객체지향 분석-합성 부호화를 위한 효율적 움직임 파라미터 추정 알고리듬

이 창 범[†] · 박 래 홍[††]

요 약

객체지향 분석-합성 부호화는 일련의 영상들을 여러 개의 동 객체로 분할한 후 각 객체의 움직임을 추정하고 보상한다. 그것은 각 객체에 있는 움직임 정보를 추정하기 위해 변환 파라미터 기법을 적용하는데 이때 변환 파라미터 기법은 그레디언트 연산자를 사용하기 때문에 매우 복잡한 계산이 요구된다. 본 논문의 목적은 객체지향 분석-합성 부호화에서 계층적 구조를 사용한 효율적인 변환파라미터 기법을 개발하는 것이다. 이러한 목표를 달성하기 위해 본 논문은 계층적 구조를 사용한 하이브리드 변환파라미터 추정 방법과 적응형 변환 파라미터 방법의 두 가지 알고리듬을 제안한다. 전자는 파라미터 검증 방법을 사용하는데 원 영상을 1/4로 축소한 저해상도 영상에서 파라미터 검증 처리 방법에 의해 6-파라미터 또는 8-파라미터로 추정한다. 후자는 동일한 계층적 방법을 적용한 다음 변환 파라미터를 적응적으로 추정하기 위해 temporal co-occurrence 행렬에 기반한 움직임 량을 측정하는 움직임 판단기준을 사용한다. 이러한 방법은 고속이며, 병렬처리 기법을 사용할 경우 쉽게 하드웨어로 구현할 수 있는 이점이 있다. 이론 분석 및 모의시험 결과 제안한 방법이 기존 방법에 비해 약 1/4 정도로 월등한 계산량 감축을 얻을 수 있었으며, 아울러 제안한 방법들에 의해 복원된 신호대 잡음비는 6-파라미터와 8-파라미터 추정 방법에 의해 복원된 결과들 사이에 있음을 보여 준다.

Efficient Algorithms for Motion Parameter Estimation in Object-Oriented Analysis-Synthesis Coding

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ABSTRACT

Object-oriented analysis-synthesis coding (OOASC) subdivides each image of a sequence into a number of moving objects and estimates and compensates the motion of each object. It employs a motion parameter technique for estimating motion information of each object. The motion parameter technique employing gradient operators requires a high computational load. The main objective of this paper is to present efficient motion parameter estimation techniques using the hierarchical structure in object-oriented analysis-synthesis coding. In order to achieve this goal, this paper proposes two algorithms : hybrid motion parameter estimation method (HMPEM) and adaptive motion parameter estimation method (AMPEM) using the hierarchical structure. HMPEM uses the proposed hierarchical structure, in which six or eight motion parameters are estimated by a parameter verification process in a low-resolution image, whose size is equal to one fourth of that of an original image. AMPEM uses the same hierarchical structure with the motion detection criterion that measures the amount of motion based on the temporal co-occurrence matrices for adaptive estimation of the motion parameters. This method is fast and easily implemented using parallel processing techniques. Theoretical analysis and computer simulation show that the peak signal to noise ratio (PSNR) of the image reconstructed by the proposed method lies between those of images reconstructed by the conventional 6- and 8-parameter estimation methods with a greatly reduced computational load by a factor of about four.

키워드 : 객체지향 부호화(Object-Oriented Coding), 파라미터 추정(Parameter Estimation), 초저비트율 부호화(Very Low Bitrate Coding), 멀티미디어 통신(Multimedia Communication)

1. Introduction

Object-oriented analysis-synthesis coding (OOASC)[1-8] is very important for development of various multimedia applications in Internet and wireless communication networks. The three-dimensional (3-D) motion of an object was represented by eight parameters on the two-dimensional (2-D) image plane [9]. The object-oriented coder using block-based motion vectors and multiple frame prediction for motion parameters [10, 11] were proposed. This paper investigates motion detection and compensation in OOASC. OOASC divides an image into a number of moving objects and encodes each object by three sets of parameters : mo-

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tion, shape, and color information. Thus it reconstructs real motions better than conventional blockwise motion-compensated coding techniques at very low bitrates. It uses a motion parameter technique for estimating motion information of each object, which employs gradient operators, requiring a high computational load.

