Stereo Image Coder Based on MRF Analysis for Disparity Estimation and Morphological Encoding

J. N. Ellinas, M. S. Sangriotis
Department of Informatics and Telecommunications, National and Kapodistrian University of Athens, Panepistimiopolis, Ilissia, 157 84 Athens, Greece
iellinas@di.uoa.gr, sagri@di.uoa.gr

Abstract

This paper presents a stereoscopic image coder based on the MRF model and MAP estimation of the disparity field. The MRF model minimizes the noise of the disparity compensation because it takes into account the residual energy, smoothness constraints and the occlusion field. The disparity compensation is formulated as a MAP-MRF problem in the spatial domain and the MRF field consists of the disparity vector and occlusion field, which is partitioned into three regions by an initial double-threshold setting. The MAP search is conducted in a block-based sense on one or two of the three regions, providing faster execution. The reference and the residual images are decomposed by a discrete wavelet transform and the transform coefficients are encoded by employing the morphological representation of wavelet coefficients algorithm. As a result of the morphological encoding, the reference and residual images together with the disparity vector field are transmitted in partitions lowering the total entropy. The experimental evaluation on synthetic and real images shows beneficial performance of the proposed algorithm.

1. Introduction

The perception of a scene with 3-D realism may be accomplished by a stereo image pair, which consists of two images of the same scene recorded from two slightly different perspectives. The two images are distinguished as the Left and the Right image, which present binocular redundancy and for that reason can be encoded more efficiently as a pair than independently. The stereoscopic vision has a very wide field of applications in robot vision, virtual machines, medical surgery etc. Typically the transmission or the storage of a stereo image requires twice the bandwidth or the capacity of a single image. The objective on a bandwidth-limited transmission system is to develop an efficient coding scheme that will exploit the redundancies of the two images, that is, the intra-image and cross-image correlation or similarities. A typical compression scenario is the encoding of one image, which is called reference and the disparity compensation of the other, which is called target. Transform coding is a method used to remove intra-spatial redundancy both from the reference and the target images. The cross-image redundant information is evaluated by considering the disparity between the two images. The disparity compensation procedure estimates the best prediction of the target image from the reference and results in the error image, which is called residual, together with a disparity vector field. The encoded reference and residual images together with the disparity vectors are entropy coded and transmitted. Therefore, the effectiveness of the encoding algorithm, the energy of the residual image and the smoothness of the disparity field affect the overall performance of the compression scheme.

Several methods have been developed for disparity compensation. The area-based methods, including either pixel or line or area matching, are simple approaches of the disparity estimation [1], [2]. The block-based matching method, either fixed or variable size (FSBM or VSBM), finds the distance between two blocks that have similar intensities within a predefined search window [3]. The block-matching algorithm may also be applied on the objects that appear after the object contour extraction in the two images [4] or on the subbands of a wavelet decomposed stereo image pair, in a hierarchical way [5]. Nevertheless, the area matching methods, either pixel or block, often fail to estimate disparity with satisfactory results, because of the non smooth variation of the disparity field due to noise and the existence of the occlusions. This may be improved by estimating the disparity field with the Markov random field (MRF) model, which provides smoothness constraints and takes into account the occlusions [6]. Some other methods code the residual part of the predicted target image by using efficient coders for “still” images, as EZW, or mixed coding [7]-[10]. Another method predicts the blocks transform of one image from the matching blocks transform of the other [11]. Another method is the subspace projection.
technique that combines disparity compensation and residual coding by applying a transform to each block of the target image [12].

Markov random field takes into account the contextual constraints by considering that the disparity field is smooth except near object boundaries. Hence, the value of a random variable, which may be a block of pixels, is influenced by the local neighbourhood system. The probabilistic aspect of the MRF analysis is converted to energy distribution through its equivalence to Gibbs distribution (GRF) with the Hammersley-Clifford theorem. The usual statistical criterion for optimality is the maximum a posteriori probability (MAP), which provides the MAP-MRF framework. Since Geman's classical work [13], many methods have been presented in motion estimation of a monoscopic video, which is very similar to the disparity estimation case. Some works use either global or local methods for the MAP estimation problem [6], [14]. The global methods, like simulated annealing (SA), converge to a global minimum with high computational cost, whereas the local methods, like iterated conditional mode (ICM), converge quickly but they are trapped to local minima. Some other methods, based on the mean field theory (MFT), provide a compromise between efficiency and computational cost [15], [16].

