Chapter 9

How are digital TV programs compressed to allow broadcasting?

The raw bit rate of a studio video sequence is 166 Mbps whereas the capacity of a terrestrial TV broadcasting channel is around 20 Mbps.

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In 1982, the CCIR defined a standard for encoding interlaced analogue video signals in digital form mainly for studio applications. The current name of this standard is ITU-R BT.601 (ITU 1983). Following this standard, a video signal sampled at 13.5 MHz, with a 4:2:2 sampling format (double number of samples for the luminance component than for the two chrominance components) and quantized with 8 bits per component produces a raw bit rate of 216 Mbps. This rate can be reduced by removing the blanking intervals present in the interlaced analogue signal leading to a bit rate of 166 Mbps, which is still a figure far above the main capacity of usual transmission channels or storage devices.

Bringing digital video from its source (typically, a camera) to its destination (a display) involves a chain of processes, among which compression (encoding) and decompression (decoding) are the key ones. In these processes, bandwidth intensive digital video is first reduced to a manageable size for transmission or storage, and then reconstructed for display.

This way, video compression allows using digital video in transmission and storage environments that would not support uncompressed video.

In the last years, several image and video coding standards have been proposed for various applications such as JPEG for still image coding (see Chapter 8), H.263 for low-bit rate video communications, MPEG1 for storage media applications, MPEG2 for broadcasting and general high quality video application, MPEG4 for streaming video and interactive multimedia applications or H.264 for high compression requests. In this Chapter, we describe the basic concepts of video coding that are common to these standards.

9.1 Background – Motion estimation

Fig. 9.1 presents a simplified block diagram of a typical video compression system (Clarke 1995, Zhu et al. 2005). Note that the system can work in two different modes: *intra* and *inter* mode. In intra mode, only the spatial redundancy within the current image is exploited (see Chapter 8), whereas inter mode, in addition, takes advantage of the temporal redundancy among temporal neighbor images[1].

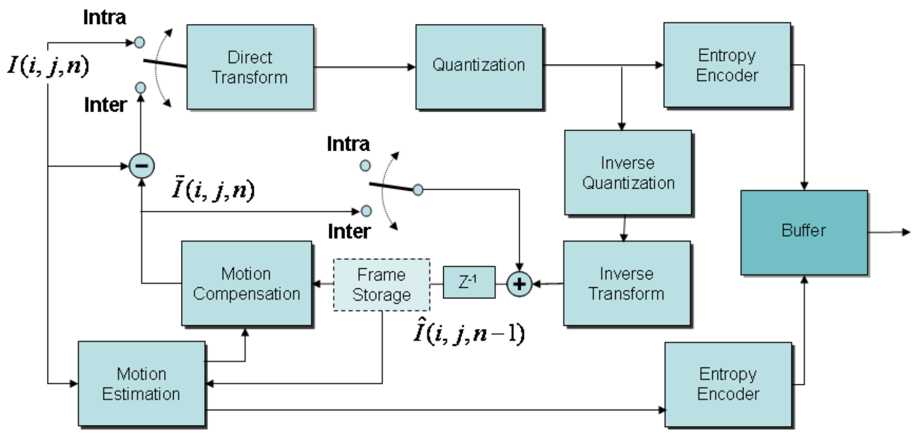


Fig. 9.1 Block diagram of video compression system.

[1] In this Chapter, for simplicity, we will assume that a whole picture is compressed either in intra or inter mode. In current standards, this decision is adopted at a more local scale within the image: at the so-called macroblock or even at block level. These concepts will be defined in the sequel (actually, the block concept has already been defined in Chapter 8)

Let us start analyzing the system in intra mode. This is the mode used, for instance, for the first image in a video sequence. In intra mode, the image is handled as it is described in Chapter 8. Initially, a transform is applied to it in order to decorrelate its information[2]. The image is initially partitioned into *blocks* of 8x8 pixels and the DCT transform is separately applied on the various blocks (Noll and Jayant 1984). The transformed coefficients are scalar quantized (Gersho and Gray 1993) taking into account the different relevancy for the human visual system of the various DCT coefficients. Quantized coefficients are zigzag scanned and entropy coded (Cover and Thomas 1991) in order to be efficiently transmitted.

The quantized data representing the intra mode encoded image is used in the video coding system to provide the encoder with the same information that will be available at the decoder side; that is, a replica of the decoded image[3]. This way, a decoder is embedded in the transmitter and, through the inverse quantization and the inverse transform, the decoded image is obtained. This image is stored in the *Frame Storage* and will be used in the coding of future frames.

This image is represented as $\hat{I}(i, j, n-1)$ where the symbol '^' denotes that it is not the original frame but a decoded one. Moreover, since the system typically has already started coding the following frame in the sequence, this frame is stored as belonging to time instant $n - 1$ (and this is the reason for including a delay in the block diagram).

Now, we can analyze the behavior of the system in inter mode. The first step is to exploit the temporal redundancy between previously decoded images and the current frame. For simplicity, we are going to assume in this initial part of the Chapter that only the previous decoded image is used for exploiting the temporal redundancy in the video sequence. In subsequent Sections we will see that the *Frame Storage* may contain several other decoded frames to be used in this step.

The previous decoded frame is used to estimate the current frame. Towards this goal, the *Motion Estimation* block computes the motion in the scene; that is, a motion field is estimated, which assigns to each pixel in the current frame a motion vector (d_x, d_y) representing the displacement that this pixel has suffered with respect to the previous frame. The information in this motion field is part of the new, more compact representation

[2] In recent standards such as H.264 (Sullivan and Wiegand 2005), several other intra mode decorrelation techniques are proposed, based on prediction.

[3] Note that the quantization step very likely will introduce losses in the process and, therefore, the decoded image is not equal to the original one.

of the video sequence and, therefore, it is entropy encoded and transmitted[4].

Based on this motion field and on the previous decoded frame, the *Motion Compensation* block produces an estimate of the current image $\tilde{I}(i,j,n)$. This estimated image has been obtained applying motion information to a reference image and, thus, it is commonly known as the *motion compensated image* at time instant *n*. In this Chapter, motion compensated images are denoted by the symbol '~'.

The system then subtracts the motion compensated image from the original image, both at time *n*. The result is the so-called *motion compensated error image* and contains all the information from the current image that has not been correctly estimated using the information in the previous decoded image. These concepts are illustrated in Fig. 9.2.

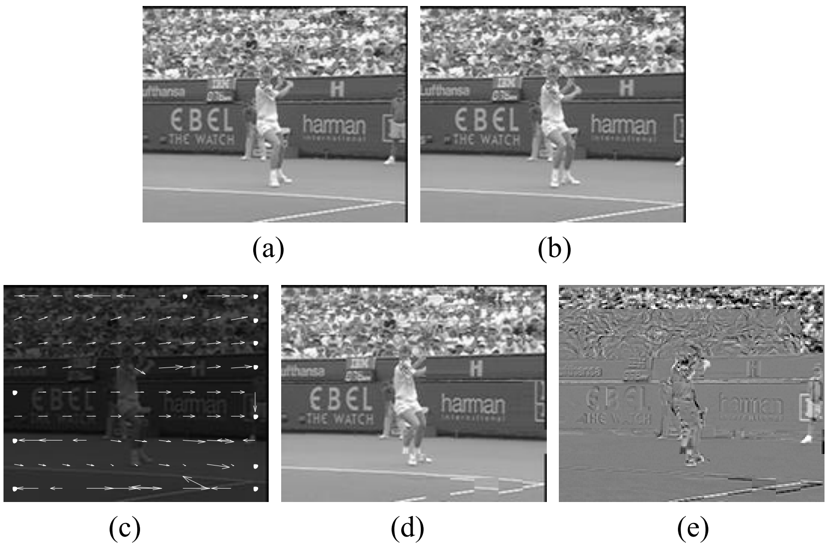


Fig. 9.2 (a) Original frame #12 of the *Stefan* sequence, (b) Original frame #10 of the sequence *Stefan*, (c) Motion field estimated between the previous images. For visualization purposes, only a motion vector for each 16x16 pixels area is represented, (d) Estimation of frame #12 obtained as motion compensation of image #10 using the previous motion field, (e) Motion compensated error image at frame #12. For visualization purposes, an offset of 128 has been added to the error image pixels, which have been afterwards conveniently scaled.

[4] As it will be discussed in Section 9.1.2, this information typically does not require quantization.

The motion compensated error image is now handled as an original image in intra mode (or in a still image coding system, see Chapter 8). That is, the information in the image is decorrelated (*Direct Transform*) typically using a DCT block transform, then the transform values are scalar quantized (*Quantization*) and finally, quantized coefficients are entropy encoded (*Entropy Encoder*) and transmitted.

As previously, the encoding system contains an embedded decoder that allows the transmitter to use the same decoded frames that will be used at the receiver side[5]. In this case, the reconstruction of the decoded image implies adding the quantized error to the motion compensated image and this is the image which is stored in the *Frame Storage* to be used as reference for subsequent frames.

Fig. 9.3 presents the block diagram of the decoder associated to the previous compression system. As it can be seen, previously decoded images are stored in the *Frame Storage*. They will be motion compensated using the motion information that is transmitted when coding future frames. Now it is even clearer the usefulness of recovering the decoded images in the encoder. If it was not the case, the encoder and the decoder would use different information in the motion compensation process. That is, the encoder would estimate the motion information using original data whereas the decoder will apply this motion information on decoded data, leading to different motion compensated images and motion compensated error images.

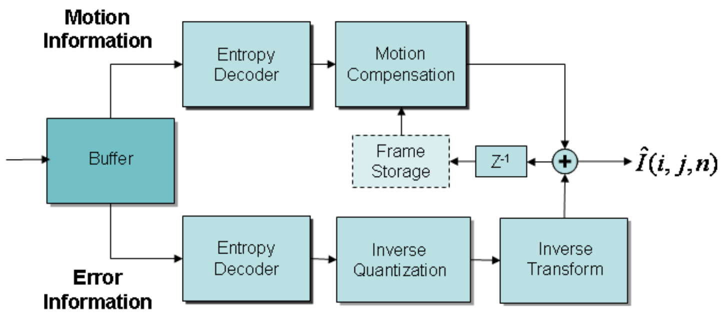


Fig. 9.3 Decoder system associated to the encoder of Fig. 9.1.

[5] Such a system is commonly referred to as a *close loop* coder-decoder *(codec)*.

9.1.1 Motion estimation: The Block Matching algorithm

In the initial part of this Section, it has been made clear that a paramount step in video coding is motion estimation (and compensation). There exist a myriad of motion estimation algorithms (some of them are presented in Tekalp 1995, Fleet and Wiess 2006) which present different performance in terms of accuracy of the motion field, computational load, compactness of the motion representation, etc. Nevertheless, the so-called *Block Matching* algorithm has been shown to globally outperform all other approaches in the coding context.

Most motion estimation algorithms rely on the hypothesis that, between two consecutive (close enough) images, changes are only due to motion and, therefore, every pixel in the current image $I(\mathbf{r}, n)$ has an associated pixel (a referent) in the reference image $I(\mathbf{r}, n\text{-}1)$:

$$I(\mathbf{r},n) = I(\mathbf{r}-\mathbf{D}(\mathbf{r}),n-1) \tag{9.1}$$

where vector $\mathbf{r}$ represents the pixel location (x, y) and $\mathbf{D}(\mathbf{r})$ the motion field (also known as *optical flow*):

$$\mathbf{D}(\mathbf{r}) = [d_x(\mathbf{r}), d_y(\mathbf{r})] \tag{9.2}$$

The hypothesis in Eq. (9.1) is too restrictive since factors other than motion influence the variations in the image values between even consecutive images; typically, changes in the scene illumination, camera noise, reflecting properties of object surfaces, etc. Therefore, motion estimation algorithms do not try to obtain a motion field fulfilling Eq. (9.1). The common strategy is to compute the so-called Displaced Frame Difference (*DFD*)

$$DFD(\mathbf{r},\mathbf{D}(\mathbf{r})) = I(\mathbf{r},n) - I(\mathbf{r}-\mathbf{D}(\mathbf{r}),n-1) \tag{9.3}$$

to define a given metric $M\{.\}$ over this image and to obtain the motion field that minimizes this metric:

$$\mathbf{D}^*(\mathbf{r}) = \underset{\mathbf{D}(\mathbf{r})}{\arg\min}\, M\left\{DFD(\mathbf{r},\mathbf{D}(\mathbf{r}))\right\} \tag{9.4}$$

Note that the image that is subtracted to the current image in Eq. (9.3) is obtained by applying the estimated motion vectors $\mathbf{D}(\mathbf{r})$ to the pixels of the reference image. This is what, in the context of video coding, we have called motion compensated image:

$$\tilde{I}(\mathbf{r},n) = I(\mathbf{r}-\mathbf{D}(\mathbf{r}),n-1) \tag{9.5}$$

Consequently, the *DFD* is nothing but the motion compensation error image and the minimization process expressed in Eq. (9.4) looks for the minimization of a metric defined over an estimation error. Therefore, a typical choice for the selection of that metric is the energy of the error[6]:

$$\mathbf{D}^*(\mathbf{r}) = \arg\min_{\mathbf{D}(\mathbf{r})} \sum_{\mathbf{r}\in R} \left\| DFD(\mathbf{r},\mathbf{D}(\mathbf{r})) \right\|^2 \tag{9.6}$$

where *R* is, originally, the region of support of the image.