The main objective of this paper is to present two motion parameter estimation methods using the hierarchical structure in object-oriented analysis-synthesis coding. One uses a hybrid motion parameter estimation method (HMPEM) whereas the other uses an adaptive motion parameter estimation method (AMPEM) which employs temporal co-occurrence matrices as a motion detection criterion. Also the proposed hybrid motion parameter estimation methods adaptively use six parameters for objects with simple motions or eight parameters for objects with complex motions. To reduce the computational complexity of motion estimation, we estimate motion parameters using a verification procedure embedded in a hierarchical structure.

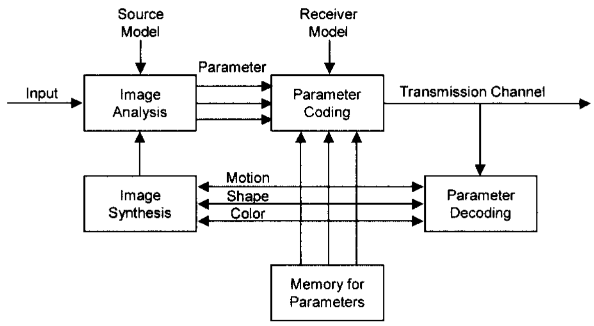
The rest of the paper is organized as follows. In Section 2, the concept and structure of object-oriented analysis-synthesis coding are briefly discussed and estimation of the motion parameters is presented. In Sections 3 and 4, the HMPEM and the AMPEM using the hierarchical structure are presented, respectively. In Section 5, experimental results are discussed. Finally in Section 6, a conclusion is given.

2. Estimation of Motion Parameters

2.1 Concept and Structure of OOASC

According to the wide range of multimedia applications, very low bitrate coding techniques are necessarily required. Up to now, a large amount of research has been done, among which a model-based coding technique is one of promising approaches to very low bitrate coding. OOASC is one of model-based coding methods. To explain the concept and structure of the object-oriented coder, its block diagram is shown in (Figure 1), where the simplified model of planar rigid objects with only translational motions is assumed. The image analysis part analyzes an input image and estimates three sets of parameters that can describe each object in an image. The image synthesis part reconstructs an image by estimated parameters and verifies estimated parameters based on the quality of a reconstructed image. The analysis fails in image areas that cannot be successfully described by the source model being applied. Therefore the success of the image analysis part is checked by a verification algorithm. Those areas that cannot be successfully described by the model are marked as special objects in a final step of the hierarchical analysis procedure. These objects are coded by a contour- texture coding method. The parameter coding (decoding) part codes (decodes) detected parameters[1-8].

Objects and their parameters are obtained by analyzing an input image at the transmitter, and using encoded parameters a reconstructed image is obtained at the receiver as well as at the transmitter. In this structure the image analysis part plays an important role because the final performance of a coder largely depends on the success of the image analysis part.



(Figure 1) A block diagram of OOASC

2.2 Computation of the Motion Parameters

Image segmentation[12-14] is one of the most important elements in automated image analysis, because it is at this step that objects or other entities of interest are extracted from an image for subsequent processing. In this paper, a region growing technique[14] is used. And the source model used in analysis is based on the assumption of rigid planar objects that move arbitrarily in the 3-D space. We assume that a point $P(x', y', z')$ moves to $P(x, y, z)$ in the 3-D space, i.e., a point (X', Y') in the 2-D image plane ($Z = 0$) is mapped to a point (X, Y) using eight motion parameters a_i's, $1 \le i \le 8$.