The novelty of the proposed coder is that employs a robust “still” image encoder and a disparity compensation process, which is performed with the MRF/GRF model for the disparity and occlusion fields. The occlusion field is initially separated in three regions by setting two threshold levels [16]. The blocks of the intermediate region, which is called uncertain, are finally characterized either as occluded or non-occluded. This reduces the number of sites needed for the MAP search procedure and makes it simpler and faster. Also, MAE instead MSE is selected in order to render our algorithm less sensitive to noise. The reference image and the resulting disparity compensated difference (DCD) or residual are decomposed by a Discrete Wavelet Transform (DWT) and encoded by employing the Morphological Representation of Wavelet Data (MRWD) coding algorithm. The disparity vectors are DPCM entropy encoded and are embedded in the formed partitions of the morphological algorithm. The outstanding features of the proposed stereoscopic coder are the inherent advantages of the wavelet transform, the efficiency and simplicity of the employed morphological compression algorithm and the effectiveness of the disparity compensation.

This paper is organized as follows. In section 2, there is an overview of the disparity compensation, the MRF model and the employed morphological encoder. In section 3, the proposed algorithm is discussed and in section 4 the experimental results are presented. Finally, conclusions are summarized in section 5.

2. Overview

2.1. Disparity in stereoscopic vision

The problem of finding the points of a stereo pair that correspond to the same 3D object point is called correspondence. The correspondence problem is simplified into one-dimensional problem if the cameras are coplanar. The distance between two points of the stereo pair images that correspond to the same scene point is called disparity. The estimation of this distance (disparity vector or DV) is very important in stereo image compression because the target image can be predicted from the reference along with the disparity vectors. Then, the difference from the original one (disparity compensated difference or DCD) is evaluated so that the redundant information is not encoded and transmitted. The disparity compensation usually employs the block matching algorithm (BMA) and estimates the residual or DCD block as:

\[
DCD(b_{i,j}) = \sum_{(x,y)\in S(i,j)} [b^R_{i,j}(x,y) - b^L_{i,j}(x+dv_x, y+dv_y)]
\]

where \(b^R_{i,j}, b^L_{i,j}\) are the corresponding blocks of the target and the reconstructed reference images respectively and \(dv_x, dv_y\) are the disparity vector components for the best match, which is defined as

\[
DV(b_{i,j}) = \arg\min_{(dv_x, dv_y)\in A} \|DCD(b_{i,j})\|
\]

where \(A\) is the window searching area and the matching criterion is the mean absolute error (MAE). The above described disparity compensation process is called closed-loop, because the prediction of the target image is performed by using the reconstructed reference image. This is quite reasonable because the reconstruction of the target image will be performed with the aid of the reconstructed reference image at the decoder’s side [8]. Alternatively, the disparity compensation may be performed with the reference image and is called open-loop disparity compensation. The open-loop systems, although they are less effective, are simpler since there is no need for an inverse quantization and an inverse wavelet transform at the encoder’s side. The disparity compensation process exploits the spatial cross-image dependency in order to remove redundant information. However, some blocks that have no correspondence may be encountered and are called occluded blocks. The sides of the stereo pair that cannot be seen directly by both eyes, as well as the areas from object overlapping are occluded regions. The occluded regions are usually tracked and excluded during the disparity compensation process.
2.2. The MRF/GRF model

In this section, the basic concepts of the MRF model are reviewed [18]. Let $S$ be a rectangular lattice of size $N$, which in this case is the disparity compensated image and that

$$D = \{D_{i,j} : (i, j) \in S\}$$

(3)
denotes a family of random variables defined on $S$ that is the random disparity field. Obviously each disparity compensated image may be viewed as a discrete sample realization of $D$, with a configuration $d$, which is a set of each random variable, i.e. block:

$$d = \{d_{i,j} : (i, j) \in S\}$$

(4)
The MRF model considers a neighbourhood system $N$ on $S$ that is defined as:

$$N = \{N_{i,j} : (i, j) \in S\}$$

(5)
where $N_{i,j}$ is the set of sites on the neighbourhood of the $(i, j)$ block. The first order neighbourhood, which is used in the present work, is a four connected structuring element shown in Fig. 1. The cliques are a subset of sites in $S$, where each site is a neighbour of the other sites in the defined neighbourhood system.

