \mathrm{PSNR_{block}} &= 10\log_{10} \frac{255^2}{\mathbf{e}_{i,j}^{p,q\,T}\mathbf{e}_{i,j}^{p,q}\Big/KL} \\ &= 10\log_{10}\frac{255^2}{\varepsilon_{i,j}^{p,q}/KL} \end{aligned} \quad (11)$$

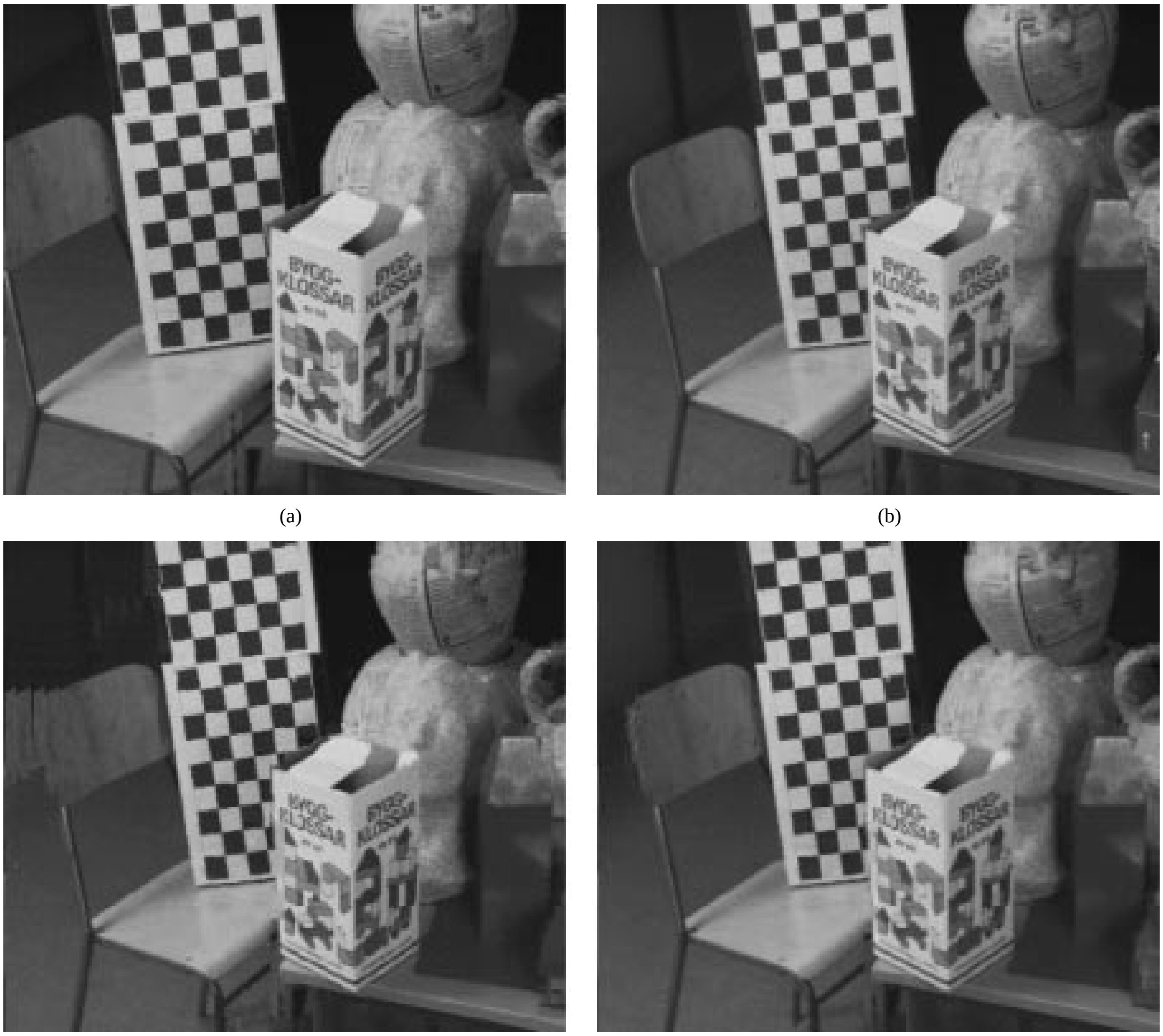
where the mean squared value of the error block, $\mathbf{e}_{i,j}^{p,q}$, is used to account for the intensity mismatching problem between two blocks instead of the variance, $\sigma^2_{\varepsilon_{i,j}^{p,q}}$.

