Predictive Motion Estimation for Reduced-Resolution Video from High-resolution Compressed Video

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Abstract

To convert a compressed video sequence to a lower-resolution compressed video, one typically needs to decompress the original sequence, down-sample each frame, and recompress it. It involves motion estimation in the reduced sequence which is computational intensive. In this paper, we propose a novel fast algorithm to predict the motion vector of the reduced video by using the original motion information in the compressed bitstream. We achieve a much higher quality than existing algorithms with low additional complexity.

1. Introduction

Nowadays, delivery of digital video through different kinds of network, such as internet, local area network, wireless network, cable TV network, is very common. Owing to the huge storage size of video, most stored video is only available in compressed format. For applications like previewing of a movie from Internet, transcoding to a lower bitrate in wireless network and down-conversion of HDTV video for low-resolution display, there is a need to reduce the resolution of the compressed video sequence which is stored in the video server and encode the reduced video into a compatible bitstream for the decoder.

In this paper, we are concerned of video compressed by ITU-T H.261, H.263, MPEG-1, MPEG-2. One thing common to these standards is that they employ motion estimation and compensation to reduce temporal redundancy between successive frames in a video sequence in order to achieve high compression efficiency.

A straight forward way to scale down the compressed video sequence is to decompress the whole sequence, apply anti-aliasing lowpass filtering, down-sample the video and then re-encode the reduced sequence by conventional video encoders which have to perform the computational intensive motion estimation again. If brute force motion estimation is used, more than 60% of the computational power of the encoder can be used by the motion estimation. Therefore, fast motion estimation is highly desirable.

In downscaling a video sequence from a frame size of $P \times Q$ to $P/2 \times Q/2$, a 16×16 macroblock in the reduced video corresponds to four 16×16 macroblocks in the original video. In Figure 1, it can

Figure 1. Two possible relationships among motion vectors of the original frame and reduced frame.

be seen that the motion vector of the macroblock in the reduced video is closely related to the motion vectors of the four macroblocks in the original video. As the original motion information is available in the compressed bitstream and should be highly correlated to the motion of the reduced video, it is possible to estimate the new motion vectors from the original motion vectors in order to save much of the computational cost. There are some existing algorithms for this propose but they do not perform very well.

In this paper, we propose a new motion estimation algorithm called predictive motion estimation (PME) to approximate the optimal motion vector for reduced video sequence using the motion information of the original compressed video sequence. We will show that PME is much better than the existing algorithms.

2. Existing Algorithms

Let $\{MB_{o,i}\}_{i=1}^4$ be four macroblocks of the original video with corresponding motion vectors $\{V_{o,i}\}_{i=1}^4$. The four macroblocks are reduced to form one macroblock MB_r of the reduced video with corresponding motion vector V_r .

The simplest algorithm of getting the new motion vectors is to take the mean of the motion vectors of the four corresponding macroblocks in the original video and reduce it by one half and we call this MEAN which can be represented by the following equation:

$$V_r = \frac{1}{2} \text{truncate} \left(\frac{\sum_{i=1}^4 V_{o,i}}{4} \right)$$

The MEAN is a good estimate if the four macroblocks have motion vectors pointing to similar directions with similar magnitude, as in the case of Fig. 1b. However, if the four motion vectors have different directions and/or magnitude, the resulting MEAN can be poor and meaningless as in the case of Fig. 1a. The simple arithmetic mean of the four different motion vectors is inadequate to describe all situations. In [2], an algorithm called adaptive motion vector resampling (AMVR) was proposed to estimate the motion vector of the reduced video

using a weighted mean of the original motion vectors.

In the compressed video bitstream of MPEG-1, MPEG-2, H.261 and H.263, only the inter-coded macroblocks in the interframes (P or B frames) contain motion vector information. AMVR applies only to these inter-coded blocks. AMVR uses a weighted mean of the four V_o to estimate V_r .

$$V_r = \frac{1}{2} \frac{\sum_{i=1}^4 V_{o,i} \cdot A_i}{\sum_{i=1}^4 A_i}$$

where A_i denotes the activity measurement of residual macroblock i (in the original video). In [2], the number of non-zero AC coefficients was used as A_i . The complexity of AMVR is also very low but it is not necessarily good. Actually, it gives a rather low peak signal-to-noise ratio (PSNR) when compared with full search in the reduced video as we will show in section 4.

3. Predictive Motion Estimation (PME)

Here we propose a new algorithm to predict the motion vector for the reduced video with significantly higher accuracy than AMVR. We will construct a weighted motion vector different from AMVR as a candidate. We will also consider the four original motion vector as four other candidates. All five candidates will be tested in search of the best motion vector.

We observe that in many cases the motion vector of a MB_r in the reduced video found by full search is similar to one or more of the four original motion vectors reduced by half. In these cases, taking the mean or weighted mean is usually inappropriate. In addition, all four original motion vectors appear to be equally likely. They should all be considered possible candidates.