![Figure 1](#)

**Figure 1.** (a) First order neighborhood system; (b) single-site clique; (c) double-site cliques.

The MRF model states that the disparity field on site $(i, j)$ has local characteristics, which means that depends only on the disparity field of the neighbourhood sites $N_{i,j}$.

According to Hammersley-Clifford theorem [19], the probabilistic consideration of the MRF model is converted to Gibbs energy distribution in a form like:

$$U(d) = \sum_{c \in C} V_c(d) = \sum_{(i,j) \in C_1} V_1(d_{i,j}) + \sum_{(i,j) \in C_2} V_2(d_{i,j})$$

(6)
where $V_c(d)$ is the clique potential of all the possible first order clique sets which are the single-site $C_1$ and the double-site $C_2$.

The practical value of the above is that the probability of a configuration $d$ may be specified in terms of the prior potentials $V_c(d)$ for all the cliques. Let us assume that the configuration $d$, the a priori probability $P(d)$ and the likelihood density $p(r|d)$, where $r$ is the observation model, are known. Normally, the best estimate of $d$ is given by the maximum a posterior probability (MAP) which can be expressed with Bayes formula, as:

$$P(d|r) = \frac{p(r|d)P(d)}{p(r)}$$

(7)
where $p(r)$ is the density function of the observation model that does not affect the solution of (7). Therefore, MAP solution is given by

$$d = \arg \max_{d \in S} P(d|r) = \arg \max_{d \in S} \left[ p(r|d)P(d) \right]$$

(8)
According to Gibbs distribution, MAP solution is converted to the following form:

$$d = \arg \min_{d \in S} U(d|r) = \arg \min_{d \in S} \left[ U(d) + U(r|d) \right]$$

(9)
where $U(d)$ is the prior and $U(r|d)$ the likelihood energy. Finally, a configuration $d$ may be estimated by the minimization of energy equation (9), knowing the prior and the likelihood energies for a given neighbourhood system.

2.3. The morphological encoder

The conventional wavelet image coders decompose a “still” image into multiresolution bands [20], providing better compression quality than the so far existing DCT transform. The statistical properties of the wavelet coefficients led to the development of some very efficient coding algorithms such as, the embedded zero tree wavelet coder (EZW) [21], the coder based on set partitioning in hierarchical trees (SPIHT) [22] and the coder based on the morphological representation of wavelet data (MRWD) [23].

The MRWD algorithm, which is used in the present work, exploits the intra-band clustering and inter-band directional spatial dependency of the wavelet coefficients. Hence, there is a prediction of the significant coefficients in a hierarchical manner starting from the coarsest scale by using a structuring element for the morphological dilation operation. A dead-zone uniform step size quantizer quantizes all the subbands and the coefficients of the coarsest detail subbands constitute either the map of significance or insignificance, that is, a binary image with two partitions for every subband. The intra-band dependency of wavelet coefficients or the tendency to form clusters, suggests that applying a morphological dilation operator may capture the significant neighbours. The finer scale significant coefficients, in the children subbands, may be predicted from the significant ones of the coarser scale, parent subbands,
by applying the same morphological operator to an enlarged neighbourhood because the children subbands have double size than their parents. Each of these two partitions can be further partitioned into two groups. Fig. 2 shows the binary images of the detail subbands, with the formed clusters after the above described morphological operation. The black areas denote the significant coefficients, the white areas the insignificant ones, while the grey areas illustrate the insignificant coefficients that are captured as significant by dilation operation with a 3X3 structuring element. The approximation subband, which contains the low frequency components, is not subjected to this operation and all of its coefficients are considered as significant.

3. The proposed algorithm

The disparity field of a stereo image pair is a MRF/GRF model consisting of the disparity, \( D \) and occlusion, \( O \) fields. The problem is to determine the disparity and occlusion fields from the observations, which are the pair of images. The configurations \( d \) and \( o \) of the disparity and occlusion fields may be estimated by equation (9):

\[
(d, o)^{\wedge} = \arg \min_{(d, o) \in S} [U(S^R_{i,j}|S^L_{i,j}, d, o) + U(d|o) + U(o)]
\]

where \( S^L_{i,j} \) and \( S^R_{i,j} \) represent the reference and target images respectively. The first term represents the likelihood energy, the second term, called smoothness constraint, represents the prior disparity field when occlusion field is given and the third term represents the prior occlusion constraint.