The disparity vector and the filter weights are first estimated using the full order filtering scheme. To estimate the quality of each reconstructed block, the $\mathrm{PSNR_{block}}$ threshold value is specified. If the (i,j)th right image block can be reconstructed with only the representative disparity vector (lag of the largest weight of the full order filter) satisfying the image quality threshold, only the disparity vector is encoded, and the process moves to the next block in the desired (right) image. Otherwise, a 1st order filter at the same lag (position) will be used and the image quality threshold is computed again. To reconstruct the block, the weight at this tap is re-estimated. The filter order is increased until the image quality is satisfied or until the full-order filter is reached.

C. Fast Filtering Scheme

To reduce the computational complexity even further, the standard block-matching algorithm can first be used to estimate all the disparity vectors. Then, the 2-D transversal filtering is applied only to those blocks which suffer from mismatching problems. In this scheme, the filtering is performed only on the support region of the block at which

$$\hat{\mathbf{X}}_r = \begin{bmatrix} X(r,jL+q) & X(r,jL+q-1) & \cdots & X(r,jL+q-N+1) \\ X(r,jL+q+1) & X(r,jL+q) & \cdots & X(r,jL+q-N+2) \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ X(r,jL+q+L-1) & X(r,jL+q+L-2) & \cdots & X(r,jL+q-N+L) \end{bmatrix} \quad \text{(5b)}$$



(a) (b)

(c) (d)

Fig. 2. (a) and (b) Original stereo image pair of "Chair." (c) Reconstructed image using the standard block-matching. (d) Full-order (four weights) filtering.

the disparity is estimated. This is in contrast to the previous filtering schemes where the filtering was applied to all the blocks inside the search region.

Assume that the disparity vector for the (i, j)th right image block is estimated as $\hat{d}_{i,j} = (\hat{p}, \hat{q})$ using the block-matching method. The input matrix, $\mathbf{X}_{i,j;\hat{p},\hat{q}}$, is formed by (5a) and (5b) with support region, $R_{i,j:\hat{p},\hat{q}}$, given by $R_{i,j:\hat{p},\hat{q}} = X(iK + \hat{p} - m + k, jL + \hat{q} - n + l)$, $k \in [0, K-1], l \in [0, L-1], m \in [-M/2, M/2], n \in [-N/2, N/2]$, where the filter order is $(M + 1) \times (N + 1)$. The 2-D block filtering in (6) is then applied and the optimal filter weights are estimated using the LS method in (10).

Although this scheme offers much faster filtering process, the compensation ability is somewhat inferior to the previous scheme. Nevertheless, this scheme is very useful in practice as it adds compensation ability to the block matching method without significantly increasing the computational overhead.

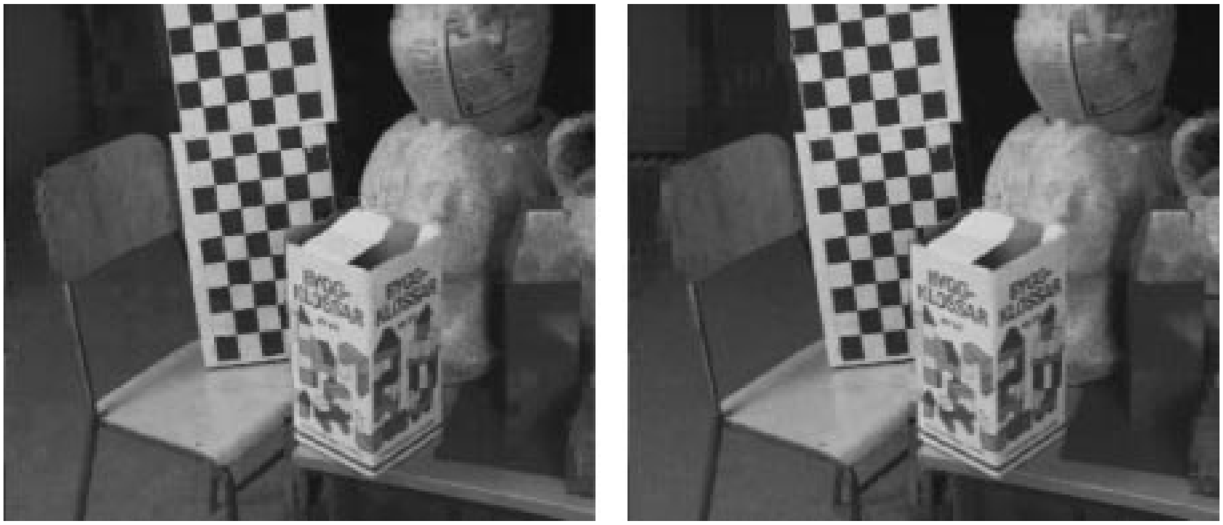
III. Simulation Results and Comparison

The performance of the proposed schemes was compared to that of the standard block-matching method on the stereo image pair, "Chair," shown in Fig. 2(a) and (b). This image pair involves several mismatching problems, thus making it ideal to test the compensation ability of the algorithms. To simplify the performance comparison of the reconstructed images, the original left image is used here instead of the encoded one. To estimate the performance of the reconstructed image, the peak signal-to-noise (PSNR) is used, i.e.,

$$\mathrm{PSNR} = 10 \log_{10} \frac{255^2}{\sigma^2_{(D-\hat{D})}} \tag{12}$$

where $\sigma^2_{(D-\hat{D})}$ is the variance of the difference or error image between the original and the reconstructed right images.