For each reduced macroblock, if the 4 reference V_o ($V_{o,1}$, $V_{o,2}$, $V_{o,3}$, $V_{o,4}$) are the same, we will just take the common value and reduce it by half as the V_r . Otherwise, we will go through the following steps to get the V_r .

Step 1: Compute 4 candidate vectors ($V_{r,i}$) as

$$V_{r,i} = \text{truncate}(V_{o,i}) / 2 \quad \text{for } i = 1, 2, \dots, 4$$

The $V_{r,i}$ will be in half pixel precision.

Step 2: Compute the mean absolute difference (MAD_i) in the reduced video for each of the four candidates $\{V_{r,i} \mid i = 1, 2, \dots, 4\}$. If one of the MAD_i value is equal to zero, assign the corresponding $V_{r,i}$ as the new V_r and stop searching. Otherwise, go to step 3.

Step 3: Compute a new candidate vector $V_{r,5}$ by

$$V_{r,5} = \frac{\sum_{i=1}^4 \left[V_{r,i} \cdot \left(\frac{1}{MAD_i} \right) \right]}{\sum_{i=1}^4 \left(\frac{1}{MAD_i} \right)}$$

Step 4: If the $V_{r,5}$ is not equal to one of the first 4 candidates, compute MAD_5 using $V_{r,5}$ as the motion vector.

Step 5: The $V_{r,i}$ with the minimum MAD value is chosen as the final V_r .

We call this algorithm predictive motion estimation (PME). For the MB_o that are skipped blocks or intra blocks which do not provide any motion information, we set the V_o of these blocks to be zero.

For better performance, we can perform an optional additional step. We can search the 8 surrounding full or half pixel of the optimal V_r found by PME.

The PME with a local full pixel search will be PME-LS1. The PME with a local half pixel search will be called PME-LS2. Both algorithms have the following addition step.

Step 6: Compute the MAD for the surrounding 8 full pixels or half pixels. The one with the minimum MAD will be the new motion vector V_r .

Note that step 6 is needed anyway if half pixel accuracy is needed in the full search.

4. Results

We tested our algorithms on several MPEG I video sequence with CIF resolution (352×288) and a GOP of 15 frames with IPPP frame structure in each GOP. The reduced-resolution sequence is in QCIF resolution (176×144). In order to compare the performance of different algorithms, we calculate the PSNR between the predicted frames of the reduced video using different algorithms and the original reduced frames.

Figure 2 shows the PSNR difference from full search of AMVR, MEAN and PME-LS1 for the “football” sequence. The search area for full search is ± 7 .

Figure 2. Plot of PSNR difference of various algorithms with Full search

Figure 3. Plot of PSNR difference between PME-LS1 and AMVR

Figure 3 shows the PSNR difference between PME-LS1 and AMVR in football sequence. It shows a maximum of about 3.5 dB improvement over AMVR and an average of 0.8388 dB.

Table 1 shows the mean PSNR values of different algorithms, the difference in mean PSNR values between full search and different algorithms and the average search point for each macroblock for the "football" and "salesman" test sequences. For the fast moving scene, it seems that PME-LS1 has better performance than PME-LS2. However, for the head-and-shoulder scenes, PME-LS2 is better.

If we use the PME without step 3 and step 4, i.e. without the $V_{r,5}$ (we call this PV4 in Table 1), the PSNR will be much lower than PME. This shows that the fifth candidate $V_{r,5}$ is very important.

In PME, we calculate the MAD for at most 5 points for each macroblock and do not need to calculate for those blocks with four identical motion vectors. In the case of the fast moving scenes in football sequence, the average search points for each motion vector is about 0.6 which is much less than full search of 225 search points. In the case of the head-and-shoulder scene like salesman, the average search point is about 0.016. We can achieve a even better quality with the additional local search in PME-LS1 or -LS2 at the price of more search points.

5. Conclusions

In this paper, we propose a fast algorithm to estimate the best motion vector for reduced resolution video sequences using the motion information of the original compressed video sequence. The computational need of the proposed algorithm is minimal and the prediction is much better than AMVR in terms of PSNR.

6. Acknowledgement

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7. References

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Sequence	Football			Salesman		
	Mean PSNR	PSNR difference	Average Search points	Mean PSNR	PSNR difference	Average Search points
Mean only	22.2758	-1.8317	*	35.8721	-1.1519	*
AMVR	22.6499	-1.4576	*	35.9382	-1.0857	*
PV4	22.8599	-1.2476	0.6551	36.2721	-0.7521	0.01643
PME	23.3042	-0.8033	0.6597	36.9447	-0.0792	0.0169
PME-LS1	23.5418	-0.5657	5.937	36.9519	-0.0721	0.1521
PME-LS2	23.4887	-0.6188	5.937	36.996	-0.028	0.1521
Full search	24.1075	0	225	37.0242	0	225

Table 1. mean PSNR and mean PSNR difference from full search for various algorithms and various test sequences.

* These two algorithms have negligible computation compared with full search.