3.1. The likelihood energy

The likelihood energy, which is also called similarity constraint, indicates how similar the two corresponding images are, when disparity and occlusion fields are known. Actually this may be expressed as:

\[
U(S^R_{i,j}|S^L_{i,j}, d, o) = \sum_{(i,j) \in S}(1-o_{i,j}) \sum_{(k,l) \in b_{i,j}} (c_{k,l} - c_{k,l})^2
\]

where \( o_{i,j} \) is the configuration of the occluded blocks and \( c_{k,l} \) the pixels of the processed block \( b_{i,j} \). The best matching between two corresponding blocks is decided by the minimum value of their mean absolute error (MAE).

3.2. The smoothness constraint

The prior disparity field, when occlusion field is given, is also called smoothness constraint. The minimization of the respective term in the general equation (10) provides a smooth disparity field except on the occluded points. This is expressed as follows:

\[
U(d|o) = \sum_{N_{i,j}} (1 - o_{N_{i,j}})(d_{i,j} - d_{N_{i,j}})^2
\]

where \( d_{N_{i,j}} \) is the disparity field of the first order neighbourhood system. As it is clear from the above equation, occluded neighbours are not taken into account since they represent local discontinuities. The effect of this procedure is to result in a more uniform disparity field that provides better encoding. In this work, as a measure of the energy terms in the likelihood and occlusion equations MAE is selected instead MSE, because is simpler and less sensitive to outliers.

3.3. The occlusion constraint

The prior occlusion field, called occlusion constraint, is a binary field that defines the local discontinuities. The occluded blocks are not compensated and their disparity vector is set to zero. The energy equation of the occlusion field has the following form:
\[ U(\hat{x}) = \sum_{c \in C} V(a_{ij}, \omega_{N}) + \sum_{i,j} V(a_{ij}, \omega_{N_i}) + \frac{\lambda}{2} \sum_{i,j} \| \hat{d}_{ij} - d_{ij} \|^2 \]

where \( \omega_{N_{ij}} \) are the occluded neighbours of the processed \( a_{ij} \), \( C_1 \) and \( C_2 \) are the single and double clique sites respectively. The first term provides the energy cost if a block becomes occluded and the second term encourages occlusion connectivity.

3.4. The final equation for disparity estimation

The MRF/GRF model general equation (10), taking into account (11), (12) and (13), may be expressed as:

\[ \hat{d}_{ij} = \arg\min_{d_{ij} \in S} \left\{ (1 - \lambda_d) \sum_{(i,j) \in S} (1 - a_{ij}) \sum_{(k,l) \in b_{ij}} \left( c_{ij}^R - c_{kl}^L \right) + \frac{\lambda_\delta}{N_{ij}} \sum_{(i,j) \in C_1} V(a_{ij}, \omega_{N_{ij}}) + \frac{\lambda_\alpha}{N_{ij}} \sum_{(i,j) \in C_2} V(a_{ij}, \omega_{N_{ij}}) \right\} \]

where \( \lambda_d \) and \( \lambda_\alpha \) are weighting constants that control each of the participating fields.

3.5. The proposed disparity compensation

The disparity field, which is estimated by equations (1) and (2), consists of the disparity field. The initial occlusion field is formed by employing a double threshold procedure as in [16]:

- **non-occluded block at** \((i, j) \in S_{ij} \) if \( c_{ij}^R - c_{ij}^L < T_1 \)
- **occluded block at** \((i, j) \in S_{ij} \) if \( c_{ij}^R - c_{ij}^L \geq T_2 \)
- **uncertain block at** \((i, j) \in S_{ij} \) if \( T_1 \leq c_{ij}^R - c_{ij}^L \leq T_2 \)

Thus, the occlusion field is separated in three regions:

- The non-occluded region where the blocks are always predictable.
- The occluded region where the blocks are always occluded and excluded from the MAP search.
- The uncertain region where the blocks are subjected in MAP search in order to become occluded or non-occluded.