$$(X', Y') = \left(\frac{a_1 X + a_2 Y + a_3}{a_7 X + a_8 Y + 1}, \frac{a_4 X + a_5 Y + a_6}{a_7 X + a_8 Y + 1} \right). \quad (1)$$

Then the frame difference (FD) $FD(X, Y)$ between two successive frames can be formulated as

$$\begin{aligned} FD(X, Y) &= S_{k+1}(X, Y) - S_k(X, Y) \\ &= S_k(X', Y') - S_k(X, Y) \\ &= S_k(A(X, Y)) - S_k(X, Y) \end{aligned} \quad (2)$$

where $S_{k+1}(X, Y)$ and $S_k(X, Y)$ represent the $(k+1)$th and kth frames, respectively, and A denotes coordinate transformation from (X, Y) to (X', Y'). An important problem in motion estimation is the question how to judge the accuracy of the estimate. In [15], these tasks are investigated for gradient-based estimation methods. Therefore the equation describing motion of a pixel is rewritten as

$$\begin{aligned} FD(X, Y) = \ & G_X X \Delta a_1 + G_X Y \Delta a_2 + G_X \Delta a_3 + G_Y X \Delta a_4 \\ & + G_Y Y \Delta a_5 + G_Y \Delta a_6 - X(G_Y X + G_Y Y)\Delta a_7 \\ & - Y(G_X X + G_Y Y)\Delta a_8 \equiv H \cdot \Delta a \end{aligned} \quad (3)$$

where Δa is a 8-parameter vector defined by $(\Delta a_1, \Delta a_2, \Delta a_3, \Delta a_4, \Delta a_5, \Delta a_6, \Delta a_7, \Delta a_8)^T$ and $H = [G_X X, G_X Y, G_X, G_Y X, G_Y Y, G_Y, -X(G_X X + G_Y Y), -Y(G_X X + G_Y Y)]$. Also $G_X(X, Y)$ and $G_Y(X, Y)$ are given by

$$G_X = \frac{1}{2}\left\{\frac{\partial S_{k+1}(X, Y)}{\partial X} + \frac{\partial S_k(X, Y)}{\partial X}\right\}$$

$$G_Y = \frac{1}{2}\left\{\frac{\partial S_{k+1}(X, Y)}{\partial Y} + \frac{\partial S_k(X, Y)}{\partial Y}\right\}$$

where $G_X(X, Y)$ and $G_Y(X, Y)$ denotes local gradients in the X and Y directions, respectively.

The 8-parameter vector Δa can be obtained by linear regression :

$$\Delta a = (H^T H)^{-1} H^T FD \quad (4)$$

where $FD = (FD_1, FD_2, \cdots, FD_N)^T$ denotes an $N \times 1$ FD vector, FD_i represents an FD value at the ith point between 1 and N, and N signifies the number of point pairs considered in motion parameter estimation. $H = (H_1, H_2, \cdots, H_N)^T$ signifies an $N \times 8$ matrix, where H_i consists of gradient components of intensity and pixel positions.

If objects are far from a camera, we can simplify (1) by six motion parameters :

$$(X', Y') = (a_1 X + a_2 Y + a_3,\ a_4 X + a_5 Y + a_6). \quad (5)$$

Similarly, we can estimate six motion parameters.

3. Proposed Method based on HMPEM

3.1 Hierarchical Structure

In the proposed method, we generate difference images in a hierarchical structure. We obtain a low-resolution FD image by subtracting the previous frame from the current frame and then by selecting the largest value with a sharp change in a 2×2 block, i.e., we decimate an FD image by a factor of two in horizontal and vertical directions. Then we apply the proposed HMPEM to a low-resolution image.

