# MODIFIED BLOCK MATCHING ALGORITHM IMPROVING RATE-DISTORTION PERFORMANCE FOR STEREOSCOPIC IMAGE CODING

*Aysha Kadaikar, Gabriel Dauphin, Anissa Mokraoui*

L2TI, Institut Galilée, Université Paris 13 Sorbonne Paris Cité
99, Avenue Jean-Baptiste Clément, 93430 Villetaneuse, France
{kadaikar, gabriel.dauphin, anissa.mokraoui}@univ-paris13.fr

## ABSTRACT

This paper deals with the block-based disparity map estimation of stereoscopic image. While most existing algorithms estimate this map by minimizing a dissimilarity metric, the proposed optimization algorithm aims at minimizing the rate-distortion compromise where the disparity map yielded by the traditional block matching algorithm is used as an initial reference map. The algorithm analyzes the performance impact of the permutation of each disparity of the reference map with all possible disparities. The retained disparity is one that improves the joint rate-distortion metric. This process is repeated as long as improvements are observed. Moreover, a particular attention is given to the updating process of the joint metric so that the computational cost of the algorithm is not affected. Simulation results clearly show that our approach achieves better performance than the traditional block matching algorithm in terms of rate-distortion compromise.

***Index Terms***— Block matching algorithm, Optimization, Disparity estimation, Entropy, Distortion.

## 1. INTRODUCTION

A growing number of 3D-applications have emerged in the last decade such as free viewpoint television and 3D visioconferencing [1–3]. Such applications require efficient coding solutions that exploit the redundant information often shared among different views of the same scene. Indeed same objects in both views are slightly shifted. This shift is referred as the disparity and is considered as a cue for the depth perception. Here, disparity is used to take advantage of the redundant information as in most stereoscopic image coding approaches. Disparity compensated coding approaches generally achieve better performance than encoding separately each view. Usually these approaches are based on four main steps: (i) coding the base view (known as a reference view in the literature); (ii) estimating the disparity map; (iii) reconstructing the predicted view with the disparity map; and (iv) coding the residual image (i.e. difference between the predicted view and base view).

Many disparity estimation algorithms exploit primitives to match corresponding pixels from both views. Finding the best match is addressed as an energy-function minimization problem, and solved locally in [4] or globally in [5, 6]. In the coding context, the Block Matching Algorithm (BMA) remains the most widespread thanks to its implementation simplicity and its coding efficiency. It yields a blockwise disparity map by selecting for each block a disparity that locally minimizes a dissimilarity measure, usually the Sum of Absolute Differences (SAD) or the Sum of Square Differences (SSD) [7]. Other methods have been introduced using a regularization constraint in the energy function ( [8–10]), or a joint entropy-distortion metric in [11].

This paper proposes a block-based disparity estimation algorithm using the disparity map provided by the BMA as an initial reference disparity map. The developed algorithm, denoted R-algorithm, aims at minimizing the rate-distortion compromise which consists of updating the reference map as long as improvements in terms of rate-distortion are observed.

The remainder of the paper is organized as follows. Section 2 introduces the principle concepts where the rate-distortion compromise is formalized as a Lagrangian minimization of a cost function. Section 3 deals with the proposed sub-optimal rate-distortion approach, referred as R-algorithm, where the proposed strategies not only improve the rate-distortion performance but also update the cost function without affecting the computational cost of the algorithm. Section 4 discusses simulation results. Finally, Section 5 concludes this work.

## 2. PRINCIPLE CONCEPTS OF THE PROPOSED BLOCKWISE DISPARITY MAP ESTIMATION

This section focuses on the principle concepts of the proposed algorithm. This algorithm estimates a blockwise disparity map where the left view is considered as the base view and the right view as the predicted view. Disparities are estimated by matching blocks under the assumption that these matching blocks are found along the same scan lines either thanks to a rectifying algorithm or because particular care was given in the shooting. Therefore all pixels within a block of the image to be predicted have the same disparity. Introduce below some notations to define the location, size, pixel-intensity and disparity of blocks.