The disparity and occlusion fields are iteratively updated according to the non-optimal deterministic method proposed in [24] in order to reduce complexity:

- Given the best estimate of the disparity field, update the disparity field by minimizing the first two terms of the final equation (14). This phase refers to the blocks that belong to the non-occluded and uncertain regions as the occluded blocks are not compensated.
- Given the best estimate of the disparity field, update the occlusion field by minimizing the last two terms of the final equation. This phase is applied on the blocks that belong to the uncertain region that should be enrolled in one of the other two regions. The first term penalizes the conversion of an uncertain block to an occluded or non-occluded block and the second term favours the connectivity of the processed block.
- The whole process is repeated until no further energy minimization takes place.

The potential costs for the occlusion phase are defined in a slightly different way than that in [16]:

\[ U(o_{ij}) = o_{ij} \left[ c_{ij} - \lambda_p \left( b_{ij} - h_{ij} \right) + \lambda_\alpha \sum_{(i,j) \in N_{ij}} h(o_{ij}, o_{ij}) \right] \]

where \( \lambda_p \), \( \lambda_\alpha \), \( \lambda_\delta \) are weighting constants. The first term of the above equation is the energy cost if an uncertain block is assigned as occluded block and is expressed in terms of the mean residual block. The second term penalizes the connectivity of an uncertain block to its neighbours. The function \( h(\cdot) \) is defined as:

\[ h(o_{ij}, o_{ij}) = \begin{cases} \left| o_{ij} - o_{ij} \right| & \text{if } (i', j') \notin \text{uncertain} \\ \left| 2 - 2 \delta(o_{ij} - o_{ij}) \right| & \text{if } (i', j') \in \text{uncertain} \end{cases} \]

where \( \delta \) is the Kronecker delta function and \( \text{sign} \) is the sign function.

If the neighbours of an uncertain block are occluded or non-occluded blocks, the cost increases with the number of neighbours that are of different kind. This term favours the connectivity of an uncertain block to its neighbourhood. If a neighbour of an uncertain block is also uncertain the cost depends on their disparity vectors difference. If this is greater than a threshold, \( \lambda_\delta \), there is no energy cost. If the difference is less than the pre-specified threshold, the energy cost increases if the two uncertain blocks are of different kind. The threshold \( \lambda_\delta \) becomes smaller over the iterations.

4. Experimental results

In this section, the experimental evaluation of the proposed coder is reported. Three grey scale stereo image pairs were used for the experimental evaluation, from which there are two synthetic images: "Room" (256X256) and "SYN.256" (256X256) and one real image: "Fruit" (512X512) [26], [27]. The proposed stereoscopic coders employ four level DWT with symmetric extension, based on the 9/7 biorthogonal Daubechies filters [25]. The parameter values are obtained by trial and error and are listed in Table 1.
• $T_1, T_2$ are the thresholds, which define an initial occlusion field.
• $\lambda_d$ controls the smoothness of the disparity vector field. Large values of this parameter may lead to blurring around object boundaries.
• $C_0, \lambda_p$ control the energy cost of an uncertain block to be assigned as occluded.
• $\lambda_o$ controls the double site cliques and enforces the connectivity of the neighbours.
• $\lambda_q$ is a variable threshold value in each iteration, which penalizes the disparity vector difference between neighbouring uncertain blocks.

The criteria employed in order to show the effectiveness of the proposed methods are the following:
• The objective quality measure of the reproduced images, which is expressed by the PSNR value in terms of the total bit-rate.
• The subjective quality measure, which is the optical quality of the reproduced target image at a specific bit rate.
• The disparity vector field entropy, $H_{DV}$, which depends on the probability of the horizontal and vertical disparity vector components. This measure indicates the randomness of the disparity field and it is intended to be as low as possible.
• The normalized average energy or MSE of the residual image, which is defined as:

$$E_{DCD} = \frac{\sum_{(i,j)\in S} [DCD(i, j)]^2}{N \times N}$$

where $S$ is the target lattice of $N \times N$ dimensions. Lower residual energy means that fewer bits are needed for encoding.

In this coder, the disparity compensation process is implemented by the classical BMA on blocks of 8X8 pixels in a searching area of 16 pixels. Table 2 shows the normalized average energy of the residual image and the entropy of the disparity vector field for BMA and MRF processes at a specific total bit rate.