Computational complexity of the conventional 6-and 8-parameter methods and the proposed hierarchical one can be explained as follows. Let N be the number of pixels of an arbitrary object. In the 6- (8-) parameter estimation method, H and FD represent an $N \times 6$ ($N \times 8$) matrix and $N \times 1$ vector, respectively. Whereas in the proposed hierarchical method, the number of pixels is reduced to $N/4$ by decimation, resulting in reduced dimensions of a matrix and vector. Neglecting the computational complexity of 6×6 (8×8) matrix inversion, numbers of multiplications/divisions and additions/ subtractions required for estimation of motion parameters in (4) are reduced by a factor of about four, resulting in a fast motion parameter estimation method by introducing a hierarchical structure in difference images. Comparison of computational loads for the 8-parameter method and proposed hierarchical one is shown in <Table 1>, with N = 100.

⟨Table 1⟩ Comparison of computational requirements for the 8-parameter method and proposed hierarchical one (N = 100)

	8-parameter method	proposed method	ratio(%)
multiplication/division	14,112	3,912	27.72
addition/subtraction	13,120	3,520	26.83

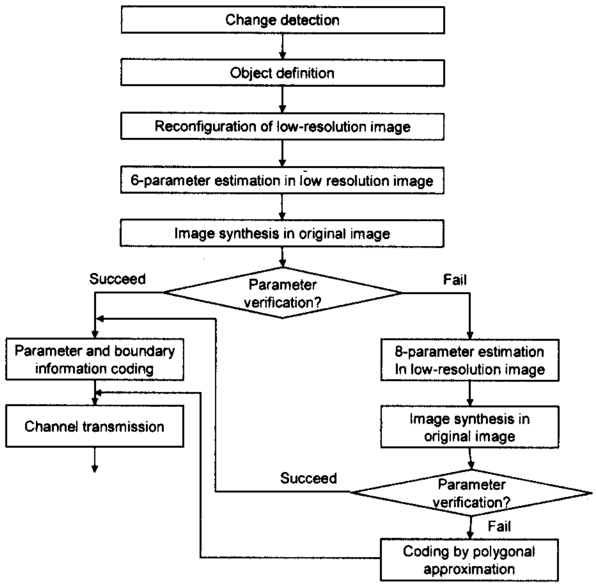
3.2 Verification Test

In an image analysis scheme, an internal image synthesis step should be performed, which is achieved with the estimated motion parameters. For each object, the success of image analysis is checked by the verification test that controls the coincidence of the estimated and real object motions based on the mean squared displaced frame difference (DFD). Note that motion parameter estimation is based on minimization of the DFD. If there are moving objects in front of currently considered objects, i.e., if occlusion occurs, then the motion parameter description is valid only in a part of an object. For that reason, the verification test results in additional detection of areas that are not correctly described by a given parameter motion model.

If the verification test succeeds, the motion parameters and object boundaries are coded. Otherwise, the regions are coded by second-order polynomial approximation [14].

3.3 Structure of the Proposed Method

(Figure 2) shows a block diagram of the proposed method. The change detection part extracts regions having significant motions between two successive frames.



(Figure 2) A block diagram of the HMPEM

The proposed hybrid algorithm using adaptively six or eight parameters is described as follows. The object definition part first splits the change region into a number of objects by a region growing technique [14] and labels each object. Then a low-resolution image is obtained using the proposed hierarchical structure. Next six motion parameters are estimated for each object in a low-resolution image, size of which is equal to one fourth of that of an original image. Then these parameter values are verified by computing the peak signal to noise ratio (PSNR) between an original object image and the image synthesized by detected six parameters. If the verification test succeeds, the motion parameters and object boundaries are coded. Otherwise, eight motion parameters are estimated in a low-resolution image. Then the verification test is again performed with an image reconstructed by estimated parameters. If it succeeds, the parameters and object boundaries are coded, otherwise, the regions are coded by second-order polynomial approximation [14]. The proposed HMPEM adaptively uses six parameters for objects with simple motions or eight parameters for objects with complex motions.