So far, we have not imposed any constraints on the motion vector field and all its components are independent. This pixel independency is neither natural, because neighbor pixels are likely to present similar motion, nor useful in the coding context, because it leads to a different displacement vector for every pixel, which results into a too large amount of information to be coded.

Parametric vector fields impose a given motion model to a specific set of pixels in the image. Common motion models are translational, affine, linear projective or quadratic. If we assume that the whole image undergoes the same motion model, the whole motion vector field can be parameterized **D**(**r**, **p**), where **p** is the vector containing the parameters of the model, and the *DFD* definition depends now on these parameters **p**:

$$DFD(\mathbf{r},\mathbf{p}) = I(\mathbf{r},n) - I(\mathbf{r}-\mathbf{D}(\mathbf{r},\mathbf{p}),n-1) \tag{9.7}$$

The minimization process of Eq. (9.6) aims now at obtaining the optimum set of parameters:

$$\mathbf{D}^*(\mathbf{r},\mathbf{p}) = \arg\min_{\mathbf{p}} \sum_{\mathbf{r}\in R} \left\| DFD(\mathbf{r},\mathbf{p}) \right\|^2 \tag{9.8}$$

[6] Although this is a useful choice when theoretical deriving the algorithms, when actually implementing them, the square error (L2 norm) is commonly replaced by the absolute error (the L1 norm) given its lower computational load.

The perfect situation would be to have a parametric motion model assigned to every different object in the scene. This solution requires the segmentation of the scene into its motion homogeneous parts. However, motion based image segmentation is a very complicated task (segmentation is often named an ill-posed problem). Moreover, if the image is segmented, the use of the partition for coding purposes would require transmitting the shapes of the arbitrary regions and this boundary information is extremely difficult to compress.

The adopted solution in video coding is to partition the image into a set of square blocks (usually referred to as *macroblocks*) and to estimate the motion separately within each one of these macroblocks. Therefore, a fixed partition is used which is known beforehand by the receiver and does not require to be transmitted. Since this partition is independent of the image contents, data contained in each macroblock may not share the same motion. However, given the typical macroblock size (e.g.: 16x16 pixels), motion information within a macroblock can be considered close to homogenous. Furthermore, the imposed motion model is translational; that is, all pixels in a macroblock are assumed to undergo the same motion which, for each macroblock, is represented by a single displacement vector.

As it has been previously said, the motion (displacement) of every macroblock is separately determined. Therefore, the global minimization problem is divided into a set of local minimization ones where, for the i^{th} macroblock MB_i, the optimum parameters $\mathbf{p_i}^* = [d_x^*, d_y^*]_i$ are obtained:

$$\mathbf{p}_{\mathrm{i}}^* = \left[d_x^*, d_y^* \right]_i = \arg\min_{\mathbf{p}} \sum_{\mathbf{r} \in MB_i} \left\| DFD(\mathbf{r}, \mathbf{p}) \right\|^2 \tag{9.9}$$

The common implementation of this minimization process is the so-called *Block Matching* algorithm. In the Block Matching, a direct exploration of the solution space is performed. In our case, the solution space is the space containing all possible macroblock displacements. This way, for each macroblock in the current image, a *search area* is defined in the reference image. The macroblock is placed at various positions within the search area in the reference image. Those positions are defined by the *search strategy* and the *quantization step* and every position corresponds to a possible displacement; that is, a point in the solution space. At each position, the pixel values overlapped by the displaced macroblock are compared (matched) with the original macroblock pixel values. The way to perform this comparison is defined by the selected *metric*. The vector representing the displacement leading to the best match (lowest metric value) is the motion vector assigned to this macroblock. The final result of the Block Matching algorithm is a set of displacements (motion vectors), each one associated to a different macroblock of the current image.

Therefore, several aspects have to be fixed in a concrete implementation of the Block Matching; namely[7]:

- the *metric* that defines the best match, while the square error is the optimum metric in case of assessing the results in terms of PSNR (see Chapter 8), it is common to implement the absolute error given its lower computational complexity;
- the *search area* in the reference image, which is related to the maximum allowed displacement, that is, to the maximum allowed speed of objects in the scene (see Section 9.2.2);
- the *quantization step* to represent the parameters of the motion model, in our case the coordinates of the displacement, which is related to the accuracy of the motion representation;
- the *search strategy* in the parameter space, which defines which possible solutions (that is, different displacements) are analyzed in order to select the motion vector.

The size of the search area is application dependent. For example, it is clear that the maximum displacement expected by objects in the scene is very different for a sport video than for an interview program. A possible simplification is to fix the maximum displacement in any direction close to the size of a macroblock side. This leads to space solutions covering zones of, for example, size [-15, 15] x [-15, 15].

The quantization step is related to the precision used to represent the motion parameters. Objects in the scene do not move in terms of pixels and, therefore, to describe their motion by means of an integer number of pixels is to reduce the accuracy of the motion representation. In current standards, techniques to estimate the motion with a quantization step of ½ and even ¼ of pixel are implemented[8]. The quantization step samples the space solution and defines a finite set of possible solutions. For instance, if we fix the quantization step to 1 pixel, the previous space solution of size [-15, 15] x [-15, 15] leads to 31x31 = 961 possible solutions; that is, 961 different displacement vectors that have to be tested to find the optimum one. Note that, if we use a quantization step of 1/N of pixel, we are increasing the number of possible solutions by a factor N^2.

[7] We could add here other aspects such as the macroblock shape and size but, as previously commented, we are assuming in the whole Chapter that square macroblocks of size 16x16 pixels are used.

[8] Sub-pixel accuracy requires interpolation of the reference image. This kind of techniques, although very much used in current standards mainly to reach high quality decoded images, is out of the scope of this Chapter.

A search strategy is necessary to reduce the amount of computations required by the Block Matching algorithm. Following with the previous example, let us see the computational load of an exhaustive analysis of the 961 possible solutions[9]. For each possible displacement (solution), the pixels in the macroblock have to be compared with the pixels in the reference subimage overlapped by the macroblock at this position. Since we are assuming macroblocks of size 16x16, this leads to (16x16x31x31) 246.016 comparisons between pixels, and this is for a single macroblock! Suboptimal search strategies (Ghanbari 2003) have been proposed to reduce the amount of solutions to be analyzed per macroblock[10]. These techniques rely on the hypothesis that the metric (the error function) to be minimized is a (close to) U-convex function and, therefore, by analyzing a few solutions, the search algorithm can be lead to the optimum one (see Fig. 9.4).

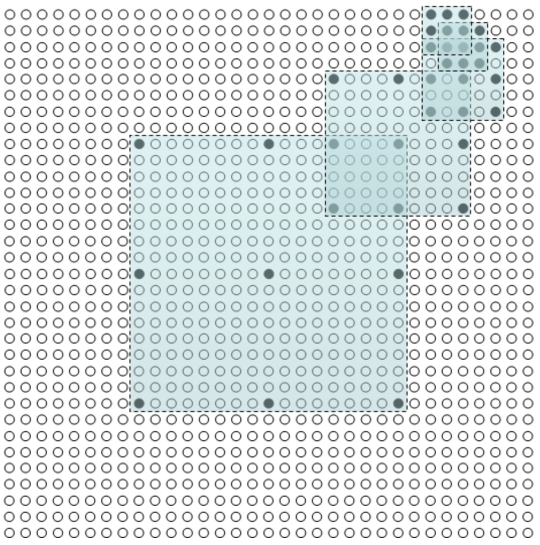


Fig. 9.4 Example of suboptimal search strategy: the so-called *nstep-search* strategy. Nine possible solutions are analyzed corresponding, initially, to the center of the solution space and eight other solutions placed in the side centers and corners of a square of a given size (usually, half the solution space). The solution leading to a minimum is selected and the process is iterated by halving the size of the square and centering it in the current solution, until the final solution is found.

[9] This is commonly referred to as *full search* strategy.

[10] There exists another family of techniques that, rather than (or in addition to) reducing the amount of solutions to be analyzed, aims at reducing the amount of comparisons to be performed at each analyzed solution.

9.1.2 A few specificities of video coding standards

The complexity of current video standards is extremely high, incorporating a large variety of techniques for decorrelating the information and allowing the selection of one technique or another at, even, the sub-block level (see, for instance, Sullivan and Wiegand 2005). Analyzing all these possibilities is out of the scope of this Chapter and, instead, we are going to concentrate on a few additional concepts that (i) are basically shared by all video standards, (ii) complete the description of a simple video codec and (iii) help understanding the potential of the motion estimation process. This way, we present the three different types of frames that are defined and the concept of Group of Pictures (GOP), we discuss how the motion information is decorrelated and entropy coded and, finally, we comment on the main variations that the specific nature of the motion compensated error image introduces in its coding.

I-Pictures, P-Pictures and B-Pictures

The use of motion information to perform temporal prediction improves the compression efficiency as it will be shown in Section 9.2. However, coding standards are not only required to achieve high compression efficiency but to fulfill other functionalities as well. Among these additional features, a basic one is *random access*. Random access is defined as “the process of beginning to read and decode the coded bitstream at an arbitrary point” (MPEG 1993). Actually, random access requires that any picture can be decoded in a limited amount of time, which is an essential feature for video on a storage medium[11]. This requirement implies having a set of access points in the bitstream, associated to specific images, which are easily identifiable and can be decoded without reference to previous segments of the bitstream. The way to implement these requirements is by breaking the temporal prediction chain and introducing some images encoded in intra mode, the so-called Intra-Pictures or *I-Pictures*. The spacing of two I-Pictures per second depends on the application. Applications requiring random access may demand short spacing, which can be achieve without significant loss of compression rate. Other applications may even use I-Pictures to improve the compression where motion compensation reveals ineffective; for instance, in a scene cut. Nevertheless, since I-Pictures will be used as reference for future frames in the sequence, they are coded with good quality; that is, with moderate compression.

[11] Think, for example, about the functionalities of fast forward and fast reverse playback that we commonly use in a DVD player.

Relying on I-Pictures, new images can be temporally predicted and encoded. This is the case of Predictive coded pictures (*P-Pictures*), which are coded more efficiently, using as reference image a previous I-Picture or P-Picture, commonly, the nearest one. Note that P-Pictures are used as reference for further prediction and, therefore, their quality has to be high enough for that purpose.

Finally, a third type of images is defined in usual video coding systems, which are the so-called Bidirectionally-predictive coded pictures (*B-Pictures*). B-Pictures are estimated combining the information of two reference images, one preceding it and the other following it in the video sequence (see Fig. 9.5). Therefore, B-Pictures use both past and future reference pictures for motion compensation[12]. The combination of past and future information has several implications.

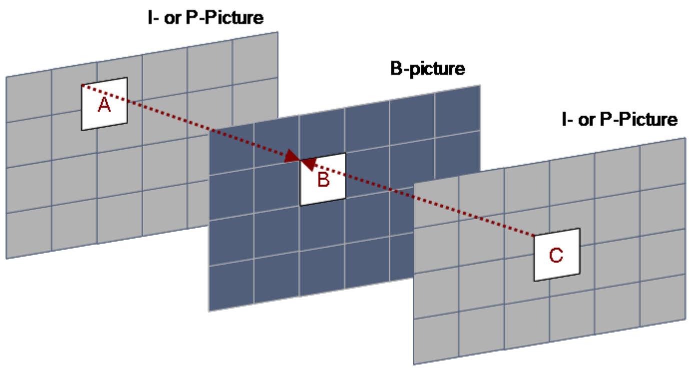


Fig. 9.5 Illustration of the motion prediction in B-Pictures.

First, in order to allow using future frames as references, the image transmission order has to be different from the displaying order. This concept will be further discussed in the sequel. Second, B-Pictures may use past, future or combinations of both images in their prediction. In the case of combining both references, the selected subimages in the past and future reference images are linearly combined to produce the motion compensated estimation[13]. This selection of references leads to an increase in motion compensation efficiency. In the case of combining past and future references, the linear combination may imply a noise reduction. Moreover, in

[12] Commonly, estimation from past references is named *forward prediction* whereas estimation from future references is named *backward prediction*.

[13] Linear weights are inversely proportional to the distance between the B-Picture and the reference image.

the case of using only a future reference, objects appearing in the scene can be better compensated using future information (see Section 9.2.6 for a further discussion on that topic). In spite of the double set of motion information parameters that they require, B-Pictures provide the highest degree of compression.

Group of Pictures (GOP)

The organization of the three types of pictures in a sequence is very flexible and the choice is left to the encoder. Nevertheless, pictures are structured in the so-called *Group of Pictures* (*GOP*), which is one of the basic units in the coding syntax of video coding systems. GOPs are intended to assist random access. The information of the length and organization of a GOP is stored in its header, allowing therefore easily identifiable access points in the bitstream. Let us use a simplified version of a GOP in order to illustrate its usage and usefulness.

