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LETTER

A Fast Block Matching Technique Using a Gradual Voting Strategy

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SUMMARY In this letter, a novel technique for fast block matching using a new matching criterion is proposed. The matching speed and image quality are controlled by the one control parameter called matching region ratio. An efficient matching scheme with a gradual voting strategy is also proposed. This scheme can greatly boost the matching speed. The proposed technique is fast and applicable even in the presence of speckle noise or partial occlusion.

key words: *block matching, gradual voting strategy, direct-address table*

1. Introduction

The block matching technique has been widely used for image coding, stereo vision, visual tracking and so on. However, the full-search algorithm (FSA) requires heavy computational burden so that faster algorithms have been proposed in last two decades. They can mainly be divided into four categories: 1) fast search techniques that reduce the number of candidate locations, such as the three step search (TSS), the block-based gradient decent search (BBGDS), and the hexagon-based search (HEXBS) [1]–[3]; 2) techniques based on pixel patterns or motion field decimation like N-Queen decimation [4]; 3) algorithms using a mathematical inequality based on sum norms, such as the block sum pyramid (BSP) and the winner-update algorithm (WUA) [5], [6]; and 4) exploitation of different matching criteria [7]–[9].

Because the search pattern in the above group 1) and the template decimation pattern in group 2) have been determined on the basis of off-line statistical analyses, the performance of the block matching is degraded in real applications. In a dynamic environment, the best search pattern and the best template decimation pattern cannot be easily determined.

Based on the property that the best match also has a spatial intensity distribution similar to the template block, we propose a new matching method. It gradually increases the number of candidate locations and matching parts of the template block. As a result, the proposed method allows a dynamic decision for the search pattern and the template decimation pattern. In addition, an efficient matching scheme with a gradual voting strategy is proposed that boosts the processing speed. The proposed technique is fast and applicable even in the presence of speckle noise or partial occlusion.

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2. Matching Criterion

2.1 Conventional Criterion

Common block matching algorithms utilize the sum of absolute differences for the cost function. Let us assume that there are two images, I_{t-1}, reference image, and I_t, current image. The matching error between the block at position (x, y) in I_t and the candidate block at position $(x + u, y + v)$ in I_{t-1} is usually defined as following: $\mathrm{SAD}_{(x,y)}(u, v) = \sum_{j=0}^{B-1} \sum_{i=0}^{B-1} |I_t(x + i, y + j) - I_{t-1}(x + u + i, y + v + j)|$, where the block size is $B \times B$. Most matching techniques search for the best estimate $(\hat{u}, \hat{v})$ that gives the global minimum of the matching error. That means, $(\hat{u}, \hat{v}) = \arg\min_{(u,v)\in A} \mathrm{SAD}_{(x,y)}(u, v)$, where A is the search area.

2.2 Proposed Matching Criterion

Let us assume that there is a candidate block at position $(\hat{u}, \hat{v})$ in the search area that has the same appearance as the template block. Then, the matching error of the candidate block is zero: $\mathrm{SAD}_{(x,y)}(\hat{u}, \hat{v}) = 0$.

In this case, we can find the best matching position not by calculating all matching errors, but by searching for the block which has the same appearance. For example, the best match that is similar to the template (Fig. 1 (a)) can be found at position (2, 1) in the search area (Fig. 1 (c)).

In order to measure similarity to the template block, the block matching score S and the pixel matching score P are defined as

$$S_{(x,y)}(u, v) = \sum_{j=0}^{B-1} \sum_{i=0}^{B-1} P_{(x,y,u,v)}(i, j) \tag{1}$$

$$P_{(x,y,u,v)}(i, j) = \begin{cases} 1, & |I_t(x+i,y+j) \\ & -I_{t-1}(x+u+i,y+v+j)| \le \delta_I \\ 0, & \text{otherwise,} \end{cases} \tag{2}$$

where δ_I is the margin of the intensity difference, which increases gradually during the matching process. If we calculate the block matching score $S_{(x,y)}(2, 1)$ in Fig. 1 (c), where B is 4 and δ_I is 0, we have $S_{(x,y)}(2, 1) = B^2 = 16$. This score indicates that the candidate block at (2, 1) is perfectly matched to the template.