4. Proposed Method based on AMPEM

4.1 Motion Detection Criterion

In this proposed method, the motion detection criterion using co-occurrence matrices [16, 17] is applied. It determines whether six motion parameters or eight motion parameters are used for each object. The temporal co-occurrence matrices are applied to interframe video coding generally. The co-occurrence matrix can be defined as the second-order joint conditional probability density function $f(i, j \mid d, \theta)$. Each element of $f(i, j \mid d, \theta)$ denotes the probability of going from gray level i to another level j, given that the intersample interval is d and the direction is specified by the angle θ. The elements can be written in matrix form, as the so-call co-occurrence matrix. The definition of the co-occurrence matrix can be extended to the temporal domain if the pair of pixels is taken from two successive coordinates. This can be written as

$$\begin{aligned} f_t(i,j) = (&\textit{Number of pairs of pixels where} \\ & g(x,y,t_1)=i \text{ and } g(x,y,t_2)=j)/ \\ & (\textit{Total number of pixel pairs in the region}) \end{aligned} \quad (6)$$

where t_1 and t_2 represent the time indices corresponding to two successive frames of the image sequence. The construction of the temporal co-occurrence matrix is simple and fast. For every block or sub-image of $N_x \times N_y$ pixels from two successive frames, $g_1(x, y, t_1)$ and $g_2(x, y, t_2)$, the following operations are performed :

```
For y = 0, 1, ···, Ny
begin
    For x = 0, 1, ···, Nx
    begin
        increment the element
        ft (g1(x, y, t1), g2(x, y, t2)) by one
    end
end                                             (7)
```

This requires $N_x \times N_y$ operations with each operation being simply a comparison and an addition. The definition in (6) implies that the diagonal elements of the temporal co-occurrence matrix represent the numbers of unchanged pixels, and the off-diagonal elements give the number of changed pixels from one frame to another. This property can be used to define a criterion for the amount of motion within an image given by

$$\textit{Motion detection criterion} = \frac{\textit{Sum of off-diagonal elements}}{\textit{Sum of all elements}}. \quad (8)$$

The motion detection criterion takes values between 0 and 1, where 0 corresponds to identical successive frames (no motion at all) and 1 corresponds to completely different frames (e.g., scene change). The temporal co-occurrence matrices can also classify the interframe difference picture into several layers. A quantitative measure for the pixel classification can be defined by the temporal classification ratio (TCR).

$$TCR = \frac{Sum\ of\ the\ most\ important\ elments}{Sum\ of\ the\ non-diagonal\ elements}. \quad (9)$$

TCR is used for obtaining a threshold Th_2 in the moving criterion process.

4.2 Structure of the Proposed Method

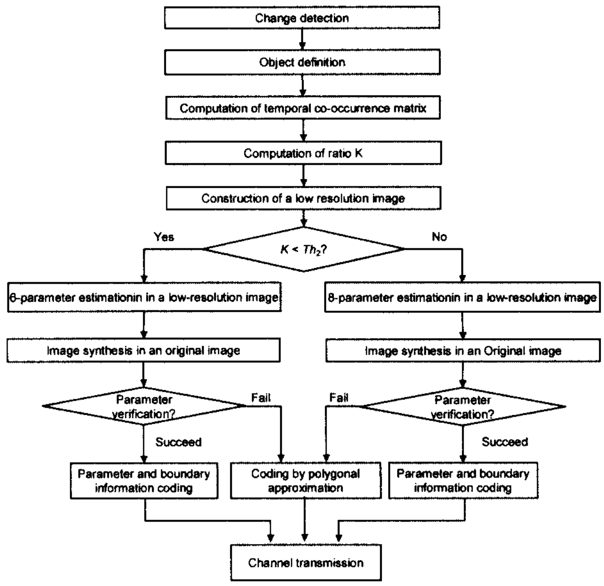
The AMPEM is proposed in this paper. The HMPEM as mentioned in Section 3 estimates six motion parameters for each object in a low-resolution image. If the verification test succeeds, the motion parameters and object boundaries are coded. Otherwise, eight motion parameters are estimated in a low-resolution image. So it requires a higher computational load. However, this adaptive motion parameter estimation can classify an object by the temporal co-occurrence matrix whether the object has simple motion or complex motion. This process is described as follows.