First, let us clarify that, given their usually lower quality, B-Pictures are not (actually, seldom) used as reference for prediction. That is, the reference images for constructing a P-Picture or a B-Picture are either I-pictures or P-Pictures. Now, let us fix the following GOP structure:

I(1) B(2) B(3) P(4) B(5) B(6) I(7) B(8) B(9) P(10) B(11) B(12) I(13) …

Frame I(1) is coded in intra mode and therefore does not need any reference and can be directly transmitted. However, frames B(2) and B(3) are B-Pictures and they need a past and a future reference to be encoded and transmitted before they can be processed. Therefore, prior to encoding B(2) and B(3), frame P(4) is encoded as a P-Image, having as reference the previous I(1). Once P(4) has been transmitted, B(2) and B(3) can be encoded as B-Images and transmitted. A similar situation happens now for B(5) and B(6), since they require as well a future reference. In that case, the GOP structure imposes I(7) to be an I-Picture and this is first encoded and transmitted[14]. After that, B(5) and B(6) can be encoded as B-Pictures, having as references P(4) and I(7).

In order to allow bidirectional prediction, a reordering of the images in transmission has to be imposed. This way, the previous GOP structure forces the following ordering in transmission:

I(1) P(4) B(2) B(3) I(7) B(5) B(6) P(10) B(8) B(9) I(13) B(11) B(12) …

[14] Note that the GOP structure could have imposed P(7). In that case, the only change would have been that P(7) should be predicted from P(4).

These concepts are further illustrated in Fig. 9.6, where images are associated to their order in the transmission process. For the sake of clarity, only arrows showing the temporal dependency among a few images are shown.

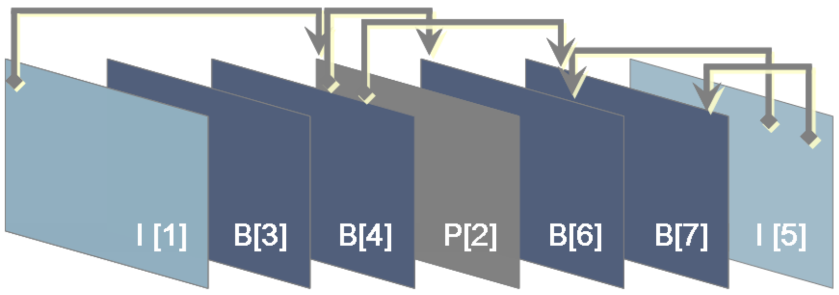


Fig. 9.6 Example of GOP structure. Frames are presented in display order but numbers associated to each frame represent its order of transmission.

A final remark has to be made regarding the reordering imposed by B-Pictures. Note that this technique demands much more processing and storing at the receiver side. First, more complicated motion estimation strategies are defined in which combinations of past and future estimations are performed. Second, the receiver can no longer decode, display and remove from memory a given image but, to allow decoding B-Pictures, it has to keep decoded I-Pictures and B-Pictures into memory before displaying them.

Coding of motion vectors

As it has been said (and will be further illustrated in Section 9.2), motion information is very relevant for the performance of the video coding system. Due to that, no quantization of the motion vectors is performed, so that no losses are introduced in this information.

As in the case of the DC coefficients in neighbor blocks in the JPEG standard (see Chapter 8), motion vectors in neighbor macroblocks are usually quite correlated. Therefore, a differential coding is performed in which a prediction based on previously decoded macroblocks is used. Depending on the standard and on the type of image, the way to perform this prediction varies.

DCT coefficient quantization of the motion compensated error image

When presenting the procedure for quantizing the DCT coefficients in still image coding (see Chapter 8), it was commented that a specific quantization table was used to take into account the different relevance of each coefficient for the human visual system. It that case, the study of the human visual system lead to the use of the so-called Lohscheller tables that, roughly speaking, impose a stronger quantization step to higher frequency coefficients.

In the case of coding the motion compensated error image, this strategy is no longer useful. Note that the presence of high frequency components in the error image may not be related to high frequency information in the original image but, very likely, to poor motion compensation. Therefore, a flat default matrix is commonly used (all matrix components set to 16).

9.2 MATLAB proof of concept

In the following Section we are going to illustrate the main concepts behind compression of image sequences. Image sequences present temporal as well as spatial redundancy. In order to correctly exploit the temporal redundancy between temporally neighbor images, the motion present in the scene has to be estimated. Once the motion is estimated, the information in the image used as reference is motion compensated to produce a first estimation of the image to be coded. Motion estimation is performed by dividing the image into non-overlapping square blocks and estimating the motion of each block independently.

9.2.1 Macroblock processing

Typically, for motion estimation, images are partitioned into blocks of 16x16 pixels[15], which will be referred to as *macroblocks* (see Fig. 9.7). The macroblock partition is hierarchical with respect to the block partition (see Chapter 8) and, therefore, every macroblock contains 4 blocks. As in the block case, images are padded to allow an exact partition in terms of macroblocks.

```
for i=1:3,
```

[15] Current standards allow finer partitions using both smaller square blocks (e.g.: 8x8) and smaller rectangular blocks (e.g.: 16x8, 8x16, etc.)

```
        table{i} =
imread(sprintf('seqs/table/gray/table_%03d_g.bmp',i-1));
        imshow(table{i});
        addgridtofigure(size(table{i}),[16 16]);
end;
```

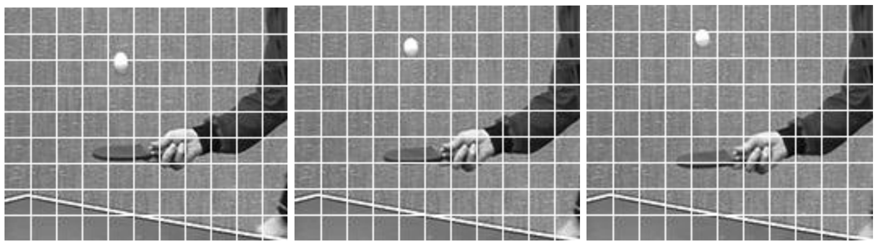


Fig. 9.7 Original frames of the *Table Tennis* sequence and macroblock partitions

In Section 9.1, we have discussed that usual coding systems work in close loop; that is, the encoder uses decoded data (instead of the original one) to perform the prediction steps. This ensures that the transmitter and the receiver work in the same conditions. However, for the sake of simplicity, in the following Sections we are going to use original data in the prediction steps. Results in close loop will be presented in Section 9.2.9 when the complete coding system will be analyzed.

9.2.2 Block matching motion estimation

Now, we are going to analyze how our basic motion compensation unit (that is, a generic 16x16 pixel macroblock) is processed. Among all the different techniques for estimating the motion associated to a macroblock with respect to a given reference image, the Block Matching algorithm has been shown to present very good coding properties.

The *Block Matching* algorithm (BM) works independently for each macroblock of the current image and, for each macroblock, it looks for the best representation in the reference image, assuming that the whole macroblock has only undergone a translational movement (see Section 9.1.1). Therefore, the selected macroblock is placed at various positions in the reference image (those positions defined by the search area and the search strategy) and the pixel values overlapped by the displaced macroblock are compared (matched) with the original macroblock pixel values. The vector representing the displacement leading to the best match is the motion vector assigned to the selected macroblock. The final result of the BM algorithm is a set of displacements (motion vectors), each one associated to a different macroblock of the current image.

As commented in the Section 9.1.1, several aspects have to be fixed in a concrete implementation of the BM; namely: (i) the metric that defines the best match; (ii) the search area in the reference image, which is related to the maximum allowed speed of objects in the scene; (iii) the quantization step to represent the coordinates of the motion vector, which is related to the accuracy of the motion representation; and (iv) the search strategy in the parameter space, which defines how many possible solutions (that is, different displacements) are analyzed in order to select the motion vector.

The MATLAB function `estimatemotion` performs the BM of a given image with respect to a reference image. In it, the previous aspects are implemented as follows: (i) the selected *metric* is the absolute difference; (ii) the *search area* can be set by the fourth parameter (actually, this parameter does not directly set the search area but the maximum displacement allowed to the motion vector, so a value of [16 12] indicates that the motion vector can have values from (-16,-12) to (16,12)); (iii) the *quantization step* has been set to 1 pixel; and (iv) as *search strategy* both a full search and an nstep-search (see Fig. 9.4) within the search area are implemented.

```
t = 2;
[mvv mvh] = estimatemotion(table{t},table{t-1},[16 16],...
   [15 15],'fullsearch');
```

Fig. 9.8 presents the result of computing the BM between frames #1 and #0 of the *Table Tennis* sequence. BM motion vectors are plotted in white over each of the macroblocks of frame #1 (motion vector field). Since an exhaustive search is performed, the estimated motion vectors are the optimum ones under the selected metric, search area and quantization step.

```
plotmv(table{t},mvv,mvh,[16 16]);
```

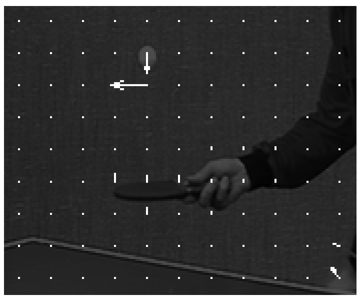


Fig. 9.8 Motion vectors for Block Matching estimation between frame #1 and frame #0 of the *Table Tennis* sequence

In order to illustrate how these vectors are computed, let us analyze the specific case of two different macroblocks. In Fig. 9.9, we show the information associated to the first of these macroblocks which is placed 5 blocks from the left and 2 from the top:

```
posr = 2; posc = 5;
f = table{t}*0.2;
bs = 16;
f(bs*(posr-1)+1:bs*(posr-1)+bs,bs*(posc-1)+1:bs*(posc-1) ...
  +bs) = table{t}(bs*(posr-1)+1:bs*(posr-1)+bs,bs*(posc-1) ...
  +1:bs*(posc-1)+bs);
imshow(f);
```

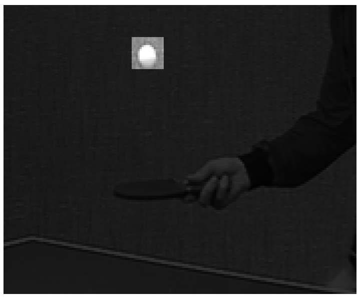


Fig. 9.9 Macroblock at position [2,5] (highlighted)

Fig. 9.10 shows a magnification of the selected macroblock:

```
b = table{t}(bs*(posr-1)+1:bs*(posr-1)+bs, ...
   bs*(posc-1)+1:bs*(posc-1)+bs);
```

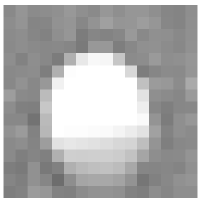


Fig. 9.10 Magnification of the macroblock at position [2,5]

Fig. 9.11 shows the search area in the reference image (frame #0). The search area is centered at the same position of the macroblock under analysis and, in this case, the search area has been set to 46x46 pixels (parameter `sa` set to [15 15]). The macroblock from the current image (frame #1) is compared to all possible 16x16 subimages within the search area in the reference image (frame #0) (that is, 31x31 = 961 possible positions for each macroblock, see Section 9.1.1)

```
sa = [15 15];
f = table{t-1}*0.2;
f(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1),...
   bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2)) = ...
   table{t}(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1),...
   bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2));
imshow(f);
```

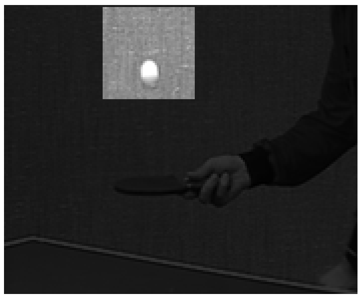


Fig. 9.11 Search area at frame #0 for the macroblock at position [2,5]

Fig. 9.12 shows a magnification of the search area:

```
br = table{t}(bs*(posr-1)+1-sa(1):bs*(posr-1)+ ...
   bs+sa(1),bs*(posc-1)+1-sa(1):bs*(posc-1)+bs+sa(2));
figure,imshow(kron(br,uint8(ones(8))));
```

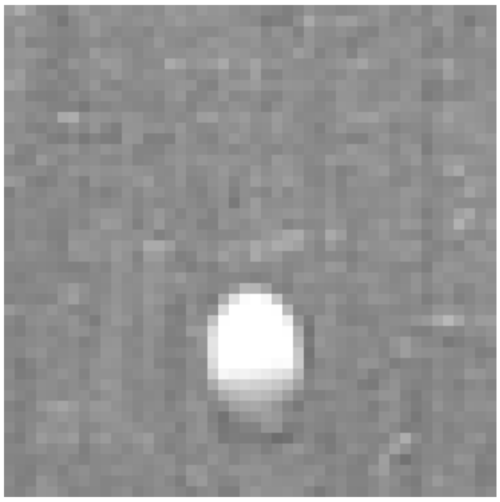


Fig. 9.12 Magnified search area in image #0 for the macroblock at position [2,5]

Fig. 9.13 shows the error prediction surface; that is, the function containing the metric values of the comparison between the macroblock under analysis and all possible 16x16 subimages within the search area. Darker values of the error function (lower points in the 3D surface) correspond to lower error values between the macroblock and all possible subimages and, thus, better candidates to be the reference for the current macroblock.

```
% function estimate_macroblock does the same as estimatemotion
% but for only 1 macroblock
[bcomp, bvv, bvh, errorf] = estimate_macroblock(b, ...
   table{t-1}, [posr posc], [16 16], ...
   [15 15],'fullsearch');
figure,mesh(-15:15,-15:15,errorf);
colormap('default'); colorbar; view(-20,22);
hold on; pcolor(-15:15,-15:15,errorf);
axis([-15 15 -15 15]);
```

