

# Video Coding Algorithm for Video Sequences with Abrupt Luminance Change

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**Abstract**—In this paper, a fast motion compensation algorithm is proposed that improves coding efficiency for video sequences with brightness variations. We also propose a cross entropy measure between histograms of two frames to detect brightness variations. The framewise brightness variation parameters, a multiplier and an offset field for image intensity, are estimated and compensated. Simulation results show that the proposed method yields a higher peak signal to noise ratio (PSNR) compared with the conventional method, with a greatly reduced computational load, when the video scene contains illumination changes.

**Keywords**—Motion estimation, Fast motion compensation, Brightness variation compensation, Brightness change detection, Cross entropy.

## I. INTRODUCTION

FOR video coding, many motion estimation and compensation algorithms have been proposed with the considerable performance and low computational complexity. But their performance is shown using well-known test sequences usually acquired in fixed or indoor environment. So video coding using these test sequences does not yield desirable estimation and compensation results for sequences with brightness variations between frames. Most video sequences obtained from general users or various environments can often have significant brightness variations such as abrupt illumination changes and camera operations (fade in/out effects, camera iris adjustment, camera flashes, and so on).

This paper proposes the efficient motion estimation and compensation algorithms based on the brightness variation model. Several methods which estimate brightness variation parameters between frames have been presented [1-2]. But they, though yielding a high peak signal to noise ratio (PSNR) by employing a brightness change model, require a high computational load for motion estimation and compensation. For small brightness variations, the motion estimation and compensation method considering brightness variations between frames is not needed. Thus, we propose the fast motion compensation algorithms using the decision step based on the cross entropy between two histograms of successive frames, which can reduce not only the computational but also the computational redundancy.

Motion estimation and compensation methods are classified into three groups: gradient-based approaches, phase-correlation-based techniques, and block matching

algorithms (BMAs). A gradient-based technique [2-4] is based on the relationship among the spatial and temporal derivatives estimated from the successive images. The motion estimation method of the brightness change model using a gradient-based technique has been proposed [2], in which estimation of small motion is possible and hierarchical algorithms are needed to estimate the large motion. BMAs[5-7] minimize the distortion measure such as the mean squared error (MSE) or mean absolute error (MAE) between two corresponding blocks in a pair of successive frames. The motion estimation and compensation method for video sequences with brightness variations, combined with a BMA, was also proposed, however it required a high computational load.

In this paper, to overcome these drawbacks, frame classification based on the cross entropy of histograms is used and this classification step can greatly reduce the computational complexity because the adequate motion estimation model is applied to each input frame. The proposed algorithm employs the global brightness compensation using DC images and a BMA, in which search window subsampling with a local brightness variation model is used to reduce the computational complexity. We describe the proposed structure for motion estimation and compensation with a local brightness variation model and compare the performance of the proposed and conventional algorithms in terms of the computational complexity and the PSNR.

## II. FAST ALGORITHM USING BRIGHTNESS VARIATION MODEL

The proposed local brightness variation compensation (LBVC) algorithm globally consists of two parts. The first part tests the input frame based on the cross entropy if the brightness variation model is to be used or not. For frames with large cross entropy values, the second part estimates and compensates the frame using a brightness variation model, in which a multiplier  $\alpha(t)$  and an offset field  $\beta(t)$  of the brightness variation are estimated. For frames with small cross entropy values, only motion vectors are estimated to reduce the computational complexity.

The second part for a brightness variation model consists of three steps. In the first step, global brightness compensation is implemented using DC images. In the second step, search window subsampling[6-7], is employed to select two points yielding the small MAE without employing brightness variation parameters. In the third step, we choose the best matching point with brightness variation parameters and compensate the brightness variations. The MAE at  $(i, j)$  on the  $t$ th frame with brightness variation parameters  $\alpha(t)$  and  $\beta(t)$  is defined by

$$MAE(i, j, t) = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N |I(m, n, t) - \alpha(t) \cdot I(m+i, n+j, t-1) + \beta(t)| \quad (1)$$

where  $I(m, n, t)$  represents the gray level at position  $(m, n)$  in the  $M \times N$  subblock on the  $t$ th frame. Arguments  $i$  and  $j$  denote the relative displacements in search area, and  $\alpha(t)$  and  $\beta(t)$  signify a constant multiplier and an offset field of local brightness variations, respectively.