① Step 1 : The temporal co-occurrence matrix is computed for each object using two successive frames.
② Step 2 : The ratio K is computed, where K represents the ratio of important elements in the temporal co-occurrence matrix to the total number of pixels in the object. Note that important pixels have values greater than a threshold Th_1.
③ Step 3 : If the ratio computed in step 2 is lower than a threshold Th_2, it is considered as the object with simple motion. Otherwise, it is considered as the one with complex motion.

Using the moving criterion process, the adaptive motion parameter estimation employs a 6-parameter method for an object with simple motion and an 8-parameter method for an object with complex motion. The method also uses the hierarchical structure as mentioned in Section 2. (Figure 3) shows a block diagram of the proposed method.

The proposed adaptive algorithm using six or eight parameters based on the motion detection criterion is described as follows. The object definition part first divides the change region into a number of objects by a region growing technique and labels each object. Then the temporal co-occurrence matrix and the ratio K according to a given threshold Th_1 for each object are computed.

Then a low-resolution image is obtained using the proposed hierarchical structure. Next, if K is smaller than a threshold Th_2, it is considered as the object with simple motion, otherwise, it is considered as the one with complex motion. This parameter estimation employs the 6-parameter method for an object with simple motion whereas the 8-parameter method for an object with complex motion. Then these parameter values are verified by computing the PSNR between an original object image and the image synthesized by estimated 6- or 8- parameters. If the verification test succeeds, the motion parameters and object boundaries are coded, otherwise, the regions are coded by second-order polynomial approximation [11].



(Figure 3) A block diagram of the AMPEM

5. Experimental Results and Discussions

In computer simulations, the performance of conventional methods and the proposed ones are compared. We use 150 frames of "Miss America" and "Salesman" sequences, each of which consists of 360×288 pixels, and is quantized uniformly to eight bits/pixel. For performance comparison of motion estimation, PSNR graphs for the "Miss America" and "Salesman" sequences are shown in (Figure 4), where five methods include the 8-parameter method[9], 6-parameter method[3], proposed methods Ⅰ, Ⅱ, and Ⅲ. The proposed method Ⅰ represents a hybrid parameter estimation method. The proposed methods Ⅱ and Ⅲ denote the hybrid method and adaptive one implemented in a hierarchical structure, respectively. (Figure 3) shows that the PSNRs of the images reconstructed by the proposed methods lie between those by the conventional 6- and 8-parameter estimation methods. In the proposed method Ⅲ, the thresholds Th_1 and Th_2 are experimentally set to 5 and 0.4, respectively.

<Table 2> and <Table 3> list the average PSNR and the average percentage of region classification in an image

reconstructed by five different methods, respectively. For the "Miss America" sequence, the average PSNR of the proposed method Ⅰ is higher than that of the 6-parameter method by 0.22 dB, whereas lower than that of the 8-parameter method by 0.51 dB. Note that 59.2% of change regions employs the 6-parameter method for estimating motion parameters, where change regions consist of pixels whose FD values are greater than the given threshold. And the average PSNR of the proposed method Ⅲ is higher than that of the proposed methods Ⅰ and Ⅱ by 0.41 dB and 0.57 dB, respectively. The size of 8-parameter regions which is 49.66% of change regions is larger than that of 6-parameter regions. Note that 38.95 % of change regions in the proposed method Ⅰ and 17.05 % of the change regions in the proposed method Ⅱ use the 8-parameter method for estimating motion parameters. The proposed method Ⅲ using the temporal co-occurrence matrices has the low processing time because of the utilization of the temporal co-occurrence matrix. But the accuracy of the moving criterion is lower than the proposed methods Ⅰ and Ⅱ using the parameter verification because the proposed method doesn't have a verification process.