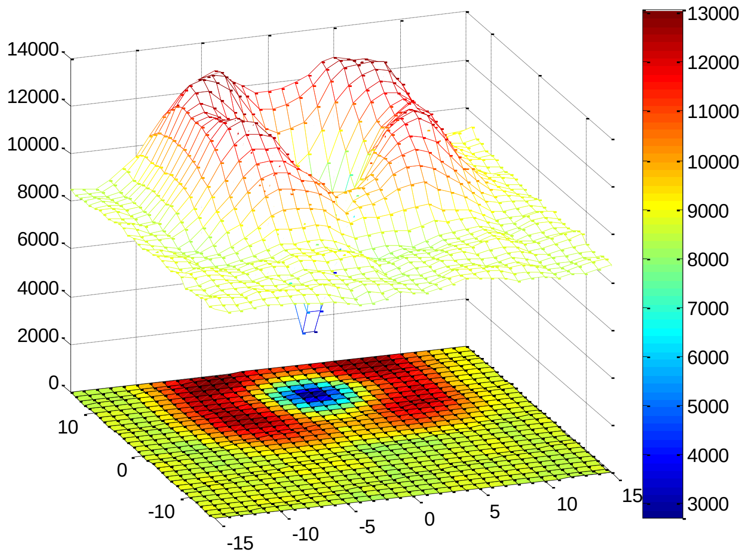


Fig. 9.13 Error prediction function for the macroblock at position [2,5]. The surface represents the error function as a 3D curve. For clarity, at the bottom (on plane z=0) the same error function is represented as a 2D image

In this case, even if the error function presents several local minima, there is a global minimum (which correspond to the movement of the ball between frames #0 and #1) at position [0,8] (motion vector). That is, the best possible reference subimage (within the search area) for this macroblock is situated 8 pixels below and 0 pixels to the right of the original macroblock position. As the selected search strategy (full-search) performs an exhaustive search through the entire search area, it is guaranteed that the global minimum is always found. Other search strategies such as the nstep-search (See Section 9.1.1), which visits less positions in the search area, may be able to obtain similar (or even the same) results as the exhaustive search. For instance, for the case of the macroblock at position [2, 5], an nstep-search also finds the global minimum, as shown in Fig. 9.14:

```
[bcomp2, bvv2, bvh2, errorf2] = estimate_macroblock(b, ...
   table{t-1}, [posr posc], [16 16], [15 15],'nstep');
figure,surf(-15:15,-15:15,errorf2);
colormap('default'); colorbar;
view(-20,22);
hold on; pcolor(-15:15,-15:15,errorf2);
axis([-15 15 -15 15]);
```

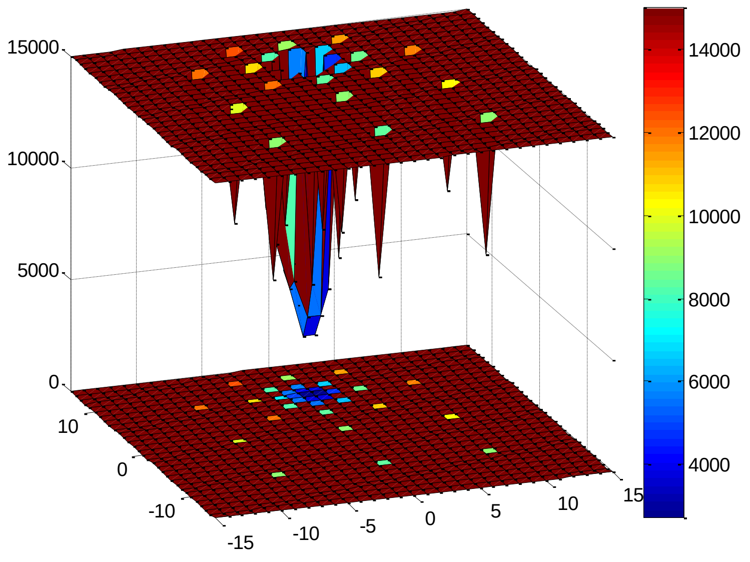


Fig. 9.14 Error prediction function for the selected macroblock (at position [2,5]) using an nstep-search strategy. The surface represents the error function as a 3D curve where the highest values (in that case 15000) are unvisited positions in the search. At the bottom (on plane z=0), the error function is represented as a 2D image (white pixels correspond to unvisited positions due to the search strategy)

In this example, both search strategies implemented in the MATLAB function `estimatemotion` (full-search and nstep-search) lead to the same result, a motion vector of [0,8]. Fig. 9.15 shows the selected reference subimage applying a motion vector of [0,8] within the search range.

```
f = table{t-1}*0.2;
f(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1),bs*(posc-1)+1-
sa(2):bs*(posc-1)+bs+sa(2)) = ...
    0.45*table{t-1}(bs*(posr-1)+1-sa(1):bs*(posr-
1)+bs+sa(1),bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2));
f(bs*(posr-1)+1+bvv:bs*(posr-1)+bs+bvv,bs*(posc-
1)+1+bvh:bs*(posc-1)+bs+bvh) = ...
    table{t-1}(bs*(posr-1)+1+bvv:bs*(posr-1)+bs+bvv,bs*(posc-
1)+1+bvh:bs*(posc-1)+bs+bvh);
```

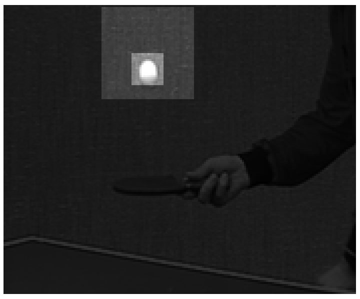
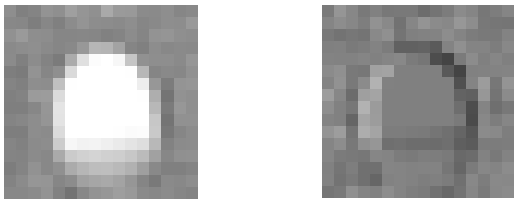


Fig. 9.15 Selected reference subimage within the search area at frame #0

Fig. 9.16 represents the magnification of the reference subimage and the corresponding compensated error (between the reference subimage at frame #0 and the macroblock at frame #1).

```
br = table{t-1}(bs*(posr-1)+1+bvv:bs*(posr-1)+bs+bvv,bs*(posc-
1)+1+bvh:bs*(posc-1)+bs+bvh);
figure,imshow(kron(br,uint8(ones(8))));

e = double(b)-double(br);
figure,imshow_merror(kron(e,ones(8)),250);
sum(sum(e.*e)),
```



Reference subimage

Compensated error
Energy = 65.728

Fig. 9.16 Magnification of the selected reference subimage at frame #0 and the corresponding compensated error

Through this Chapter, in order to present error images, an offset of 128 is added to all pixel values and, if necessary, they are clipped to the [0, 255] range. This way, zero error is represented by a 128 value

A second example is analyzed to further illustrate the algorithm. Fig. 9.17 and Fig. 9.18 show the information associated to a macroblock from frame #1 placed at a different position. In this case the position of the macroblock under analysis is 6 macroblocks from the top and 6 from the left:

```
posr = 6; posc = 6;
f = table{t}*0.2;
bs = 16;
f(bs*(posr-1)+1:bs*(posr-1)+bs,bs*(posc-1)+1:bs*(posc-1)+bs) =
   table{t}(bs*(posr-1)+1:bs*(posr-1)+bs, ...
   bs*(posc-1)+1:bs*(posc-1)+bs);
```

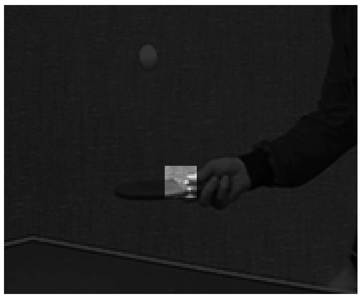


Fig. 9.17 Macroblock at position [3,5] (highlighted)

Fig. 9.18 shows a magnification of the macroblock under analysis:

```
b = table{t}(bs*(posr-1)+1:bs*(posr-1)+bs, ...
   bs*(posc-1)+1:bs*(posc-1)+bs);
imshow(kron(b,uint8(ones(8))));
```

Fig. 9.18 Magnification of the macroblock at position [3, 5]

The search area at frame #0 corresponding to the macroblock under analysis can be seen in Fig. 9.19 and Fig. 9.20.

```
sa = [15 15];
f = table{t-1}*0.2;
f(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1),...
   bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2)) = ...
   table{t-1}(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1), ...
   bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2));
```

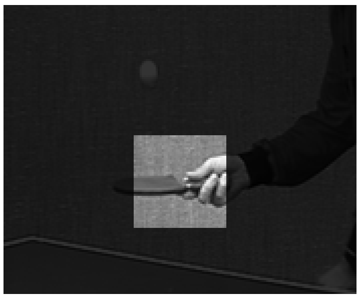


Fig. 9.19 Search area at frame #0 for the macroblock at position [3,5]

```
br = table{t-1}(bs*(posr-1)+1-sa(1):bs*(posr-
1)+bs+sa(1),bs*(posc-1)+1-sa(1):bs*(posc-1)+bs+sa(2));
figure,imshow(kron(br,uint8(ones(8))));
```

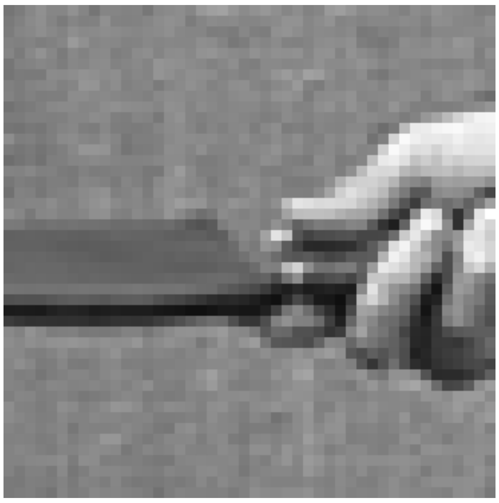


Fig. 9.20 Magnification of the search area for the macroblock at position [3, 5]

As in the previous example, we show the error surface (see Fig. 9.21 and Fig. 9.22) corresponding to both full-search and nstep-search strategies

```
[bcomp, bvv, bvh, errorf] = estimate_macroblock(b, ...
   table{t-1}, [posr posc], [16 16], [15 15],...
   'fullsearch');bvv,bvh,
figure,mesh(-15:15,-15:15,errorf);
colormap('default'); colorbar; view(-20,22);
hold on; pcolor(-15:15,-15:15,errorf);
axis([-15 15 -15 15]);
```

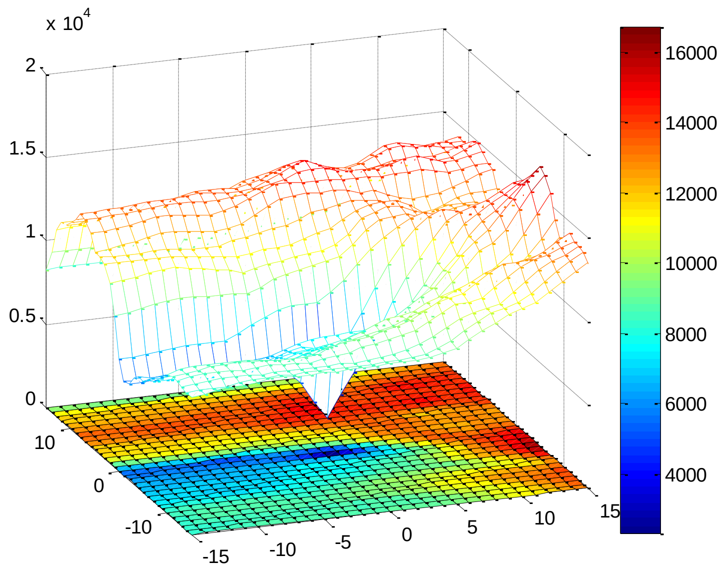


Fig. 9.21 Error prediction function for the macroblock at position [6, 6]. The surface represents the error function as a 3D curve. For clarity, at the bottom (on plane z=0) the same error function is represented as a 2D image

```
 [bcomp2, bvv2, bvh2, errorf2] = estimate_macroblock(b, ...
   table{t-1}, [posr posc], [16 16], [15 15],'nstep');
figure,surf(-15:15,-15:15,errorf2);
colormap('default'); colorbar;
view(-20,22);
hold on; pcolor(-15:15,-15:15,errorf2);
axis([-15 15 -15 15]);
```

In this example, the full-search obtains a motion vector of [0,-2] while the nstep-search obtains a motion vector of [-14,-1]. Note that, in this case, the nstep-search strategy does not lead to the optimum result. In particular, for the nstep-search, the initial step in the search is 8 pixels. The nine solutions that are evaluated overlooked the global minimum and following steps of the algorithm get trapped in a distant local minimum.