### 2.1. Block notations

The left and right images (respectively $I_l$ and $I_r$) are of size $K \times L$ pixels and are divided into $T = X \times Y$ non-overlapped blocks, each of size $N_X \times N_Y$ pixels. Each block is represented by its block-coordinate $(i_b, j_b)$ and its pixel-coordinate $(i_p, j_p)$ indicating the top left pixel of the block.

Pixel-coordinates are linked to block-coordinates as follows : $i_p = i_b \times N_X$ and $j_p = j_b \times N_Y$. Therefore pixels inside a block have the following coordinates $(i_p + u, j_p + v)$ with $u = 0, \ldots, N_X - 1$ and $v = 0, \ldots, N_Y - 1$. $I_l(i_p + u, j_p + v)$ and $I_l(i_p + u, j_p + v)$ are respectively the pixel intensity on the left and right views.

A disparity $d(i_b, j_b)$ is assigned to each block. The blockwise disparity map, denoted **d**, is thus given by:

$$\mathbf{d} = \{d(i_b, j_b) \text{ with } i_b = 0, ..., X-1; j_b = 0, ..., Y-1\}. \quad (1)$$

For better accuracy, the considered disparities (i.e. $d(i_b, j_b)$) are not necessarily integers. Therefore the set $W$ of all possible disparities is defined with a precision of $\frac{1}{\alpha}$ where $\alpha \in \{1, 2, 4, 8\}$ and is given as follows:

$$W = \{w_{min}, w_{min} + 1/\alpha, ..., w_{max} - 1/\alpha, w_{max}\}, \quad (2)$$

where $w_{min}$ and $w_{max}$ are the searching region bounds corresponding to a length, denoted $N$, equal to $N = w_{max} - w_{min} + 1$ pixels. Note that the size of the set $W$ is different from its length $N$ and is given by $(N - 1) \times \alpha + 1$.

As a result, the pixel-intensities related to non-integer coordinates in the left view are interpolated using weighted intensities of neighbouring pixels. The left interpolated view is denoted $I_{lint}$. Intensities of pixels located at positions $(i_p + u, j_p + v)$ inside a block of the right view are thus predicted according to:

$$\widehat{I}_r(i_p + u, j_p + v) = I_{lint}(i_p + u, \alpha(j_p + v + d(i_b, j_b))) \quad (3)$$
$$\text{with } u = 0, ..., N_X - 1 \text{ and } v = 0, ..., N_Y - 1.$$

### 2.2. Rate-distortion optimization problem

This section is concerned with the problem of estimating the disparity map (i.e. **d**) achieving the best compromise in terms of rate-distortion (i.e. minimizing the distortion for a given bitrate, or minimizing the bitrate for a given quality). Before presenting the formalization of the rate-distortion optimization problem, we first define the necessary information to solve our problematic.

The required bitrate to encode the disparities is measured with the entropy, denoted $H(\mathbf{d})$, which is deduced from the empirical probabilities of each disparity within the map **d** (see equation (1)) and is given as follows:

$$H(\mathbf{d}) = -\sum_{w \in W} \frac{V(\mathbf{d}, w)}{T} \log_2 \left( \frac{V(\mathbf{d}, w)}{T} \right), \quad (4)$$

where $V(\mathbf{d}, w)$ is the number of occurrence of each disparity $w$ within the blockwise disparity map; $T$ is the total number of blocks; and $\frac{V(\mathbf{d},w)}{T}$ is thus the empirical probability of the disparity $w$ within the disparity map **d**.