#### A. Frame Classification based on the Cross Entropy

The effectiveness of brightness change detection depends on the suitable choice of a similarity metric between two frames. In this paper, we introduce the cross entropy between the histograms of the previous and current frames. The cross entropy  $H(p, q)$  between the histogram  $p(x)$  of the previous frame and the histogram  $q(x)$  of the current frame is given by

$$H(p, q) = \int_{-\infty}^{\infty} p(x) \log \frac{p(x)}{q(x)} dx \quad (2)$$

where  $p$  and  $q$  represent probability density functions (pdfs) of the gray level in previous and current frames, respectively, and  $x$  denotes the gray level.

The cross entropy represents mutual information between the previous and current frames. To satisfy the symmetry of the measure, we use the mean value of the cross entropy, i.e.,  $A = B = 0.5$

$$F(p, q) = A \int q(x) \log \frac{q(x)}{p(x)} dx + B \int p(x) \log \frac{p(x)}{q(x)} dx. \quad (3)$$

Eq. (3) represents the directed divergence of  $p$  and  $q$  [8]. The large cross entropy values signify abrupt scene changes such as brightness variations. By thresholding the cross entropy value, the frames having large brightness variations can be detected.

#### B. Fast Local Brightness Variation Compensation Algorithm

We assume that the brightness intensity  $I(x_1, y_1, t)$  of pixel point  $(x_1, y_1)$  at frame  $t$  changes to  $I(x_2, y_2, t+1)$  of pixel point  $(x_2, y_2)$  at frame  $t+1$  according to the local brightness variation model, i.e.,  $I(x_2, y_2, t+1) = \alpha(t) \cdot I(x_1, y_1, t) + \beta(t)$ , where  $\alpha(t)$  is a multiplier and  $\beta(t)$  denotes an offset field of local brightness variations. The motion vector and two parameters  $\alpha(t)$  and  $\beta(t)$  are estimated by minimizing the MAE in the search window. To reduce the computational complexity of a local brightness variation model for computing two parameters, a fast algorithm is used, in which search window subsampling is employed. It consists of three steps:

1) In the first step, global brightness estimation and compensation is implemented using DC images.

2) In the second step, without brightness variation estimation, 4 to 1 search window subsampling is employed and two points yielding the smallest MAE are chosen.

3) In the third step, eight surrounding blocks for each of two selected points are generated. Among these 18 blocks, the block yielding the smallest MAE is regarded as the best matching one with brightness variation estimation, and the brightness variation compensation is refined.

The DC images are obtained from input frames [9]: The DC images can be obtained by

$$\bar{C}(t) = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N I(m, n, t) \quad (4)$$

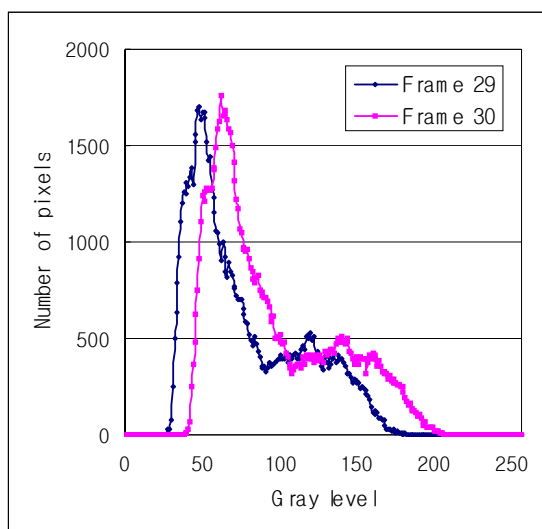
where  $I(m, n, t)$  represents the input image at point  $(m, n)$  in the  $t$ th frame and  $\bar{C}(t)$  denotes the DC value of the  $M \times N$  block. So DC images can represent the global brightness and easily extract the luminance variation parameters between frames.

In this paper, the fast algorithms also have applied to pixel decimation [7] with search window subsampling to reduce the computational load and these results are shown in Section III.