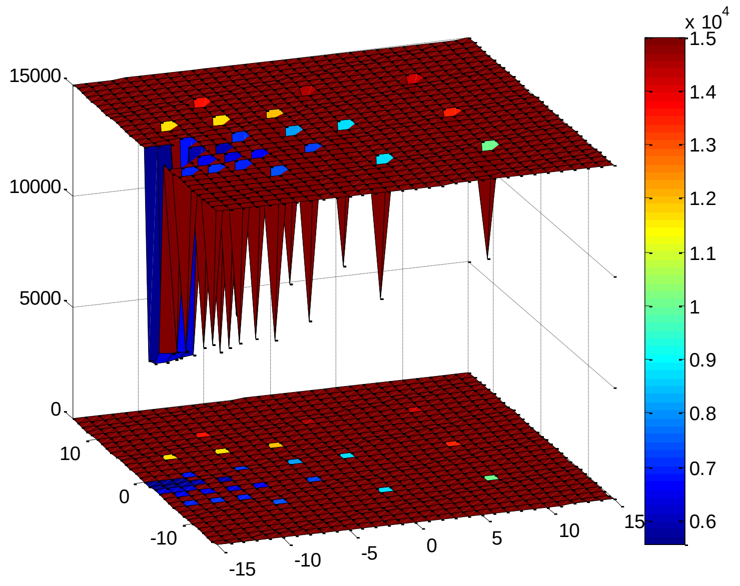


Fig. 9.22 Error prediction function for the macroblock at position [6, 6] using an nstep-search. The surface represents the error function as a 3D curve where the highest value (in that case 15000) represents unvisited positions in the search. At the bottom (on plane z=0) the same error function is represented as a 2D image (white pixels correspond to positions not visited in the search)

Fig. 9.23 shows the selected reference subimage leading to a motion vector of components [0,-2] (computed with the full-search approach).

```
f = table{t-1}*0.2;
f(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1),...
   bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2)) = 0.45* ...
    table{t-1}(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1),...
   bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2));
f(bs*(posr-1)+1+bvv:bs*(posr-1)+bs+bvv,...
   bs*(posc-1)+1+bvh:bs*(posc-1)+bs+bvh) = ...
   table{t-1}(bs*(posr-1)+1+bvv:bs*(posr-1)+bs+bvv,...
   bs*(posc-1)+1+bvh:bs*(posc-1)+bs+bvh);
```

Fig. 9.24 represents the magnification of the reference subimage and the corresponding compensated error.

```
br = table{t-1}(bs*(posr-1)+1+bvv:bs*(posr-1)+bs+bvv,...
   bs*(posc-1)+1+bvh:bs*(posc-1)+bs+bvh);
figure,imshow(kron(br,uint8(ones(8))));
e = double(b)-double(br);
figure,imshow_merror(kron(e,ones(8)),70);
sum(sum(e.*e)),
```

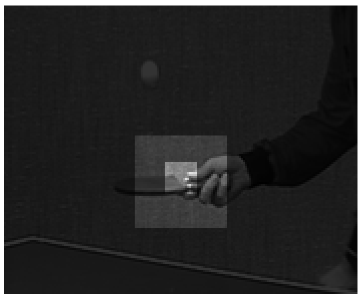


Fig. 9.23 Selected reference subimage (leading to a motion vector of components [0,-2]) within the search range at frame #0

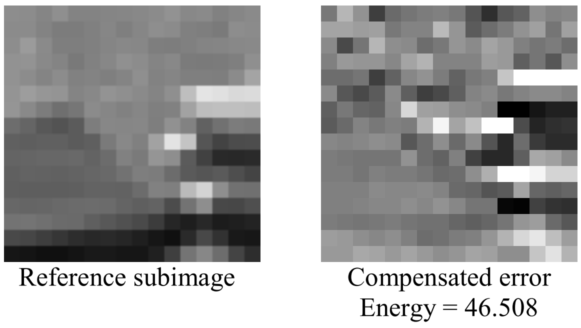


Fig. 9.24 Magnification of the selected reference subimage (with a motion vector [0,-2]) and the corresponding compensated error

In the case of the suboptimal strategy (nstep-search), Fig. 9.26 shows the selected reference subimage (leading to a motion vector of [-14,-1] and the corresponding compensated error. As the selected reference subimage is not the optimum one (within the search range), the final compensated error energy is greater in the case nstep-search.

```
f = table{t-1}*0.2;
f(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1),...
   bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2)) = 0.45* ...
    table{t-1}(bs*(posr-1)+1-sa(1):bs*(posr-1)+bs+sa(1),...
   bs*(posc-1)+1-sa(2):bs*(posc-1)+bs+sa(2));
f(bs*(posr-1)+1+bvv2:bs*(posr-1)+bs+bvv2,...
   bs*(posc-1)+1+bvh2:bs*(posc-1)+bs+bvh2) = ...
   table{t-1}(bs*(posr-1)+1+bvv2:bs*(posr-1)+bs+bvv2,...
   bs*(posc-1)+1+bvh2:bs*(posc-1)+bs+bvh2);
```

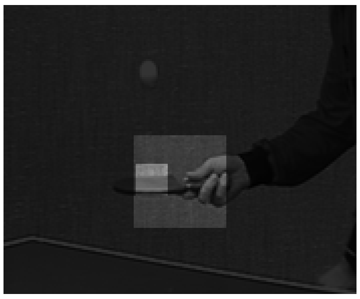


Fig. 9.25 Selected reference subimage (leading to a motion vector of components [-14,-1]) within the search range at frame #0

```
br = table{t-1}(bs*(posr-1)+1+bvv:bs*(posr-1)+bs+bvv,...
   bs*(posc-1)+1+bvh:bs*(posc-1)+bs+bvh);
figure,imshow(kron(br,uint8(ones(8))));
e = double(b)-double(br);
figure,imshow_merror(kron(e,ones(8)),70);
sum(sum(e.*e)),
```

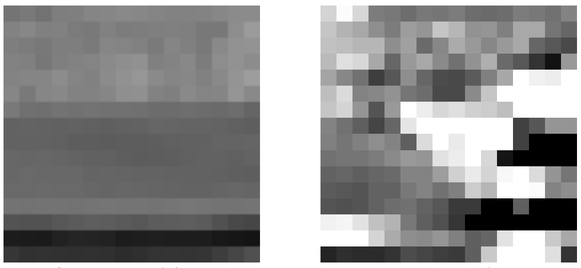


Fig. 9.26 Magnification of the selected reference subimage (with a motion vector [-14,-1]) and the corresponding compensated error

The use of suboptimal search strategies can lead to the selection of reference subimages which are not the best representation of the macroblock under study. This translates into an increase of the prediction error and, therefore, a decrease in the coding performance.

Note that, even in the case of using an exhaustive search, the resulting motion vectors may not represent the real motion in the scene. Vectors are computed for a fixed partition and obtained by minimization of a given metric in a specific neighbourhood. These constrains impose a scenario that may not be coincident with the real one. This problem is common in areas with very similar texture that may lead to different solutions with close values. Another situation that produces such kind of results is that of having two objects (or portions of objects) in the same macroblock undergoing different motions.

9.2.3 Motion compensation

The estimation of the original frame #1 is obtained by motion compensating the reference image (in this example the frame #0) using the motion vectors from the BM algorithm, which created the so-called motion compensated image (see Fig. 9.27). In our implementation, the MATLAB function `applymotion` is responsible for compensating the reference image with the motion vectors computed using the previous function `estimatemotion`.

```
t = 2;
[mvv mvh] = estimatemotion(table{t},table{t-1},[16 16],...
   [15 15],'fullsearch');
tablec{t} = applymotion(table{t-1},mvv,mvh,[16 16]);
imshow(tablec{t});
```

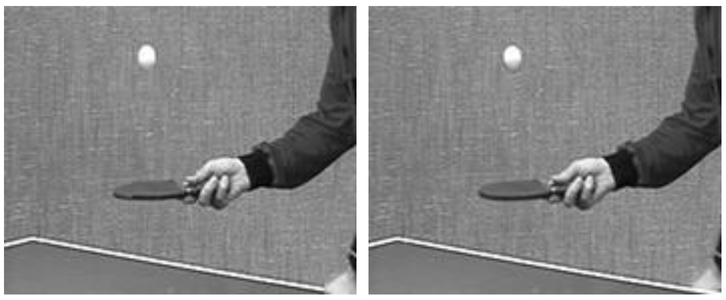


Fig. 9.27 (a) Motion compensated image using frame #0 as reference and full search motion vectors (see Fig. 9.8) and (b) Original image at frame #1

Fig. 9.28.a shows the error image between the original and the motion compensated image (*compensation error*).

```
error{t} = double(tablec{t})-double(table{t});
imshow_merror(error{t},250);
```

As it can be seen, the errors in the compensated image are located in the moving objects of the scene. However, as the computed motion vectors compensate somehow this motion (even if it is not translational) the final compensation error is relatively small.

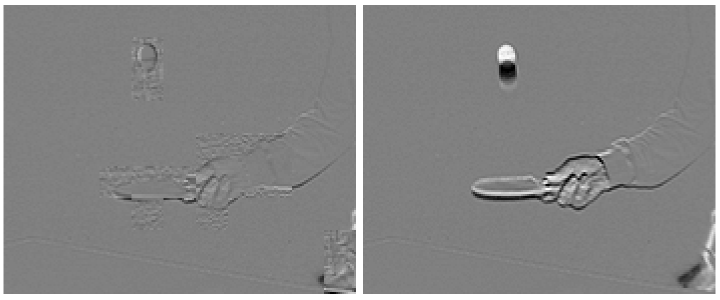
```
Ee{t} = sum(sum(error{t}.*error{t}));
Ee{t},

ans = 932406
```

To have an idea of the improvement obtained by using motion compensation with BM, the direct difference between images #1 and #0 is presented in Fig. 9.28.b. This result can be interpreted as motion compensating image #0 with a motion vector field in which all motion vectors are `[0,0]`. It can be observed that the compensation error without motion compensation is larger than in the previous case, and the energy of the error would increase around 420%.

```
    error_nocompen{t} = double(table{t})-double(table{t-1});
    imshow_merror(error_nocompen{t},250);
    Eenc{t} = sum(sum(error_nocompen{t}.*error_nocompen{t}));
    Eenc{t},

Eenc = 4836677
```



(a) (b)

Fig. 9.28 Comparison of motion compensated images: (a) Compensated error between the original image at frame #1 and the full search motion compensated image (from Fig. 9.27), (b) Difference image between original images at frame #1 and frame #0 (without motion compensation.

Finally, Fig. 9.29 presents the motion compensated image (and the original image) which is obtained by estimating the motion vectors using the nstep-search sub-optimal strategy. In addition, Fig. 9.30 shows the corresponding compensation error. In that case, it can be seen than the motion compensated image is not able to estimate the original image as well as with the full search and, therefore, the energy of the error is greater than in the full search case. Also, some of the errors in the nstep-search strategy can be easily seen in the compensated image. For instance, the macroblock in position [6,6] (analyzed in Section 9.2.2) does not correctly reconstruct the racket or the player's hand due to the nstep-search strategy failing to obtain the optimum reference subimage in the search area.

```
t=2;
[mvv2 mvh2] = estimatemotion(table{t},table{t-1},[16 16],...
   [15 15],'nstep');
tablec2{t} = applymotion(table{t-1},mvv2,mvh2,[16 16]);
```

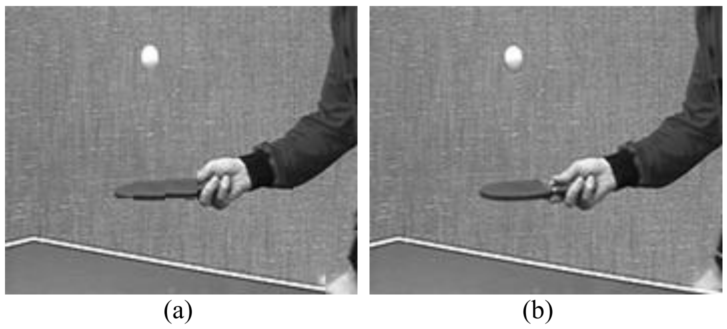


Fig. 9.29 (a) Motion compensated image using frame #0 as reference and nstep-search motion vectors and (b) Original image at frame #1

```
error2{t} = double(table{t})-double(tablec2{t});
figure,imshow_merror(error2{t},250);

Ee2{t} = sum(sum(error2{t}.*error2{t}));
Ee2{t},

ans = 1212642
```

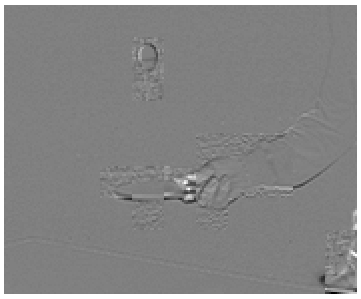


Fig. 9.30 Compensated error between the original image at frame #1 and the nstep-search motion compensated image

9.2.4 Selection of search area

Let us now analyze the effect of varying the size of the search area in the BM process. As we have previously commented, the search area is related to the maximum speed that we expect from the objects in the scene. In the case of the *Table Tennis* sequence the fastest object is the ball. We use frames #1 and #0 of the same sequence. Fig. 9.31 presents, on the top row, the motion compensated images using a search area with values 24x24, 32x32 and 46x46. On the second row the corresponding compensation errors are presented.

```
t = 2;
n = 1;
for i=[4 8 15],
    [vv vh] = estimatemotion(table{t},table{t-1},[16 16],...
       [i i]);
    mc = applymotion(table{t-1},vv,vh,[16 16]);
    imshow(mc);
    e = double(table{t}) - double(mc);
    figure,imshow_merror(e,250);
    ee = sum(sum(e.^2));
    disp(['Error energy = ' int2str(ee)]);
end;
```