The Global distortion, denoted $E_G(\mathbf{d})$, of the predicted view $\widehat{I}_r$ is calculated as follows:

$$E_G(\mathbf{d}) = \sum_{i_b=0}^{X-1} \sum_{j_b=0}^{Y-1} E_L((i_b, j_b), d(i_b, j_b)), \quad (5)$$

depending on Local quadratic distortions $E_L((i_b, j_b), d(i_b, j_b))$. Each distortion is measured between the block $(i_b, j_b)$ in the original view $I_r$ and its prediction according to the assigned disparity $d(i_b, j_b)$ given by:

$$E_L((i_b, j_b), d(i_b, j_b)) = \quad (6)$$
$$\sum_{u=0}^{N_X-1} \sum_{v=0}^{N_Y-1} (\widehat{I}_r(i_p + u, j_p + v) - I_r(i_p + u, j_p + v))^2.$$

The rate-distortion optimization problem is formalized as a Lagrangian minimization:

$$\widehat{\mathbf{d}} = \text{argmin} J(\lambda, \mathbf{d}) = \text{argmin}(E_G(\mathbf{d}) + \lambda H(\mathbf{d})), \quad (7)$$

where $\lambda$ is the Lagrangian multiplier. Equation (7) shows that the global cost $J(\lambda, \mathbf{d})$ to be minimized is a joint entropy-distortion metric. Minimizing $J(\lambda, \mathbf{d})$ for all $\lambda$ values yields to all the points on the convex hull of all possible bitrate-distortion cost.

## 3. SUB-OPTIMAL RATE-DISTORTION SOLUTION: THE PROPOSED R-ALGORITHM

This section proposes a sub-optimal solution of the joint entropy-distortion metric minimization problem expressed by equation (7). The developed optimization algorithm, denoted R-algorithm, starts with the disparity map yielded by the traditional BMA as an initial Reference disparity map. At each stage of the algorithm, this reference map is modified gradually as long as improvements are observed. The complete process is explained below.

### 3.1. Raster scanning notations

Before describing the proposed algorithm, introduce some notations. Blocks of each view are processed in a raster scanning order. For the sake of simplicity, block-coordinates $(i_b, j_b)$ are now replaced by a 1-D coordinate, denoted $t$:

$$t = i_b \times Y + j_b \text{ with } i_b = 0, ..., X - 1 \text{ and } j_b = 0, ..., Y - 1. \quad (8)$$

As a result, $t$ ranges from 0 to $T-1$ where $T$ is the total number of blocks in the right image (i.e. $X \times Y$). The block disparity of coordinate $t$ is now denoted $d_t$. The Local distortion induced by this disparity is $E_L(t, d_t)$.

The initial reference blockwise disparity map provided by the traditional BMA is defined as follows:

$$\mathbf{d}^R = \{d_0^R, d_1^R, ..., d_t^R, ..., d_{T-1}^R\}, \tag{9}$$

where $d_t^R$ is the disparity of the $t$-th block.

### 3.2. Blockwise disparity map based on the joint entropy-distortion criterion

Assume that the optimization R-algorithm has already modified the reference disparity map by processing blocks ranging from 0 to $t-1$. Therefore the updated reference blockwise disparity map $\mathbf{d}^R$ becomes:

$$\mathbf{d}^{t-1} = \{d_0, d_1, \ldots, d_{t-1}, d_t^R, \ldots, d_{T-1}^R\}, \tag{10}$$

where $d_0, d_1, \ldots, d_{t-1}$ are the disparities that may have been changed when the algorithm has processed blocks ranging from 0 to $t-1$ and $d_t^R, \ldots, d_{T-1}^R$ are the unchanged disparities of the initial reference map $\mathbf{d}^R$. The selected disparity map $\mathbf{d}^{t-1}$ generates the best global cost expressed as:

$$J(\lambda, \mathbf{d}^{t-1}) = E_G(\mathbf{d}^{t-1}) + \lambda H(\mathbf{d}^{t-1}), \tag{11}$$

where $E_G(\mathbf{d}^{t-1})$ is the global distortion induced by the predicted image and $H(\mathbf{d}^{t-1})$ is the entropy both related to the disparity map $\mathbf{d}^{t-1}$.