For the "Salesman" sequence, the average PSNR of the proposed method Ⅰ is higher than that of the 6-parameter method by 0.85 dB, whereas lower than that of the 8-parameter method by 0.16 dB.

Note that only 36.76% of change regions uses the 6-parameter method for estimating motion parameters. The average PSNR of the proposed method Ⅱ is lower than that of the proposed method I as expected, since motion parameters are coarsely estimated in a low-resolution image.

However, the average PSNR of the proposed method Ⅲ is lower than that of the proposed method I by 0.58dB, whereas lower than that of the proposed method Ⅱ by 0.21dB. Note that only 13.71% of change regions uses the 6-parameter method for estimating motion parameters. And the sizes of 6-parameter region of the proposed methods Ⅰ, Ⅱ, and Ⅲ are 5.90 %, 3.63 %, and 2.20 %, respectively, so that of the proposed method Ⅰ is largest.

Generally in the two successive images, the larger the size of the 6-parameter region, the lower the PSNR between the original image and the reconstructed image.

However, the "Salesman" sequence has more complex and faster motions than the "Miss America" sequence. The PSNR variation in the proposed method is large. Therefore, in the "Salesman" sequence the small difference in the average PSNR mentioned above is related to the degree of PSNR variations rather than to the size of 6-parameter regions. Consequently, the proposed method Ⅲ with the highest variation of PSNR has the lowest average PSNR. And the size of the "failure region" in the "Salesman" sequence is larger than that of the "Miss America" sequence. The reason is that the average percentage of change regions in the "Salesman" sequence is similar to that of the "Miss America" sequence, but the "Salesman" sequence has complex and faster motions.

Consequently the degradation of the image quality of the proposed methods is not large, and the proposed methods using a hierarchical structure can reduce the computational complexity greatly.

〈Table 2〉 Average PSNR of images reconstructed by the conventional and proposed methods

(unit : dB)

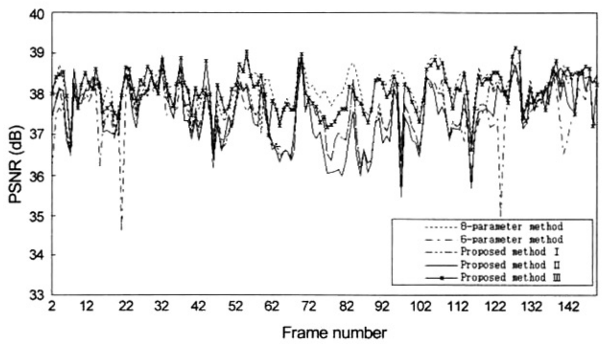
method	test image	
	Miss America	Salesman
8-parameter method	38.16	33.49
6-parameter method	37.43	32.48
proposed method Ⅰ	37.65	33.33
proposed method Ⅱ	37.49	32.96
proposed method Ⅲ	38.06	32.75

〈Table 3〉 Average percentage of region classification by the conventional and proposed methods (%)

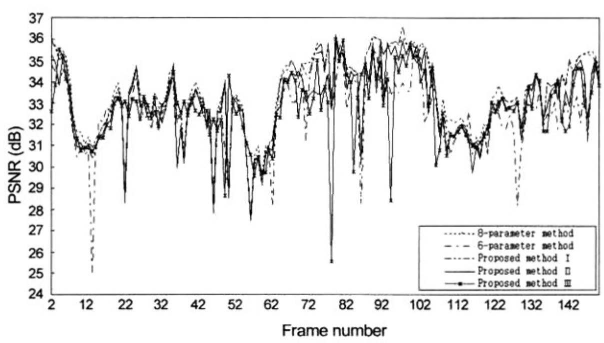
test image	region	estimation method				
		8-parameter method	6-parameter method	proposed method Ⅰ	proposed method Ⅱ	proposed method Ⅲ
Miss America	change region	16.25	16.25	16.25	16.25	16.25
	6-parameter region	-	9.62	9.62	13.18	7.55
	8-parameter region	15.73	-	6.33	2.77	8.07
	failure region	0.44	6.41	0.09	0.21	0.25
Salesman	change region	16.05	16.05	16.05	16.05	16.05
	6-parameter region	-	5.90	5.90	3.63	2.20
	8-parameter region	12.33	-	6.62	7.53	8.99
	failure region	3.30	9.82	3.20	4.65	4.68