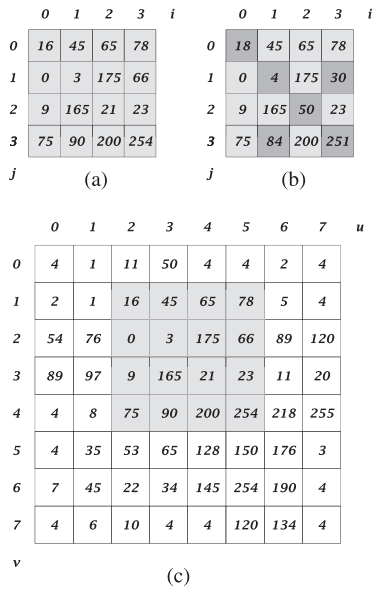


Fig. 1 Two template examples, (a), (b) and perfectly-matching case, (c).

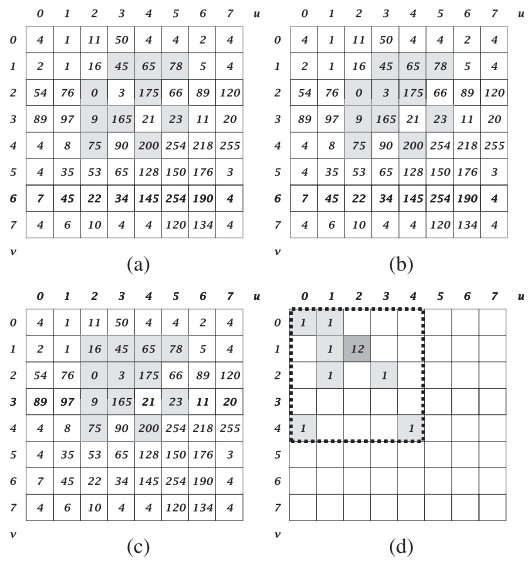


Fig. 2 The block matching score changes according to the margin of the intensity difference δ_I. Gray blocks in (a), (b) and (c) indicate matched pixels of the candidate block (2, 1) and (d) shows block matching scores of all candidate blocks when $\delta_I = 2$.

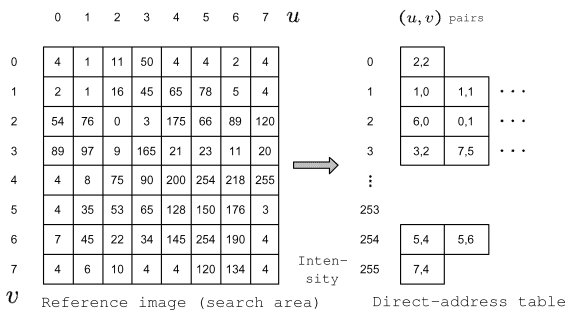


Fig. 3 The direct-address table for the search area.

2.3 Matching Procedure

Let us assume that there is no exact copy in the search area. Then the normal matching procedure is processed as follows:

1. Initialize δ_I to 0.
2. Calculate matching score $S_{(x,y)}(u, v)$ for each block at every (u, v) position.
3. Search the matching position $(\tilde{u}, \tilde{v})$ with a block matching score of $S_{(x,y)}(\tilde{u}, \tilde{v})$ that is equal to or greater than $R \cdot B^2$, where R is the matching region ratio given priorly: $S_{(x,y)}(\tilde{u}, \tilde{v}) \geq R \cdot B^2$.
4. If no candidate $(\tilde{u}, \tilde{v})$ is found, increase the margin of the intensity difference δ_I by 1 and return to Step 2).
5. If several candidates are found in Step 3, choose the best candidate that has the smallest mean of absolute difference (MAD). For fairness, MAD's should be calculated over only the matched pixels, where the pixel matching score $P_{(x,y,u,v)}(i, j)$ is 1.

Figure 1 (b) shows another template block that has 6 different intensities in comparison with the first template Fig. 1 (a). And Fig. 2 shows the matching process of a candidate block at position (2, 1) in the search area. Let us assume that R is set to 0.75. If the margin δ_I is zero, only 10 pixels are matched, which have gray color in Fig. 2 (a). However, as the margin of the intensity difference δ_I increases, the number of matched pixels also increases like Figs. 2 (b) and 2 (c). In the case $\delta_I = 2$, we can obtain the matching position with $R \cdot B^2 = 0.75 \times 4^2 = 12$ matched pixels. The final block matching scores of all candidates are shown in Fig. 2 (d) and the best candidate is located at position (2, 1).

3. Fast Matching Scheme

It is time consuming to repeatedly calculate all scores when the margin of the intensity difference δ_I varies, so we adopt a direct-address table and a gradual voting strategy to avoid excessive computation.

3.1 Direct-Address Table

First, we generate a direct-address table for the search area as depicted in Fig. 3. By using this table, all pixels with a specific intensity can be found directly. For example, if we need pixel positions that have an intensity of 254 in the search area, we can find the pixel positions at a glance, which are (5, 4) and (5, 6), as noted in Fig. 3.