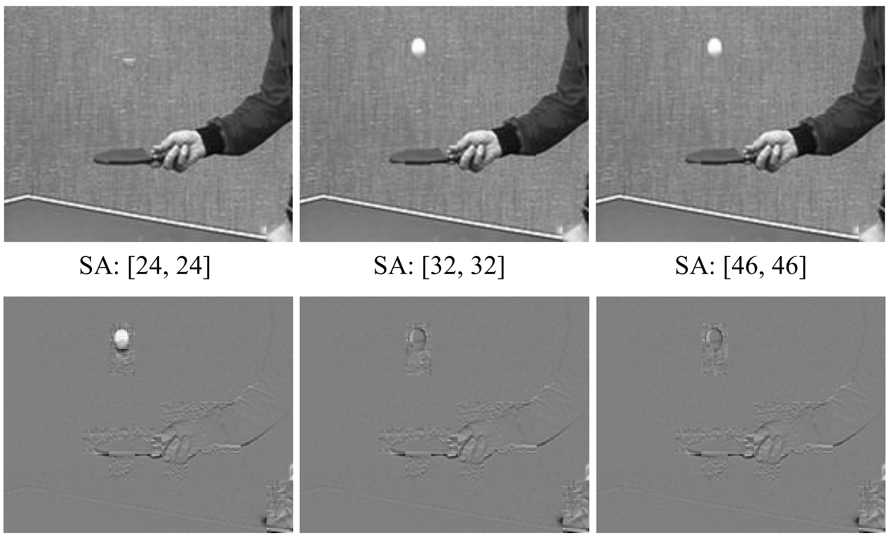


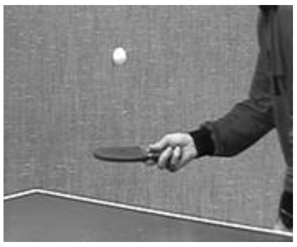
Fig. 9.31 Compensated image obtained when varying the size of the search area (SA) and the associated error compensation image with the resulting global error energy (EE).

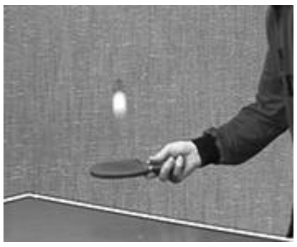
As it can be seen, a search area as small as 24x24 (corresponding to a maximum motion vector displacement of [±4, ±4]) does not allow correctly compensating the ball since its motion has displaced it outside the search area. This can be easily seen on the first column of Fig. 9.31 where the ball does not appear in the motion compensated image (so the error in the area of the ball is very high). However, when using a search area of 32x32 or 46x46, the BM is capable of following the ball movement and the corresponding motion compensated images provide smaller errors in the area of the ball.

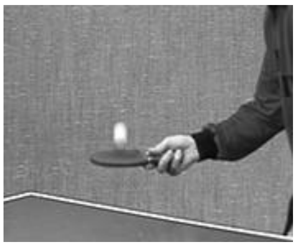
Of course, the use of larger search areas implies a trade-off: the quality of the motion vectors is increased at the expenses of analyzing a larger amount of possible displacements and, therefore, increasing the computational load of the motion estimation step.

9.2.5 Selection of reference image

Let us now analyze the impact of using a reference image different from the previous one. In order to do that, we will select frame #30 as the image to be estimated and successively use frame #28, #26, and #24 as reference images. The original images at those time instants can be seen in **Erreur ! Source du renvoi introuvable.**.


Frame #30


Frame #24


Frame #26

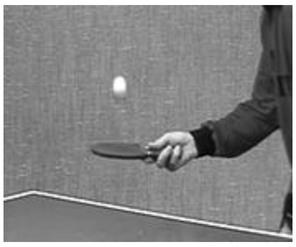

Frame #28

Fig. 9.32 Original images used in the analysis of the time difference between the image under study and the image reference

```
for i=25:2:31,
    table{i} = ...
       imread(sprintf('seqs/table/gray/table_%03d_g.bmp', i-
1));
    imshow(table{i});
end;
```

Fig. 9.33 presents the compensated images and the associated compensation error images when using as reference image frame #24, #26 and #28, respectively.

```
t = 31;
for p=29:-2:25,
    [mvv,mvh] = estimatemotion(table{t},table{p},[16 16],...
       [16 16]);
    mc = applymotion(table{p},mvv,mvh,[16 16]);
    imshow(mc);
    e = double(table{t}) - double(mc);
    ee = sum(sum(e.^2));
    imshow_merror(e,250);
end;
```

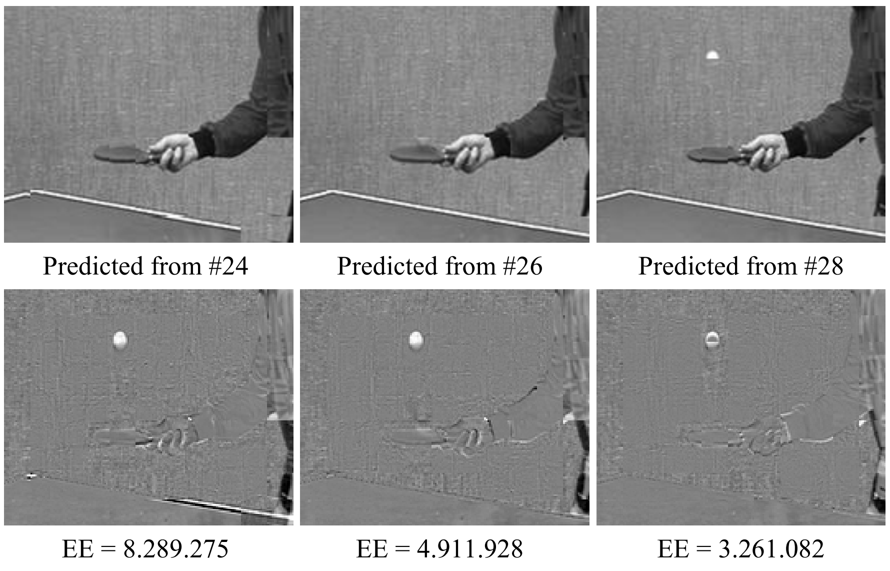


Fig. 9.33 Motion compensated images in the first row using different reference frames to compensate frame #30. At the bottom row, the corresponding compensation errors and its energy

As it can be seen, the further away the two images, the higher the energy of the compensation error. This is due to the fact that distant images are less correlated and, therefore, the prediction step cannot exploit in an efficient manner the temporal correlation. Moreover, there is an object, the player's arm at the bottom right corner, in frame #30 which is not present in frames #24 and #26. Therefore, when using these frames as references, this object does not have any referent in the reference image and the motion compensation leads to a compensation error with higher energy.

9.2.6 Backward motion estimation

The problem of having an object in the current frame without any referent in the previous images happens every time an object appears in the scene. It is clear that, in order to obtain a referent for this object, we should look into the future frames; that is, use a non-causal prediction. At this stage, we are only going to analyze the possibility of using past as well as future frames as reference images. We postpone to Section 9.2.9 the illustration of how this non-causal prediction can actually be implemented in the coding context (see Section 9.1.2).

Here, we analyze the possibility of estimating the current frame using as reference image the following frame in the sequence. If non-causal prediction can be used (that is, motion compensate future frames is possible), the information in past and future images can be used separately or combined in order to obtain a better motion compensated image. These concepts are illustrated in the next Figures.

In the first row of Fig. 9.34, we present the current image (frame #30) with the motion vector fields with respect to the previous (Fig. 9.34.a) and the following (Fig. 9.34.b) frames. In the second row, we present the motion compensated images using these motion vector fields. Finally, in the last row, the associated compensation errors are shown.

```
for i=30:32,
    table{i} = ...
       imread(sprintf('seqs/table/gray/table_%03d_g.bmp',i-
1));
end;

t=31;

% forward estimation
[fmvv,fmvh] = estimatemotion(table{t},table{t-1},[16 16],...
   [16 16],'fullsearch');
fmc = applymotion(table{t-1},fmvv,fmvh,[16 16]);
fe = double(table{t}) - double(fmc);
fee = sum(sum(fe.^2));

% backward estimation
```

```
[bmvv,bmvh] = estimatemotion(table{t},table{t+1},[16 16], ...
   [16 16],'fullsearch');
bmc = applymotion(table{t+1},bmvv,bmvh,[16 16]);
be = double(table{t}) - double(bmc);
bee = sum(sum(be.^2));
```

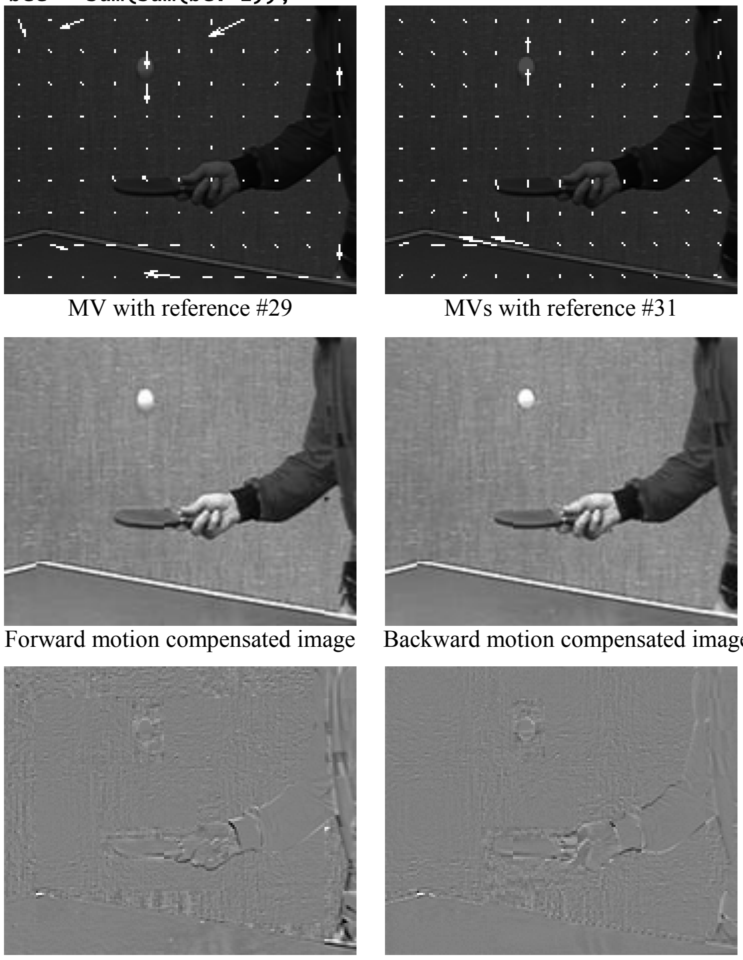
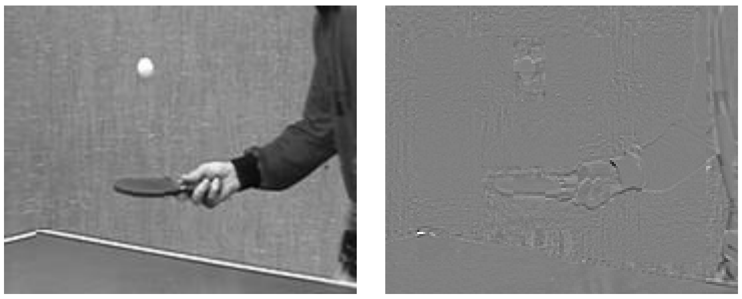


Fig. 9.34 Motion estimation and compensation using forward (#29) and backward (#31) references for frame #30

From the example above it is clear than backward motion estimation can reduce the compensation error especially when new objects appear in the scene. In this example, this is the case of the player's arm as well as a part of the background (note that the camera is zooming-out). However, in order to further reduce the compensation error, both motion compensated images (forward and backward) could be combined. Following this new idea, Fig. 9.35 shows the motion compensated image and the compensation error where, for each macroblock, the estimation is computed by linearly combining the two reference subimages with equal weights (w = 0.5).

```
bdmc = uint8(0.5 * (double(fmc) + double(bmc)));
bde = double(table{t}) - double(bdmc);
bdee = sum(sum(bde.^2));
imshow(bdmc);imshow_merror(bde,250);
```



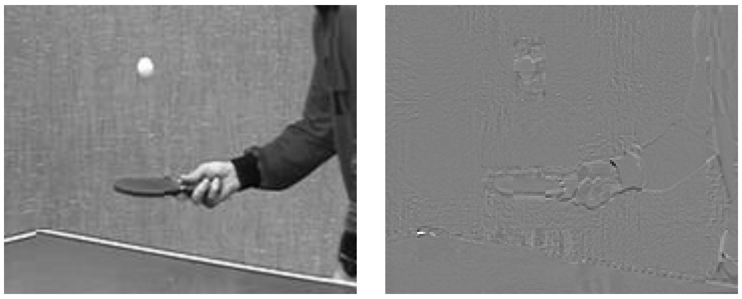
Bi-directional motion compensated image

Error Energy = 936.236

Fig. 9.35 Motion compensated image and compensation error using combined forward and backward prediction