For example of performance comparison of conventional and proposed methods, (Figure 5) shows error images from frames 113 and 114 in Miss America. (Figure 5)(a) shows the difference image magnified ten times the absolute values of the difference between two successive frames. (Figure 5)(b) to (Figure 5)(f) show error images magnified ten times the absolute values of the difference between original and reconstructed images. We show that errors of the 8-parameter method and the proposed methods Ⅰ, Ⅱ, and Ⅲ are small compared to those of the 6-parameter method. Especially the proposed method Ⅲ shows almost the same results as the 8-parameter method. The reason is because the difference of average PSNR between two methods is small by 0.1 dB as shown in <Table 2>.

In <Table 3>, the change region consists of the 6-parameter region, 8-parameter region, failure region, and small region, where the failure region represents the area in which parameter estimation fails and the small region denotes the region that need not be processed for its small size, i.e., the regions consisting of less than 64 (16) pixels in an original (low-resolution) image are denoted as small regions. Note that in this paper two-level hierarchy is assumed, however, more than two levels can be adopted if change regions are large enough.

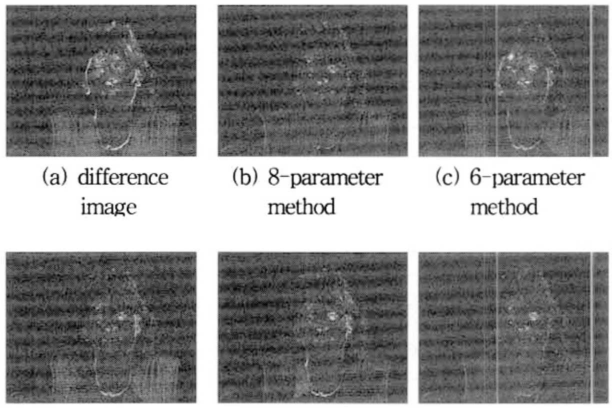


(a) Miss America



(b) Salesman

(Figure 4) PSNR graphs of the conventional methods and proposed ones



(a) difference image (b) 8-parameter method (c) 6-parameter method

(d) proposed method Ⅰ (e) proposed method Ⅱ (f) proposed method Ⅲ

(Figure 5) Example of performance comparison by error images of Miss America

6. Conclusions

This paper proposes new motion parameter estimation methods for motion detection and compensation in object-oriented analysis-synthesis coding that adaptively employ six or eight parameters. Fast parameter estimation methods with their performance similar to those of the conventional methods are described, where we employ a hierarchical structure in difference images and combine conventional 6- and 8-motion parameter estimation methods to compensate for the performance degradation caused by employment of a hierarchical structure in motion parameter estimation. Also we employ the motion detection criterion using the temporal co-occurrence matrix for the AMPEM. Especially, this method is fast and easily implemented by hardware using parallel processing techniques.

Theoretical analysis and computer simulation show that the PSNR of the images reconstructed by the proposed methods lies between those reconstructed by the conventional 6- and 8-parameter estimation methods with reduction of the computation time by a factor of about four.

Further study will focus on the investigation of automatic selection of the motion detection criterion threshold for various frames and on an optimum quantizer design for various parameters in object-oriented image coding.

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