3.2 Gradual Voting Strategy (GVS)

With the generated direct-address table, we can find the pixel position $(u, v)'s$ that have the same intensity as a pixel

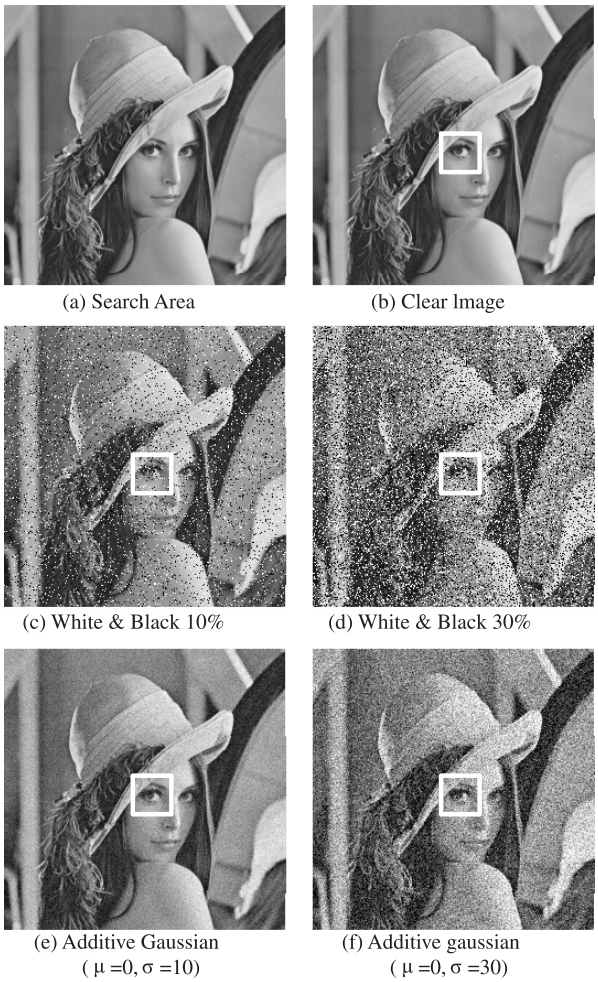
Algorithm 1 Fast Matching Scheme

I. VARIABLES

Num(k)
: number of pixels in search area which have intensity k
Direct_address_u,v(k, l)
: location (u, v) of the l-th pixel of intensity k
Template(i, j) : intensities of the template block
Vote_table(u,v) : block matching score table, $S(u, v)$
Max_vote : maximum score of $S(u, v)$
Max_vote_u, Max_vote_v: (u, v) value of the Max_vote
δ_I : margin of intensity difference
B : block size
R : matching region ratio, control parameter

II. GRADUAL VOTING STRATEGY (GVS)

```
Vote_table(u,v) = 0
Max_vote = 0
δ_I = 0
While( Max_vote < R · B^2 )
   For( j = 0 ; j < B ; j ++ )
   For( i = 0 ; i < B ; i ++ )
      k = Template(i, j) ± δ_I
      For( l = 0 ; l < Num(k) ; l ++ )
         u = Direct_addreass_u(k, l) - i
         v = Direct_addreass_v(k, l) - j
         Vote_table(u, v) ++
         If ( Max_vote ≤ Vote_table(u, v) )
            Max_vote = Vote_table(u, v)
            Max_vote_u = u
            Max_vote_v = v
         End If
      End For l
   End For i, j
   δ_I = δ_I + 1
End While
Return ( Max_vote_u, Max_vote_v )
```



(a) Search Area (b) Clear lmage
(c) White & Black 10% (d) White & Black 30%
(e) Additive Gaussian (μ =0, σ =10) (f) Additive gaussian (μ =0, σ =30)

Fig. 4 Search area and five template blocks.

at position (i, j) in the template block. Then, the candidate block at position $(u - i, v - j)$ is allotted one point. After accumulating scores, we determine the best match that has the maximum score. Until the best match reaches a threshold score $R \cdot B^2$, the margin of the intensity difference increases. The proposed algorithm is stated in Algorithm 1.

3.3 Reduction of Computational Cost

According to (1), evaluating one $S(u, v)$ requires B^2 pixel decisions for each δ_I. Without fast matching scheme, it requires $256 \times B^2$ operations to exploit full δ_I's, from 0 to 255. However, in the proposed fast matching scheme, each pixel-to-pixel matching is treated only once so that only B^2 operations are required totally. It can greatly boost the matching speed.