In practice, the combination between forward and backward prediction is done in a macroblock level. For each macroblock, a decision (based on minimum error) has been made to select a forward, backward or combined reference. Fig. 9.36 shows the motion compensated image and the compensation error where each macroblock selects the best prediction:

```
[bimc,bie,bim] = biestimatemotion(table{t}, ...
   table{t-1},table{t+1},[16 16],[15 15],'fullsearch');
imshow(bimc);
biee = sum(sum(double(bie).^2));
imshow_merror(bie,250);
```



Bi-directional motion compensated image   Error Energy = 740.191

Fig. 9.36 Motion compensated image and compensation error using a selection among forward, backward or combined prediction

For this example, combining both forward and backward predictions reduce the energy of the compensation error up to 64% and 32% with respect to only forward or backward estimation, respectively.

```
round((fee-biee)/fee*100),
```

```
ans = 64
```

```
round((bee-biee)/bee*100),
```

```
ans = 32
```

In order to be able to see which decision has been taken for each macroblocks (among forward, backward or combined estimation) Fig. 9.37 shows the decision for each macroblock encoded in gray values. Note that backward estimation (black macroblocks) has been selected in almost all the macroblocks of the perimeter of the image. This is due to the fact that, in these images, the camera is performing a zoom-out and, therefore, new information comes into the scene at each image. This way, a correct referent for the information in this zone in frame #30 has to be looked for in future frames (frame #31, in this case). Note, as well, that for the largest amount of macroblocks the best estimations are built up by combining forward or backward information (macroblocks in grey). Finally, there exist a few macroblocks which are better motion compensated using only information from the past (macroblocks in grey).

```
kbim = kron(bim, ones(16));
imshow((kbim-1)/4);
addgridtofigure(size(kbim),[16 16]);
```

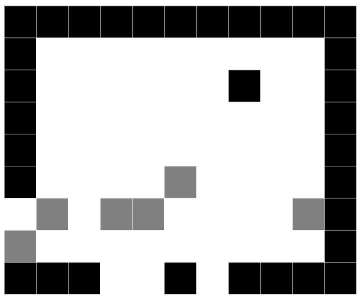


Fig. 9.37 Forward, backward or combined estimation decision: a black macroblock means backward prediction has been selected, a gray one forward prediction and a white one combined prediction

9.2.7 Coding of the compensation error

In all previous examples, it can be observed that, although motion compensated images show good quality, there is still relevant information in the compensation error. The compensation error can be understood as a still image that presents some correlation among adjacent pixels. Even though that correlation is much lower than in original images, the compensation error information is coded using the same strategy used when coding still images (see Chapter 8). This way, the motion compensation error image is partitioned into blocks of 8x8 pixels and each block is separately transformed (using a DCT transformation), quantized and entropy coded.

The same transform (DCT) and quantization table are used to code each compensation error block (as seen in the still image coding case in Chapter 8). Moreover, different `k` values can be used to obtain different qualities in the reconstructed compensation error. In our implementation, the MATLAB functions `quantizedct8diff` and `iquantizedct8diff` perform the (direct and inverse) quantization of the DCT coefficients for a compensation error block. As commented in Section 9.1.2, all values in the quantization table `Q` are set to 16.

To illustrate the transformation and quantization steps, Fig. 9.38 presents the reconstruction of the compensation error when quantizing the DCT coefficients of its blocks using `k = 1`, `k = 3` and `k = 5`. The compensation error corresponds to the block matching between frames #28 and #30 (using an exhaustive search) of the *Table Tennis* sequence (see Fig. 9.33 right column).

```
t = 31;
[mvv,mvh] = estimatemotion(table{t},table{t-2},[16 16],...
   [15 15],'fullsearch');
mc = applymotion(table{t-2},mvv,mvh,[16 16]);
e = double(table{t}) - double(mc);
Q = 16*ones(16,16);
edct = double(blkproc(e, [8 8], @dct2));
for k=[1 3 5],
    edctq = blkproc(edct, [8 8], @quantizedct8diff, k.*Q);
    edctqi = blkproc(edctq,[8 8],@iquantizedct8diff,k.*Q);
    er = uint8(blkproc(edctqi, [8 8], @idct2));
    figure,imshow_merror(er,250);
end;
```

As it can be seen, increasing the values in the quantization tables reduces the information in the decoded compensation error and, so does the quality of the reconstructed image (obtained adding the compensated image and the compensation error). In this example, this effect can be observed in the better representation of the texture of the background in the first image.

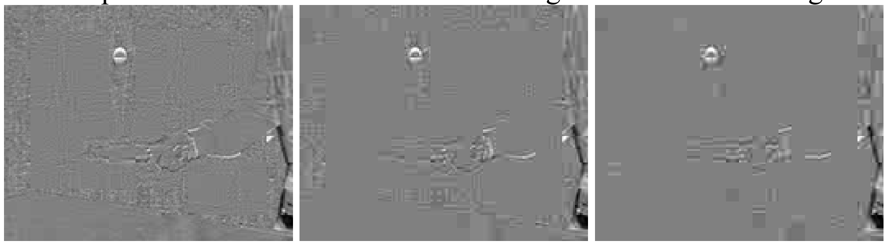


Fig. 9.38 Reconstructed compensation error using various quantization tables

Fig. 9.39 further illustrates this concept presenting the reconstructed images.

```
for k=[1 3 5],
    edctq = blkproc(edct, [8 8], @quantizedct8diff, k.*Q);
    edctqi = blkproc(edctq,[8 8],@iquantizedct8diff,k.*Q);
    er = blkproc(edctqi, [8 8], @idct2);
    tabler = mc + er;
    figure,imshow(tabler);
    disp(['k = ' int2str(k) '; ...
       psnr = ' num2str(mypsnr(table{t},tabler))]);
end;
```

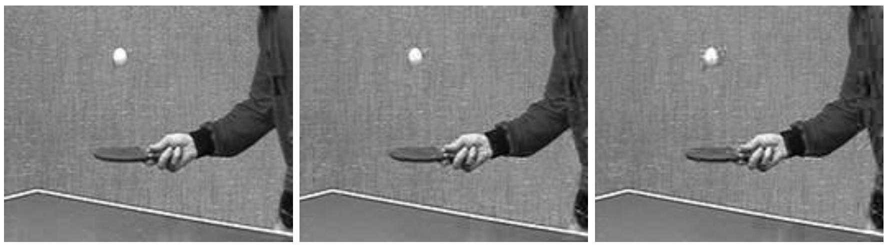


Fig. 9.39 Reconstructed images using various quantization tables and the resulting PSNR values from the original image (frame #30)

9.2.8 Entropy coding

As in the still image coding case, the quantized DCT coefficients associated to each block of the compensation error are entropy coded. In addition, the motion vectors associated with each macroblock of the image are encoded to form the final bitstream (see Section 9.1.2).

For the DCT coefficients, the same strategy as in still image coding is used. DC coefficients are decorrelated and encoded separately while AC coefficients are preceded with a runlength encoder. However, in the case of coding the compensation error, a different set of predefined Huffman codes are used. The MATLAB file "codes/immotiondiffcodes.mat" includes these Huffman codes corresponding to different values of DC coefficients (in variable dcdcode) and AC coefficients (variables nzcode and vvcode). In our implementation, the MATLAB function encodeimage quantizes and encodes the corresponding DCT coefficients.

Finally, motion vectors are also entropy coded. In our implementation, the MATLAB function encodemv is responsible for coding the motion vectors. This function imports the file "codes/mvcodes.mat" which includes the Huffman codes corresponding to the various motion vector values and returns the corresponding bitstream.

The following code shows how motion vectors and compensation error are encoded into a single bitstream. Applying it to the motion vectors estimated between frames #28 and #30 of the *Table Tennis* sequence and the corresponding compensation error results in:

```
t = 31;
[mvv,mvh] = estimatemotion(table{t},table{t-1},[16 16],...
    [15 15],'fullsearch');
[mvv,mvh] = estimatemotion(table{t},table{t-2},[16 16],...
    [15 15],'fullsearch');
mc = applymotion(table{t-2},mvv,mvh,[16 16]);
e = double(table{t}) - double(mc);
edct = double(blkproc(e, [8 8], @dct2));
mvcm = encodemv(mvv,mvh);
diffcm = encodeimage(edct,Q,'motiondifference');
bitstream = strcat(mvcm, diffcm);
final_bits = size(bitstream,2),

final_bits = 25546
```

which yields the following figure of bits per pixel used in the representation of the decoded grey image:

```
bitspixel = final_bits / (size(table{t},1)*size(table{t},2)),

bitspixel = 1.0080
```

In order to compare the final compressed frame with the original one, the produced bitstream must be decoded. The following code (using functions decodemv and decodeimage) shows how the bitstream can be decoded back into the reconstructed image. As entropy coding is a lossless process, the PSNR of the resulting reconstructed image is the same as in the previous section (see Fig. 9.39 with k = 1).

```
[mvv2, mvh2, bitstream] = decodemv(bitstream, ...
   size(table{t}),[16 16]);
[eQ bitstream] = decodeimage(bitstream, ...
   size(table{t}),Q,'motiondifference');
mc = applymotion(table{t-2},mvv,mvh,[16 16]);tabler =
uint8(limit(double(mc) + double(eQ),0,255));
mypsnr(table{t},tabler),

psnr = 36.6910
```

9.2.9 Video coding

In this section we are going to illustrate the entire video coding chain with different test sequences. In these experiments, we are going to work with color images. As in the still image coding case (see Chapter 8), the YCbCr color space is used and, to exploit the limitations of the human visual system, chrominance components are sub-sampled by a factor of two in the horizontal and vertical directions. The coding of chrominance components is done following the same steps as the luminance (grayscale) component. As it is common, the motion estimation is performed only in the luminance component and sub-sampled by two to be applied to the chrominance components.

In our implementation, the MATLAB function mpegencode is responsible of performing the motion estimation, computing and coding the prediction error, closing the coding loop and selecting a frame type for the frame in the sequence. In order to force the use of I frames at the beginning of each GOP, the function is called separately for each GOP in the sequence. As this function does not implement any rate control, the quantization tables used in the coding of the compensation error have been multiplied by a factor of 2 to ensure that the resulting PSNR for P and B frames is similar to that of I frames.

The following MATLAB code is used to encode the first 40 frames (5 GOPs of 8 frames) of the *Table Tennis* sequence. 5 different experiments are performed; using a GOP structure with no B frames (B=0), using 1 B frame between P frames (B=1), using 2 B frames between P frames (B=2), using 3 B frames between P frames (B=3) and, finally, using 4 B frames between P frames (B=4).

```
ngops = 5;
gopsize = 8;
for ng = 1:ngops,
   [cm,bits{1},type{1},psnr{1}] = mpegencode( ...
      'results/table_color','seqs/table/color', ...
      1+(ng-1)*gopsize,ng*gopsize,  1,gopsize);
   [cm,bits{2},type{2},psnr{2}] = mpegencode(...
      'results/table_color','seqs/table/color', ...
      1+(ng-1)*gopsize,ng*gopsize+1,2,round(gopsize/2));
   [cm,bits{3},type{3},psnr{3}] = mpegencode(...
      'results/table_color','seqs/table/color', ...
      1+(ng-1)*gopsize,ng*gopsize+1,3,3);
   [cm,bits{4},type{4},psnr{4}] = mpegencode(...
      'results/table_color','seqs/table/color', ...
      1+(ng-1)*gopsize,ng*gopsize+1,4,2);
   [cm,bits{5},type{5},psnr{5}] = mpegencode(...
      'results/table_color','seqs/table/color', ...
      1+(ng-1)*gopsize,ng*gopsize+1,5,2);

   for i=1:5,
      table.bits{i}(1+(ng-1)*gopsize:ng*gopsize) = ...
         bits{i}(1+(ng-1)*gopsize:ng*gopsize);
      table.type{i}(1+(ng-1)*gopsize:ng*gopsize) = ...
         type{i}(1+(ng-1)*gopsize:ng*gopsize);
      table.psnr{i}.y(1+(ng-1)*gopsize:ng*gopsize) = ...
         psnr{i}.y(1+(ng-1)*gopsize:ng*gopsize);
      table.psnr{i}.cb(1+(ng-1)*gopsize:ng*gopsize) = ...
         psnr{i}.cb(1+(ng-1)*gopsize:ng*gopsize);
      table.psnr{i}.cr(1+(ng-1)*gopsize:ng*gopsize) = ...
         psnr{i}.cr(1+(ng-1)*gopsize:ng*gopsize);
   end;
end;
```

Fig. 9.40 and Fig. 9.41 show the results of the 5 experiments for the sequence *Table Tennis*. In Fig. 9.40, the number of bits needed to encode each frame (for all 5 experiments) is represented and the corresponding PSNR (for the luminance component) is shown in Fig. 9.41. Furthermore, the average number of bits needed to represent the 40 frames and the average PSNR for all 40 frames are shown in Table 9.1.