Note that the algorithm changes the disparity of at most one block at the time. Consider the next block, i.e. the $t$-th block, to be matched. The disparity $d_t^R$ associated to this block is replaced by each of the $(N-1) \times \alpha$ other disparities $w \in W \setminus \{d_t^R\}$ thus generating $(N-1) \times \alpha$ different disparity maps $\mathbf{d}^t(w)$:

$$\mathbf{d}^t(w) = \{d_0, d_2, ..., d_{t-1}, w, d_{t+1}^R, ..., d_{T-1}^R\}. \tag{12}$$

For each modified disparity map, a global cost $J(\mathbf{d}^t(w))$ is computed as follows:

$$J(\lambda, \mathbf{d}^t(w)) = E_G(\mathbf{d}^t(w)) + \lambda H(\mathbf{d}^t(w)), \tag{13}$$

where $E_G(\mathbf{d}^t(w))$ and $H(\mathbf{d}^t(w))$ represent respectively the updated global distortion and entropy related to the choice of $\mathbf{d}^t(w)$. The global costs $J(\lambda, \mathbf{d}^t(w))$ are then sorted in an increasing order. The disparity $w = d_t$ which is associated to the smallest $J(\lambda, \mathbf{d}^t(w))$ is then retained and the disparity map according to the process of the $t$-th block becomes:

$$\mathbf{d}^t = \{d_0, d_1, ..., d_{t-1}, d_t, d_{t+1}^R, ..., d_{T-1}^R\}. \tag{14}$$

Based on this principle, the R-algorithm continues until processing the last block (i.e. $(T-1)$-th block). A new disparity map $\mathbf{d}^{T-1}$ is then estimated introducing a minimal global cost $J(\lambda, \mathbf{d}^{T-1})$.

To further improve the rate-distortion performance, the R-algorithm iterates the described process where the disparity map $\mathbf{d}^{T-1}$ is now considered as a reference disparity map. This process is repeated as long as improvements in terms of rate-distortion are observed. Figure 1 summarizes the different steps of the proposed optimization R-algorithm.

### 3.3. Entropy and distortion recursive equations

To avoid being faced with a heavy computational load due to the calculation of $E_G(\mathbf{d}^t(w)$ and $H(\mathbf{d}^t(w)$, the R-algorithm proposes to reuse the previous results obtained after processing the $(t-1)$-th block.

The global distortion is thus updated according to the following recursive equation:

$$E_G(\mathbf{d}^t(w)) = E_G(\mathbf{d}^{t-1}) - E_L(t, d_t^R) + E_L(t, w), \tag{15}$$

where $E_L(t, d_t^R)$ and $E_L(t, w)$ being the local distortion induced respectively by the disparities $d_t^R$ and $w$ for the $t$-th block:

$$E_L(t, d_t^R) = \sum_{u=0}^{N_X-1} \sum_{v=0}^{N_Y-1} (\widehat{I}_r(i_p+u, j_p+v) - I_{lint}(i_p+u, \alpha(j_p+v+d_t^R)))^2, \tag{16}$$

and

$$E_L(t, w) = \sum_{u=0}^{N_X-1} \sum_{v=0}^{N_Y-1} (\widehat{I}_r(i_p+u, j_p+v) - I_{lint}(i_p+u, \alpha(j_p+v+w)))^2. \tag{17}$$