The size of each image is 280×320 with 256 grey levels. The block size was chosen to be 8×8 and the search region was defined as: left margin 48, right margin 8, upper margin 8, and lower margin 8. The standard block-matching scheme was examined first. The PSNR of the reconstructed image shown in Fig. 2(c) was measured to be 27.93 dB. This image exhibits several problems that are not compensated for. These include: occlusion on the left side of the chair and the upper part of the top right object, blocking artifacts on the letter "B" on the front container which appears as "K," deformation of the objects as shown in some of the black squares in the checker board pattern, and reflectivity differences in the background in the top of the chair. The full-order LS-based 2-D filtering scheme of order 2×2 was then applied to this image pair. As shown in Fig. 2(d), most of the blocks are reconstructed



(a) (b)

Fig. 3. Reconstructed images of the "Chair" using (a) reduced order and (b) fast filtering schemes.

TABLE I
BLOCK NUMBERS AND PERCENTAGE OF EACH CLASS IN THE RECONSTRUCTED IMAGE USING THE REDUCED ORDER FILTERING SCHEME FOR "CHAIR" (TOTAL BLOCK NUMBER $= 1\,400$)

Class of blocks	1	2	3	4	5	weights/block
No. of weights	0	1	2	3	4	
No. of blocks	772	239	102	39	248	
Percentage(%)	55.1	17.1	7.3	2.8	17.7	1.11

TABLE II
PERFORMANCE COMPARISON OF RECONSTRUCTED IMAGES USING DIFFERENT DISPARITY ESTIMATION SCHEMES FOR "CHAIR" (TOTAL BLOCK NUMBER $= 1\,400$)

$\mathrm{PSNR_{block}}$ [dB] p	Block–matching	4–weight filtering	Reduced filtering	Fast filtering
$p \geq 34$	656	945	657	733
$32 \leq p < 34$	121	116	188	177
$30 \leq p < 32$	118	98	314	222
$28 \leq p < 30$	117	89	89	101
$26 \leq p < 28$	122	68	68	60
$24 \leq p < 26$	102	41	41	52
$22 \leq p < 24$	91	28	28	26
$p \leq 22$	73	15	15	29
Overall PSNR [dB] (Improvement)	27.93	31.80 (3.87)	30.88 (2.95)	30.60 (2.67)
Average weights/block	0	4	1.11	1.44

very well. The characters on the container are much more legible. The black squares in the checker board do not exhibit deformation and the reflectivity problem on the chair top is almost compensated for. The contour on the surface of the top right object looks more distinct. Most of all, the occlusion around the left side of the chair was almost removed. The PSNR for this case was found to be 31.80 dB. The PSNR as well as the visual evaluation of the reconstructed image in Fig. 2(d) clearly indicates the compensation ability of the filtering method for the mismatched areas.

The reduced-order filtering scheme was then applied to this image pair. The threshold value of the reconstructed block image was set to 30 dB in $\mathrm{PSNR_{block}}$. The reconstructed image is shown in Fig. 3(a) for which the PSNR was measured to be 30.88 dB. The quality of this reconstructed image is obviously comparable to that of the corresponding full order case with four weights in Fig. 2(d). Table I shows the number of weights used to reconstruct this image. The blocks are separated into five different classes depending on how a block was reconstructed. For example, the blocks in class 1 were reconstructed with only the corresponding disparity vector and the blocks in class 4 required three filter weights as well. As can be seen, over 50% of the blocks do not require any weights encoding while less than 20% require all the four weights for reconstruction. Overall, an average of only 1.11 weights/block is needed to reconstruct this image. It is very remarkable that the image quality using this average weights/block is comparable to that of the full order filtering scheme in Fig. 2(d).