Let us discuss the coding efficiency concept by analyzing Fig. 9.40 and Fig. 9.41. Coding efficiency is measured in terms of achieving the same or better quality with the same or lower bitrate. First, note that, as already commented in Section 9.1.2, I-Pictures require many more bits than P-Pictures and B-Pictures, while achieving similar PSNR (the largest difference being 2 dBs). A similar conclusion can be driven with respect to P-Pictures and B-Pictures: due to the better compensation obtained in B-Pictures, slightly better qualities can be obtained with a lower number of bits. Note, as well, that when the number of B frames in the GOP increases, so does the number of bits necessary to encode the following P-Frame (for roughly the same PSNR). As we have discussed in Section 9.2.5, a larger number of B-Pictures translates into a P-Image which is more decorrelated with respect to its reference and, therefore, more bits are necessary to code the compensation error. Nevertheless, for the *Table Tennis* sequence, it can be seen that using B frames in the GOP structure really improves the coding efficiency of the video codec.

Finally, another aspect that can be commented in Fig. 9.41 is the degradation that the prediction chain introduces. This can be very well observed in the curve associated to B = 0 where the PSNR decays at each new predicted frame, even though the number of bits is progressively increased.

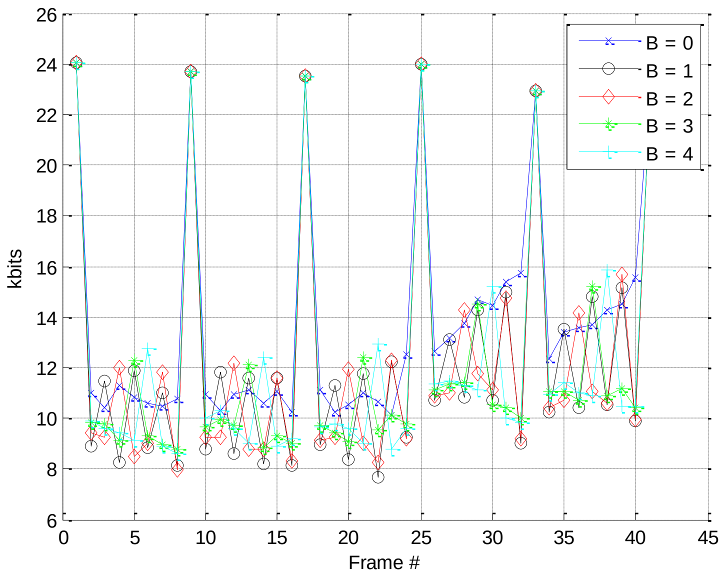


Fig. 9.40 Number of kbits needed to encode each frame of the *Table Tennis* sequence for different number of B frames in the GOP structure.

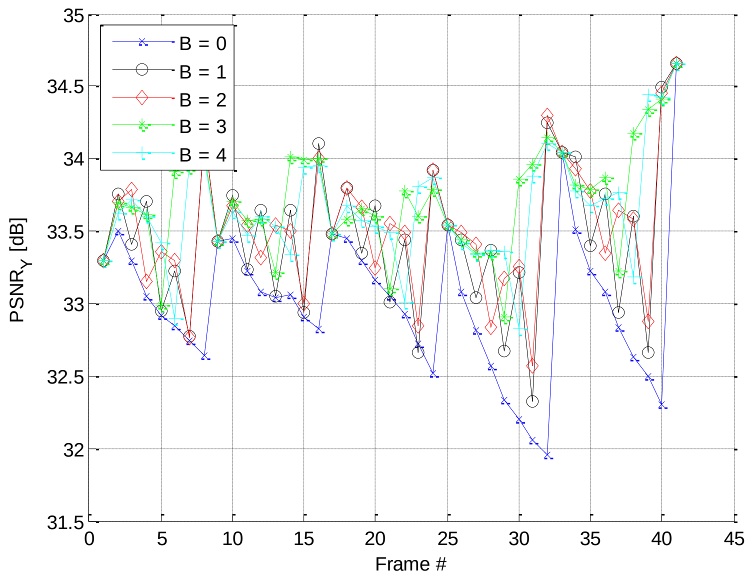


Fig. 9.41 Resulting PSNR (luminance component) for each frame of the *Table Tennis* sequence for different number of B frames in the GOP structure.

Table 9.1 Average number of bits needed to represent the 40 frames and mean PSNR for all 40 frames in the *Tennis Table* sequence

	B = 0	**B = 1**	**B = 2**	**B = 3**	**B = 4**
kbits	13.77	12.58	12.48	12.38	12.42
PSNR (Y)	32.97	33.42	33.49	33.69	33.62

Fig. 9.42 represents the average PSNR and kbps needed to encode the 40 frames of the *Table Tennis* sequence for each GOP structure and at different qualities. Qualities are selected by using a k factor which multiplies all values in the quantization tables (both for intra and inter prediction).

Fig. 9.42 shows that, for this sequence, using B frames generally improves the coding efficiency at high/normal qualities. However, for lower qualities, it is more efficient to encode using a lower number of B frames (ideally 0). This is due to the fact that, at lower qualities, reference frames in the closed loop are of very low quality and therefore the motion compensated images are not very similar to the frame being encoded. In this case, it is more efficient to use reference frames as close as possible to the frame being coded.

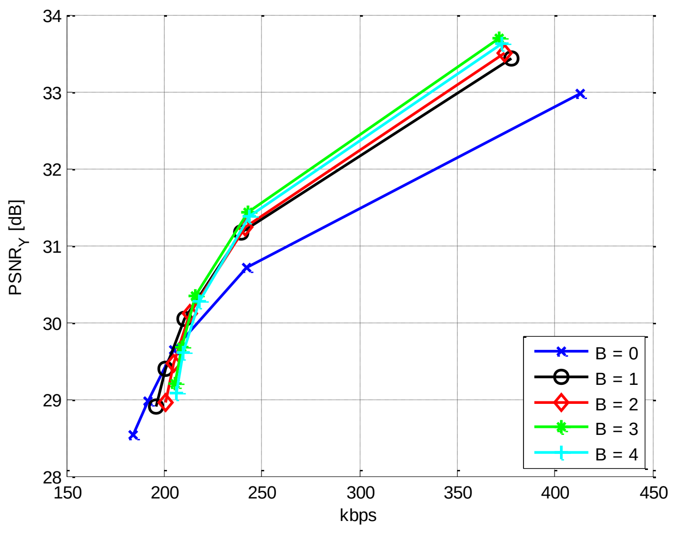


Fig. 9.42 Relation between mean PSNR and bitrate for 40 frames of the *Table Tennis* sequence for different number of B frames in the GOP structure.

Fig. 9.43, Fig. 9.44 and Fig. 9.45 show the same experiments conducted above but, this time, for 40 frames of the *Foreman* sequence. In this case, a specific part of the sequence is selected where there is a high amount of motion present. Similar conclusions can be driven as in the previous example. Nevertheless, as the motion estimation/compensation is not able to reduce the compensation error as much as in the previous test sequence, the more efficient GOP structure (at high/medium qualities) consists in using only 1 B frame between P frames (B = 1). Fig. 9.45 shows (as in the previous test sequence) that, at lower qualities, the use of B frames reduces its coding efficiency. As previously, the average number of bits needed to represent the 40 frames and the average PSNR for all 40 frames are shown in Table 9.2.

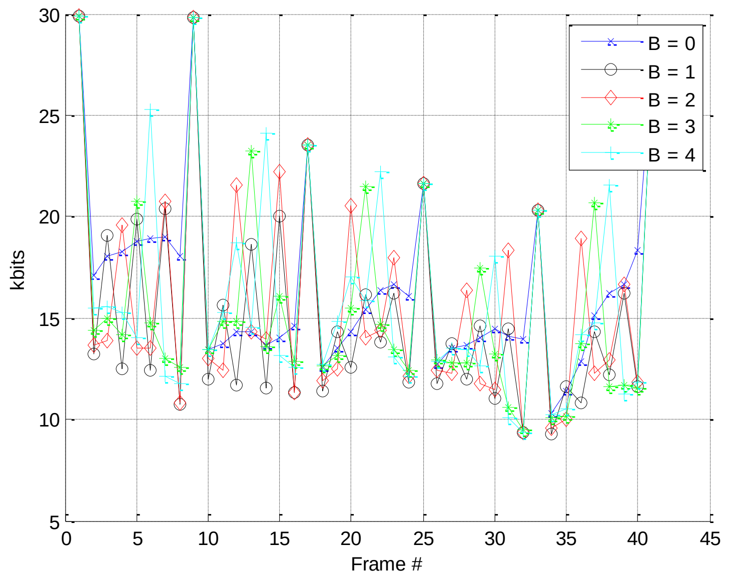


Fig. 9.43 Number of kbits needed to encode each frame of the *Foreman* sequence for different number of B frames in the GOP structure.

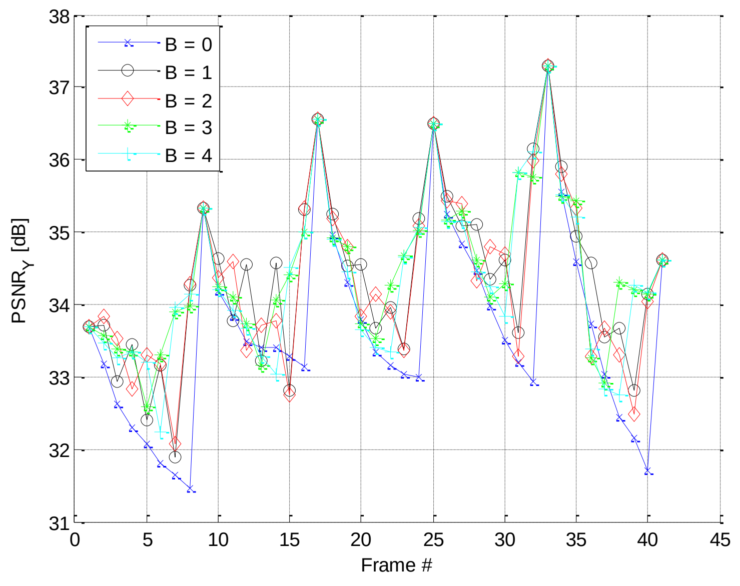


Fig. 9.44 Resulting PSNR (luminance component) for each frame of the *Foreman* sequence for different number of B frames in the GOP structure.

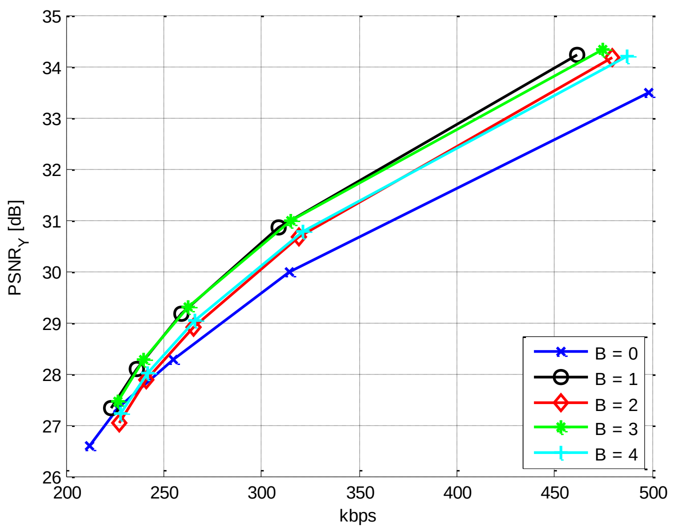


Fig. 9.45 Relation between mean PSNR and bitrate for 40 frames of the *Foreman* sequence for different number of B frames in the GOP structure.

Table 9.2 Average number of bits needed to represent the 40 frames and mean PSNR for all 40 frames in the *Foreman* sequence.

	B = 0	**B = 1**	**B = 2**	**B = 3**	**B = 4**
kbits	16.61	15.39	15.97	15.81	16.24
PSNR (Y)	33.48	34.22	34.16	34.33	34.19

9.3 Going further

In this Chapter, we have presented the basic concepts of video coding systems and we have illustrated using a few examples from two sequences. With the tools that have been provided, several other experiments could be conducted to further analyze these concepts. For example, at the end of *Tennis table* sequence there is a shot cut. The usefulness of correctly placing the beginning of a GOP at the beginning of the shot cut (that is, use an I-Picture for an image that has no previous reference) can be studied.

Current standards, although relying on the basic concepts presented in this Chapter, are extremely more complex than what has been presented here. As it has been pointed out in various Sections, there are several extensions of the previous concepts that are basic in current standards:

- The selection of the type of coding approach (I-, P- or B-Mode) is made at the macroblock level instead that at the picture level. That is, in the same image, macroblocks that are intra, predictive or bidirectional coded coexist.
- The concept of temporal prediction has been extended and several reference images can be combined in the motion compensation process.
- The size and shape of the macroblocks (that is, of the motion estimation and compensation unit) are dynamically fixed during the coding process, getting closer to the concept of motion based segmentation to improve coding efficiency.
- A large number of new prediction techniques are possible for the intra mode case.

Finally, let us comment that, nowadays, video coding systems aim at different functionalities rather than only compression. This way, concepts such as scalability, multiple description coding, error resilience, transcoding capabilities, etc are very important when currently designing a coding system. An excellent summary of the current state-of-the-art in these concepts can be found in (Zhu et al. 2005)

9.4 Conclusion

This Chapter has concentrated on the basic concepts behind all current video coding standards. Specially, we have focused on the interaction between the various components of the system and, mainly, on analyzing the so-called motion estimation and compensation blocks, which are the most relevant ones in the whole chain.

For that purpose, the Block Matching algorithm has been presented and extensively studied, although in a restricted scenario: that of using the same type of motion prediction for all macroblocks in a given image.

9.5 References

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