Note that the permutation of disparity $w$ with $d_t^R$, increases the number of occurrence $V(\mathbf{d}^t, w)$ of one unit as compared to $V(\mathbf{d}^{t-1}, w)$, while $V(\mathbf{d}^t, d_t^R)$ has decreased of one unit as compared to $V(\mathbf{d}^{t-1}, d_t^R)$. Hence, the entropy of the modified disparity map is also updated according to the following equation:

$$\begin{aligned} H(\mathbf{d}^t(w)) = H(\mathbf{d}^{t-1}) & \\ + \left(\tfrac{V(\mathbf{d}^{t-1}, d_t^R)}{T}\right) \log_2\left(\tfrac{V(\mathbf{d}^{t-1}, d_t^R)}{T}\right) & \\ - \left(\tfrac{V(\mathbf{d}^{t-1}, d_t^R)-1}{T}\right) \log_2\left(\tfrac{V(\mathbf{d}^{t-1}, d_t^R)-1}{T}\right) & \\ + \left(\tfrac{V(\mathbf{d}^{t-1}, w)}{T}\right) \log_2\left(\tfrac{V(\mathbf{d}^{t-1}, w)}{T}\right) & \\ - \left(\tfrac{V(\mathbf{d}^{t-1}, w)+1}{T}\right) \log_2\left(\tfrac{V(\mathbf{d}^{t-1}, w)+1}{T}\right). & \end{aligned} \tag{18}$$

## 4. PERFORMANCE EVALUATION

This section discusses simulation results conducted on different stereoscopic images, from Middlebury and Deimos datasets [12, 13], to evaluate the performance of the proposed optimization R-algorithm. It is compared first with the

**Input:** Left image $I_{lint}$ and right image $I_r$
**Output:** Estimated blockwise disparity map associated with $I_r$

**1.** Estimate the disparity map using the traditional BMA;
**2.** Improve the reference blockwise disparity map:
**a.** Set initial values: $\lambda$; $w_{min}$; $w_{max}$; $i_b = -1$; $j_b = -1$; $\alpha$;
**b.** Increment by 1 the row index $i_b$;
**c.** Increment by 1 the column index $j_b$;
**d.** Set the sliding matching window on the pixel $I_{lint}(i_p, j_p)$;
**e.** Replace the disparity of the current block by each of the other disparities $w$;
**f.** Update the global distortion induced by the predicted image for each choice of $w$;
**g.** Update the entropy for each choice of $w$;
**h.** Compute the global entropy-distortion cost for each $w$;
**i.** Sort the costs in a decreasing order.
**j.** Select the disparity $w$ minimizing the global cost.
**k.** Update the disparity map;
**l.** Start again from step **c** if $j_b < Y$ otherwise continue;
**m.** Start again from step **b** if $i_b < X$ otherwise continue;
**n.** Start again from step 2 if the final global cost is smaller than the initial cost, otherwise continue;
**3.** End

**Fig. 1**. Proposed optimization R-algorithm

traditional BMA. Then some additional results are provided to carry out comparisons with the Modified M-Algorithm (MMA) developed in [11].

The base image is considered as the left one. The predicted image is the right one which is derived from the uncompressed left image and the estimated blockwise disparity map using the developed R-algorithm. The bitrate associated to the disparity map is estimated by the entropy expressed in bits per pixel (bpp). The Peak Signal-to-Noise Ratio (PSNR) measures the quality of the predicted right image. For all algorithms, estimated disparities have the same quarter-pixel precision ranging from $-30$ up to $29 + 3/4$. The interpolated right image is computed using the same filters employed in the H.264 standard [14].

Figure 2 provides simulation results conducted on the stereoscopic image "Tsukuba" (Middlebury dataset) of size $288 \times 384$. The curve with circles (o) illustrates the PSNR involved by the BMA disparity map versus bpp for 13 different block sizes ($4 \times 4$ up to $16 \times 16$). For the sake of visibility, circles are joined with a dashed line.
The curves with red solid line show the performance in terms of PSNR involved by the R-algorithm disparity map versus bpp. Each curve is related to a given block size and plotted for different values of $\lambda$. Note that each curve at its right end is connected to a circle recalling that for $\lambda = 0$, the R-algorithm and the BMA have the same performance. The analysis of these curves clearly shows the advantage of our approach compared to the traditional BMA. Indeed significant gains in terms of rate-distortion are observed.