Using the fast filtering scheme the disparity vector was first estimated using the block-matching scheme. Then, the 2-D transversal filter of size 2×2 was applied to the blocks whose $\mathrm{PSNR_{block}}$ was less than the threshold. In this case, the $\mathrm{PSNR_{block}}$ threshold was set to 30 dB. The reconstructed image is shown in Fig. 3(b) for which the PSNR was measured to be 30.60 dB. As expected, the quality is not as quite good as the previous results, since the filtering is applied on the blocks which are selected in advance by the standard block-matching method using the reference image directly. Nonetheless, it is better than that of the block-matching method. The processing time is very much dependent on the size of the blocks and search region. However, the fast filtering scheme is substantially faster compared to the other proposed schemes. Comparing to the standard block-matching method, this method provides 2.67 dB PSNR improvement with 1.44 weights/block for applying the filter to 505 blocks among the total of 1400 blocks. This scheme can be used as an alternative to the full-order LS-based filtering scheme where fast processing is needed.

Table II shows the number of blocks in the reconstructed images for different $\mathrm{PSNR_{block}}$ in decibels depending on the disparity estimation schemes. It is noted that while the numbers of blocks with high $\mathrm{PSNR_{block}}$ ($\geq$34 dB) for both the full-order and reduced-order filtering schemes are prominently more and those blocks with $\mathrm{PSNR_{block}}$ ($\leq$22 dB) blocks are considerably less than those of the block-matching method, the numbers of reconstructed blocks whose $\mathrm{PSNR_{block}}$ is less than the predefined threshold (30 dB) in the reduced-order filtering scheme are pretty much the same as those of the full-order filtering scheme with four weights/block. In other words, the efficiency in the reduced order filtering scheme to minimize the number of filter coefficients for reconstruction is achieved by compromising the number of blocks with $\mathrm{PSNR_{block}} \geq 30$ dB.

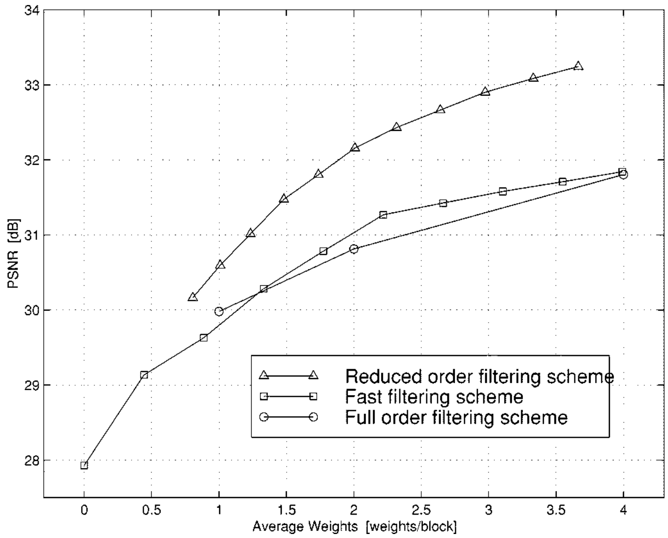


Fig. 4. Performance comparison of different schemes according to the average weights/block.

Fig. 4 represents the PSNR performance comparison of the proposed schemes with respect to the average weights/block. The plot for the full-order filter is obtained for different filter orders up to the 2×2 case, and the plots for the reduced-order and fast filtering schemes, on the other hand, are generated for different filter orders based upon the full-order 16-weight filter and the block-matching method. This is done to provide a fair comparison of these schemes based upon the same limits for the average weights/block. As can be seen from the plots, the performance of the fast filtering scheme in terms of PSNR of the reconstructed images to average weights/block is comparable to that of the full-order filtering scheme. The reduced order filtering scheme is the most effective scheme providing good quality reconstruction while reducing the encoding overhead requirement.

IV. Conclusion

A 2-D LS-based filtering scheme is proposed for removing the mismatching effects in stereo images caused by illumination/reflectivity differences, deformation, occlusion and noise. The compensation ability in this scheme is provided by using a 2-D transversal filter that models the effects of mismatching. The block implementation is employed in conjunction with the block LS method to generate the optimal weights for every block. A reduced order filtering scheme was also proposed to minimize the number of filter weights for reconstruction. Simulation results indicated the effectiveness of the proposed filtering schemes in removing the effects of mismatching problems. Future research [16] will consider development of an efficient encoding method and bit assignment strategy for the proposed filtering scheme.

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Scalable Image Coding Using Reversible Integer Wavelet Transforms

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***Abstract*—Reversible integer wavelet transforms allow both lossless and lossy decoding using a single bitstream. We present a new fully scalable image coder and investigate the lossless and lossy performance of these transforms in the proposed coder. The lossless compression performance of the presented method is comparable to JPEG-LS. The lossy performance is quite competitive with other efficient lossy compression methods.**

***Index Terms*—Integer wavelet transform, JPEG-2000, lossless, lossy, scalable compression.**

I. Introduction

The wavelet transform has been widely used in image compression. However, until recently, its use has been limited to lossy compression

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