### Table 2. Comparative results between BMA and MRF

<table>
<thead>
<tr>
<th>Image</th>
<th>Method</th>
<th>Total bit-rate</th>
<th>$E_{DCD}$</th>
<th>$H_{DV}$ (bpp)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Room</td>
<td>BMA</td>
<td>0.20</td>
<td>0.0308</td>
<td>0.1275</td>
</tr>
<tr>
<td></td>
<td>MRF</td>
<td>(bpp)</td>
<td>0.0198</td>
<td>0.0975</td>
</tr>
<tr>
<td>SYN.256</td>
<td>BMA</td>
<td>0.21</td>
<td>0.0186</td>
<td>0.1381</td>
</tr>
<tr>
<td></td>
<td>MRF</td>
<td>(bpp)</td>
<td>0.0189</td>
<td>0.1284</td>
</tr>
</tbody>
</table>

As expected, the MRF residual image has lower energy and the disparity vector field is smoother than that in BMA encoding. This lower energy and the smoothness of the vector field insure lower total entropy values. Fig. 3 shows the initial, (a) and the final occlusion fields, (b). In (a), the grey regions represent the uncertain field, the black areas represent the occluded field and the white areas represent the non-occluded field. The isolated occluded blocks are initially assigned as uncertain blocks, because it is desirable to exclude them as they increase the entropy cost. It is also apparent in (b) that occlusion connectivity is favoured. In Fig. 4, (a)-(d) show the residual image and disparity vector field of BMA and MRF processes for the “Room” stereo pair at a bit rate of 0.20 bpp. In Fig. 5, (a)-(d) show the residual image and disparity vector field of BMA and MRF processes for the “SYN.256” stereo pair at a bit rate of 0.21 bpp. In both, the performance of the MRF process is better than BMA. In Fig. 6, (a) and (b) show the reconstructed target image of the stereo image pair “Room” for BMA and MRF respectively. The quality of BMA and MRF processes is 26.02 dB and 28.24 dB respectively at a bit rate of 0.2 bpp. In Fig. 7, (a) and (b) show the reconstructed target image of the stereo image pair “SYN.256” for BMA and MRF respectively. The performance of BMA and MRF processes is 29.08 dB and 29.92 dB respectively at a bit rate of 0.21 bpp.

![Figure 3. Initial and final occlusion fields.](image-url)
Figure 4. Residual image and disparity vector field; (a), (b) BMA method; (c), (d) MRF method.

Figure 5. Residual image and disparity vector field; (a), (b) BMA method; (c), (d) MRF method.

Table 3 demonstrates the performance of the proposed coder for all the tested stereo pairs.

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR (dB) 0.25 bpp</th>
<th>PSNR (dB) 0.5 bpp</th>
<th>PSNR (dB) 0.75 bpp</th>
<th>PSNR (dB) 1 bpp</th>
</tr>
</thead>
<tbody>
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<td>Room</td>
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<td>36.98</td>
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<td>45.06</td>
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<td>30.76</td>
<td>35.60</td>
<td>38.63</td>
<td>41.20</td>
</tr>
<tr>
<td>Fruit</td>
<td>38.25</td>
<td>41.25</td>
<td>43.18</td>
<td>45.15</td>
</tr>
</tbody>
</table>

5. Conclusions

In this work, an algorithm employing the MRF model is proposed for the disparity estimation of a stereo image pair. The MRF model is a popular method in video community for a consistent evaluation of motion fields. It accomplishes smooth disparity fields without increasing the residual energy and thus allocates fewer bits to encode them. The proposed coder consists of disparity compensation and an encoding unit. The disparity compensation unit implements the disparity and occlusion fields using BMA. The occlusion field is separated into three regions by employing a two level threshold and the MAP search is performed on the uncertain region, which consists of blocks that are to be enrolled in the occlusion or non-occlusion regions. This approach permits faster
execution times, as the MAP search is conducted in a fraction of the whole image. The encoding unit decomposes reference and residual images by DWT and employs the morphological algorithm MRWD for compression. This algorithm partitions the coefficients of the wavelet transform and lowers their entropy. The obtained results show that the proposed method improves the quality of the reconstructed target images compared with the results that a plain BMA method may provide.

To further investigate the MRF model in disparity estimation, its application on the subband domain may be tested. This may be done by using BMA or coefficient matching, which can be embedded into the morphological encoder by using the same structuring element as that of the first order neighborhood system.

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6. References