Table 1 compares the performance using four stereoscopic images "Tsukuba", "Sawtooth", "Teddy" (from Middlebury dataset) and "Stereo_13" (from Deimos dataset) for low, medium and high bitrates with 3 different block sizes ($4 \times 4$, $6 \times 6$ and $8 \times 8$). Note that the R-algorithm achieves a significant reduction in terms of bpp for a small reduction of the reconstruction quality. Hence, when processing "Tsukuba" stereoscopic image using blocks of size $4 \times 4$, the BMA requires $0.338$bpp to ensure a reconstruction quality equal to $35.12$dB, while the R-algorithm requires only $0.188$bpp for a very similar reconstruction quality equal to $34.98$dB. This important bitrate reduction is obtained by a different choice of disparities yielding a lower entropy.

For equivalent PSNR (see first line of Table 1), the BMA disparity map histogram, provided by Figure 3, is composed of many bars of medium or small height. While the R-algorithm disparity map histogram, in Figure 4, contains less bars of increased height resulting in a reduction of the disparity map entropy.

Figure 5 shows the original right image "Tsukuba", it indicates with a white box the corresponding location of the close-up views of Figure 6, showing among other items, the upper part of a lampshade. This figure shows two reconstructions of the right image with the BMA on the left and with the R-algorithm on the right. Both require the same bitrate $0.14$bpp, the BMA uses blocks of size $6 \times 6$, whereas the R-algorithm uses blocks of size $4 \times 4$. When measuring the distortion of the whole image in PSNR, we can note that the R-algorithm achieves an improvement on the BMA of $1.5$dB: $34.5$dB as compared to $32.9$dB. With a closer look we can see a better reconstruction quality with the R-algorithm as a gray block is lacking on the upper left corner of the lampshade on the left image.

The following results are provided to compare the performance of the R-algorithm with the MMA. This latter sequentially estimates a block-based disparity map by building a tree as each block is being matched. Only M-best paths are retained and explored at each depth of the tree. The MMA relies on the minimization of a similar joint entropy-distortion metric to select the best disparities. Those in the unprocessed area are assumed to follow some specific distribution. Figure 7 shows results of simulations conducted on the stereoscopic image "Stereo_13". Disparities are selected amongst the set $[-30, \ldots, 29+\frac{3}{4}]$ for all the algorithms. The dashed curve joining circles depicts the performance of the BMA using sizes of blocks ranging from $4 \times 4$ to $14 \times 14$ pixels. Results obtained with the R-algorithm (resp. the MMA) are given by the set of solid lines in red joining the "x" symbols (resp. the set of solid lines in blue joining the "+" symbols). Each of these curves is obtained with a given size of blocks and by varying the parameter $\lambda$. For better clarity, the performance of both algorithms have only been plotted for three block sizes ($4 \times 4$, $6 \times 6$ and $8 \times 8$). It can be noted that both algorithms perform better than the BMA for a given bitrate as well as for a given quality of reconstruction. Therefore, the R-algorithm achieves better performance than the MMA with a gain of up to 0.2dB in terms of PSNR over the MMA (at the bitrate of 0.13bpp).