4. Simulation Results

When the size of the search area is $M \times M$ and the block size is $B \times B$, the number of operations of the full-search algorithm is $(M - B + 1)^2 B^2$. Our proposed algorithm requires only M^2 operations to generate the direct-address table and B^2 for matching in the best case. For performance evaluation, five template blocks of size 8×8 in Figs. 4 (b)-(f) were used, and the search area of size 256×256 is given in Fig. 4 (a).

The operation count and execution time per block matching are summarized in the Table 1, The four well-known block matching schemes, FSA, TSS, BSP, and WUA, were contrasted with the proposed scheme (GVS), where the matching region ratio R is 0.1. The five algorithms were implemented using Visual C++ 6.0 on a machine with the Intel Core 2 Quad Q8200 2.33 GHz processor. Five sub-tables were extracted with five different template blocks, which are noted below each sub-table. Notice that TSS is fast but its PSNR is low.

Tests I-IV show that the proposed technique outperforms the conventional algorithms. The proposed algorithm is fast and applicable even in the presence of speckle noise or partial occlusion, as emphasized in Tests II & III. A counterexample is given in Test V, where additive white gaussian noise is severe. In such case, the effect of matching region ratio become clear. As the matching region ratio increases, matching error become reduced with degradation of speed, as shown in the Table 2. The matching region ratio R is an important parameter controlling the matching speed and the

Table 1 Performance comparison.

Algo-	Operations		Execution Time		Speed	PSNR
rithm	Number	%	μs	%	Up	(dB)
FSA	3968064	100	60855	100	1	—
TSS	3648	0.09	64	0.11	951	—
BSP	62064	1.56	3819	6.28	16	—
WUA	62269	1.57	3425	5.63	18	—
GVS	24117	0.61	2355	3.87	26	—
* Test I : Template Block of Clear Image						
FSA	3968064	100	64000	100	1	17.86
TSS	3648	0.09	67	0.1	955	13.4
BSP	632273	15.93	13180	20.59	5	17.86
WUA	95385	2.4	4578	7.15	14	17.86
GVS	22175	0.56	2352	3.68	27	17.86
* Test II : Template Block of Noisy Image (White & Black 10%)						
FSA	3968064	100	66426	100	1	11.92
TSS	3648	0.09	70	0.11	949	10.54
BSP	1773525	44.69	30688	46.2	2	11.92
WUA	791765	19.95	20221	30.44	3	11.92
GVS	18214	0.46	2352	3.54	28	11.92
* Test III : Template Block of Noisy Image (White & Black 30%)						
FSA	3968064	100	62206	100	1	29.2
TSS	3648	0.09	65	0.1	957	16.71
BSP	365313	9.21	9049	14.55	7	29.2
WUA	82561	2.08	4470	7.19	14	29.2
GVS	70079	1.77	4447	7.15	14	29.2
* Test IV : Template Block of Noisy Image (Additive Gaussian, $\mu = 0$, $\sigma = 10$)						
FSA	3968064	100	65388	100	1	17.15
TSS	3648	0.09	71	0.11	921	15.46
BSP	1152905	29.05	22105	33.81	3	17.15
WUA	816485	20.58	20501	31.35	3	17.15
GVS	62862	1.58	4098	6.27	16	13.04
* Test V : Template Block of Noisy Image (Additive Gaussian, $\mu = 0$, $\sigma = 30$)						

Table 2 Effect of matching region ratio.

Ratio	Operations		Execution Time		Speed	PSNR
(R)	Number	%	μs	%	Up	(dB)
FSA	3968064	100	65388	100	1	17.15
0.1	62862	1.58	4098	6.27	16	13.04
0.2	227484	5.73	11435	17.49	6	14.49
0.3	308968	7.79	14632	22.38	4	14.01
0.4	603883	15.22	28516	43.61	2	14.25
0.5	857826	21.62	37634	57.55	2	14.91
0.6	1154511	29.1	50850	77.77	1	17.15
* Test V : Template Block of Noisy Image (Additive Gaussian, $\mu = 0$, $\sigma = 30$)						

image quality, and can be chosen by observing the statistics of speckle noise or partial occlusion.

5. Conclusion

We proposed a new matching method based on the property that the best match also has a spatial intensity distribution similar to the template block. The proposed scheme gradually enlarges the candidate locations and the matching parts of the template block. As a result, the proposed method allows a dynamic decision regarding the search pattern and the template decimation pattern. In addition, an efficient matching scheme with a gradual voting strategy is proposed that boosts the processing speed. We described the pseudo code for the proposed algorithm and compared the performance of the proposed algorithm with those of two representative algorithms: the full-search algorithm and the winner-update algorithm. Simulation results show that the proposed matching algorithm is fast and applicable even in the presence of speckle noise or partial occlusion.

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