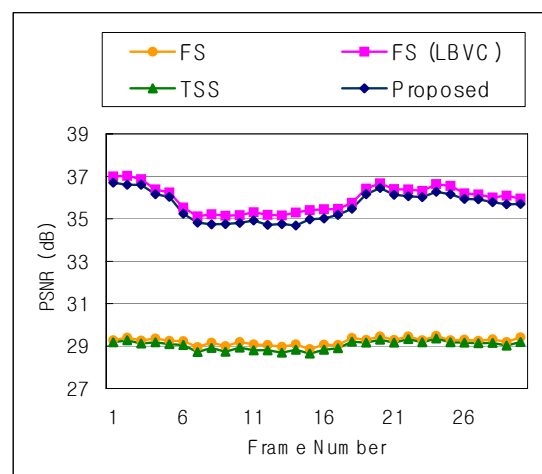
### III. EXPERIMENTAL RESULTS

#### A. Simulations for Video Sequences with Illumination Variations

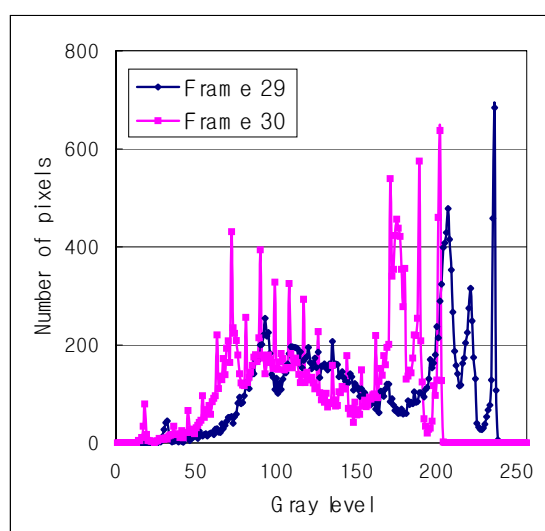
Simulations for video sequences with brightness variations are also performed using synthetically generated test sequences. To show the effectiveness of motion estimation and illumination variation estimation, we have synthesized the test sequences using Salesman and Foreman sequences, resulting in sequences with large brightness variations between frames.



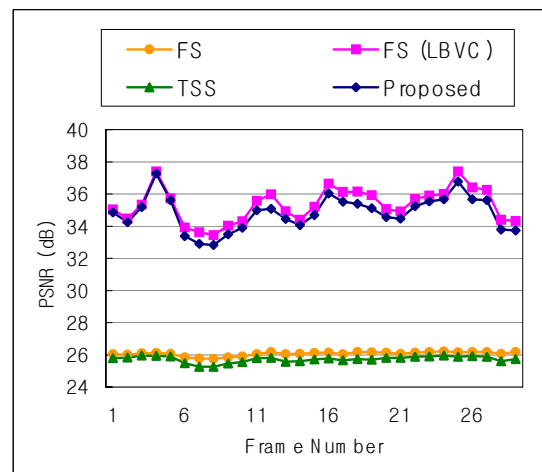
(a)



(a) Synthesized Salesman sequence



(b)



(b) Synthesized Foreman sequence

Fig. 1 Histogram comparison for two test sequences. (a) Histogram for the synthesized Salesman sequence. (b) Histogram for the synthesized Foreman sequence

Fig. 2 Performance comparison of four motion compensation methods for the synthesized sequences with large brightness variations

The Fig. 1 shows the histograms of synthesized sequences. In Fig. 1(a), frame 30 (current frame) is generated with the multiplier and offset field equal to 1.1 and 10, respectively, with respect to frame 29 (previous frame) in the synthesized Salesman sequence. Similarly, in Fig. 1(b), frame 30 (current frame) is generated with the multiplier and offset field equal to 0.9 and -10, respectively, with respect to frame 29 (previous frame) in the synthesized Foreman sequence. Test sequences are synthesized by multiplying and offsetting the intensities of the original sequences and these motion compensation results are shown in Fig. 2.

In Fig. 2, while the motion compensation methods without LBVC combined with full search (FS) and three step search (TSS) yield very low PSNR performance, FS with LBVC and the proposed fast search algorithm with LBVC give high PSNR performance when brightness variations occur between frames. It is also noted that the proposed fast search algorithm with LBVC yields high PSNR performance with little increase in the computational complexity, compared with FS with LBVC.

#### IV. CONCLUSION

In this paper, we propose a fast LBVC algorithm that can reduce the computational complexity and improve coding efficiency for video sequences with large brightness variations, in which boundary pixel decimation and search window subsampling are employed. To reduce the computational load for calculating brightness variation parameters, we propose the coarse global illumination compensation using DC images and fine local compensation algorithms. The classification method of frames using the cross entropy is presented to reduce the computational redundancy.

Simulation results show that the proposed algorithm simplifies the overall motion estimation and compensation processes with the computational complexity greatly reduced, maintaining the PSNR performance when the video sequence contains complex brightness variations. Further research will focus on the estimation of optimal brightness variation parameters and the verifications with various video sequences containing complex brightness variations.

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