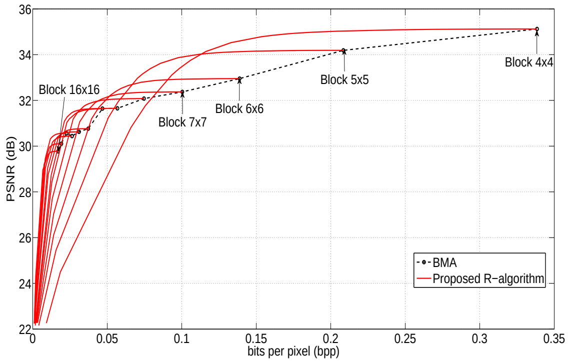


**Fig. 2**. Rate-distortion performance on "Tsukuba".

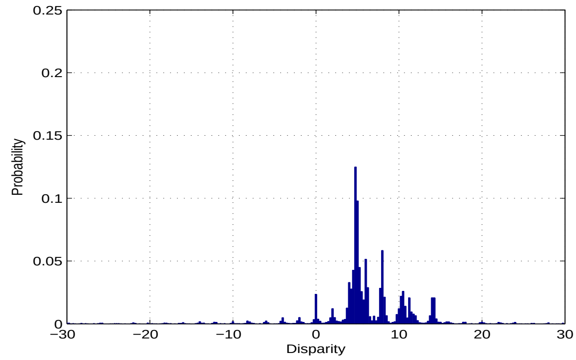


**Fig. 3**. BMA blockwise disparity map histogram.

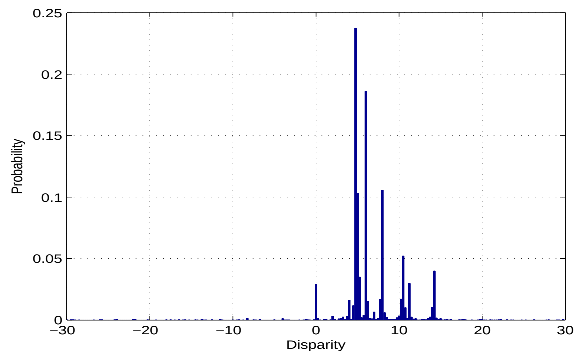


**Fig. 4**. R-algorithm blockwise disparity map histogram.

## 5. CONCLUSION

This paper focused on block-based disparity map for stereoscopic image . This problem has been formalized as an optimization problem based on the minimization of a joint entropy-distortion metric. The developed R-algorithm is a sub-optimal algorithm relying on the reference disparity map provided by the traditional BMA. This reference map is modified as long as improvements in terms of rate-distortion are observed. Moreover, this algorithm has been concerned with reducing the computational load when updating the global distortion and entropy. Simulation results conducted on stereoscopic images confirm that the proposed R-algorithm performs better results in terms of rate-distortion than the traditional BMA and also the MMA. The integration of this approach in a complete disparity compensated coding scheme will be considered in future investigations.

**Fig. 5**. "Tsukuba" original right image.

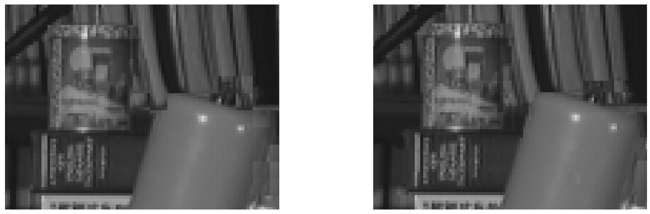

**Fig. 6**. Close-up views of the reconstructed image using the BMA (left figure) and the R-algorithm (right figure).

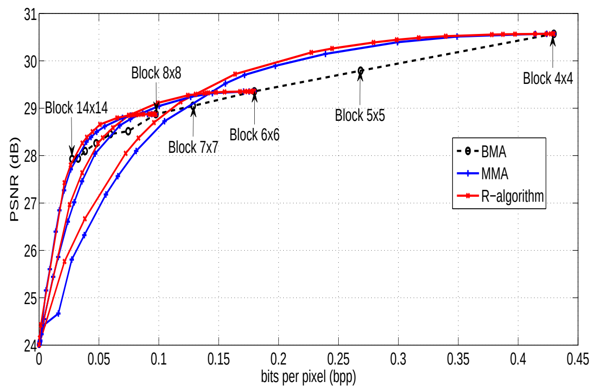


**Fig. 7**. Rate-distortion performance on "Stereo_13".

| Stereo Images | Block Size | BMA PSNR | BMA Bitrate | R-algorithm PSNR | R-algorithm Bitrate |
|---|---|---|---|---|---|
| Tsukuba | 4x4 | 35.12 | 0.338 | 34.98 | 0.188 |
| | 6x6 | 32.95 | 0.138 | 32.88 | 0.084 |
| | 8x8 | 32.08 | 0.074 | 32.00 | 0.046 |
| Stereo_13 | 4x4 | 30.57 | 0.430 | 30.48 | 0.317 |
| | 6x6 | 29.35 | 0.180 | 29.27 | 0.124 |
| | 8x8 | 28.88 | 0.097 | 28.80 | 0.065 |
| Sawtooth | 4x4 | 33.37 | 0.362 | 33.30 | 0.285 |
| | 6x6 | 31.79 | 0.154 | 31.74 | 0.126 |
| | 8x8 | 30.69 | 0.085 | 30.62 | 0.069 |
| Teddy | 4x4 | 26.14 | 0.416 | 26.06 | 0.266 |
| | 6x6 | 25.10 | 0.177 | 25.03 | 0.110 |
| | 8x8 | 24.37 | 0.095 | 24.31 | 0.062 |

**Table 1**. Comparison of rate-distortion performance.

## REFERENCES


[1] N. A. Dodgson "Autostereoscopic 3D Displays," *IEEE Computer*, vol. 38(8), pp. 31–36, Aug. 2005.

[2] M. Tanimoto, M. P. Tehrani, T. Fujii and T. Yendo "Free-viewpoint TV," *IEEE Signal Processing Magazine*, vol. 28(1), pp. 67–76, Aug. 2011.

[3] P. Kauff and O. Schreer "An immersive 3D video-conferencing system using shared virtual team user environments," *Proceedings of the 4th international conference on Collaborative virtual environments*, pp. 105–112, Sept. 2002.

[4] C. Tomasi and T. Kanade "Detection and tracking of point features.," *Pittsburgh: School of Computer Science*, Carnegie Mellon Univ., 1991.

[5] O. Veksler "Stereo Correspondence by Dynamic Programming on a Tree," *IEEE Conference Proceedings of Computer Vision and Pattern Recognition, CVPR*, vol. 2, pp. 384–390, San Diego, United States, Jun. 2005.

[6] M. Bleyer and M. Gelautz, "Graph-based surface reconstruction from stereo pairs using image segmentation," *Videometrics VIII*, vol. SPIE-5665, pp. 288–199, San Jose, United States, Jan. 2005.

[7] M. Z. Brown, D. Burschka, and G. D. Hager, "Advances in Computational Stereo," *IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI*, vol. 25(8), pp. 993–1008, Aug. 2003.

[8] W.Woo, A. Ortega, "Overlapped block disparity compensation with adaptive windows for stereo image coding," *Circuits and Systems for Video Technology, IEEE Transactions*, vol. 10(2), pp. 194–200, 2000.

[9] J. Han, Z. Lu, "Dct-based embedded coding scheme for stereo image," *Communications, Circuits and Systems, ICCCAS 2004*, vol. 1, pp. 543–547, 2004.

[10] W. Yang, K. Ngan, J. Lim, K. Sohn, "Joint motion and disparity fields estimation for stereoscopic video sequences," *Signal Processing: Image Communication*, vol. 20(3), pp. 265–273, 2005.

[11] A. Kadaikar, G. Dauphin and A. Mokraoui, "Sequential block-based disparity map estimation algorithm for stereoscopic image coding," *Signal Processing : Image Communication*, 2015.

[12] D. Scharstein and R. Szeliski, "A Taxonomy and Evaluation of Dense Two-Frame Stereo Correspondance Algorithms," *International Journal of Computer Vision, IJCV*, vol. 47(1), pp. 7–42, Apr. 2002. "http://vision.middlebury.edu/stereo/data/".

[13] M. Klima and al. "DEIMOS-an open source image database.," *Radioengineering*, vol. 20(4), pp. 1016–1023, 2011. "http://www.deimos-project.eu/tag/stereo".

[14] I. E. Richardson " The H. 264 advanced video compression standard," *John Wiley Sons*, 2011.