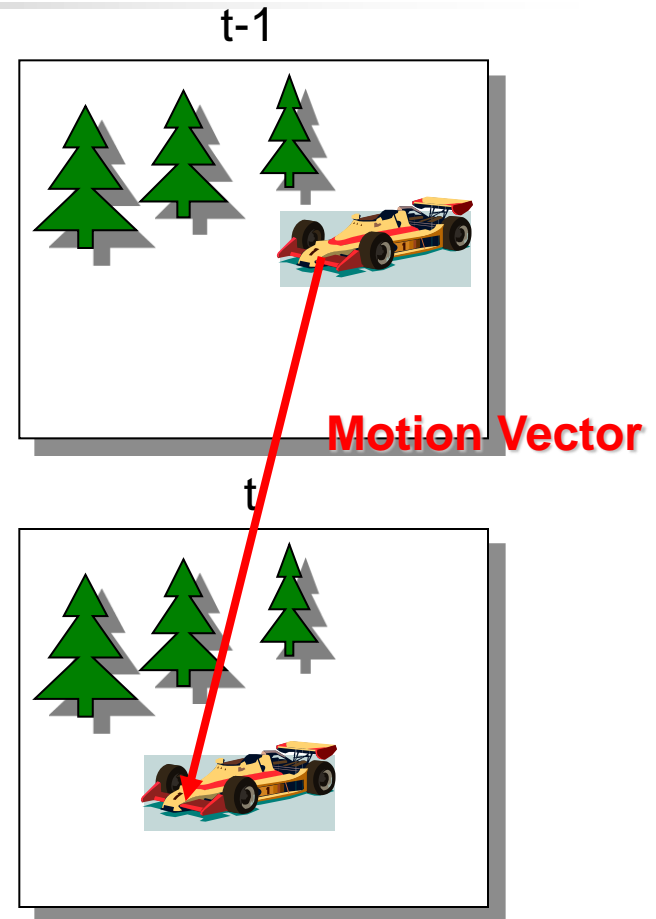




Motion Estimation and Motion Compensation

Motion Estimation (ME)

- To derive the motion information between frames
- Or, find the **corresponding points** between frames





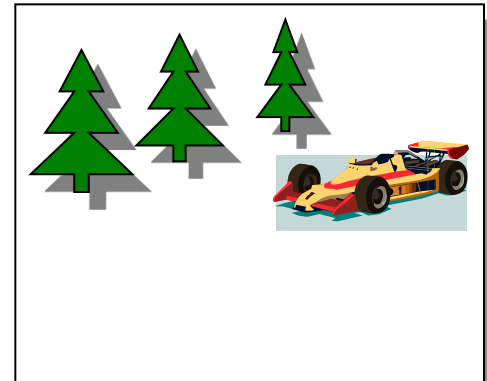
Motion Estimation

- Objective
 - Predict current frame from neighboring frames
- Motion Estimation Algorithm
 - Pixel-based method (Pel-Recursive Algorithm, Optical Flow)
 - Large computation overhead
 - Block-based method
 - Regularity and simplicity
 - Suitable for hardware implementation
 - Object-based method (content-based)
 - Frame-based method
 - ...
- Crucial to make possible a high degree of video compression (CR from tens to hundreds)

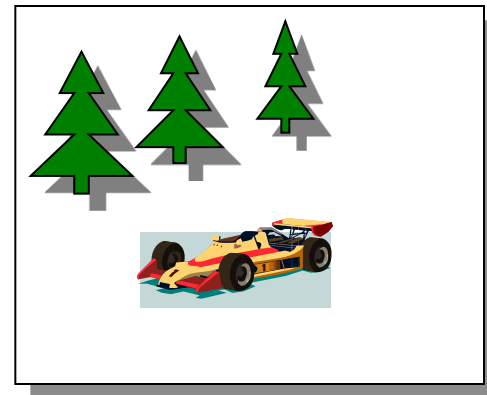
Motion Compensation (MC)

- To compensate the displacement between frames based on motion vectors
- Or, **align or warp** one frame to the other frame

t-1



t



Motion Compensation/Estimation

Original



Reconstructed



Similar to DPCM



Difference

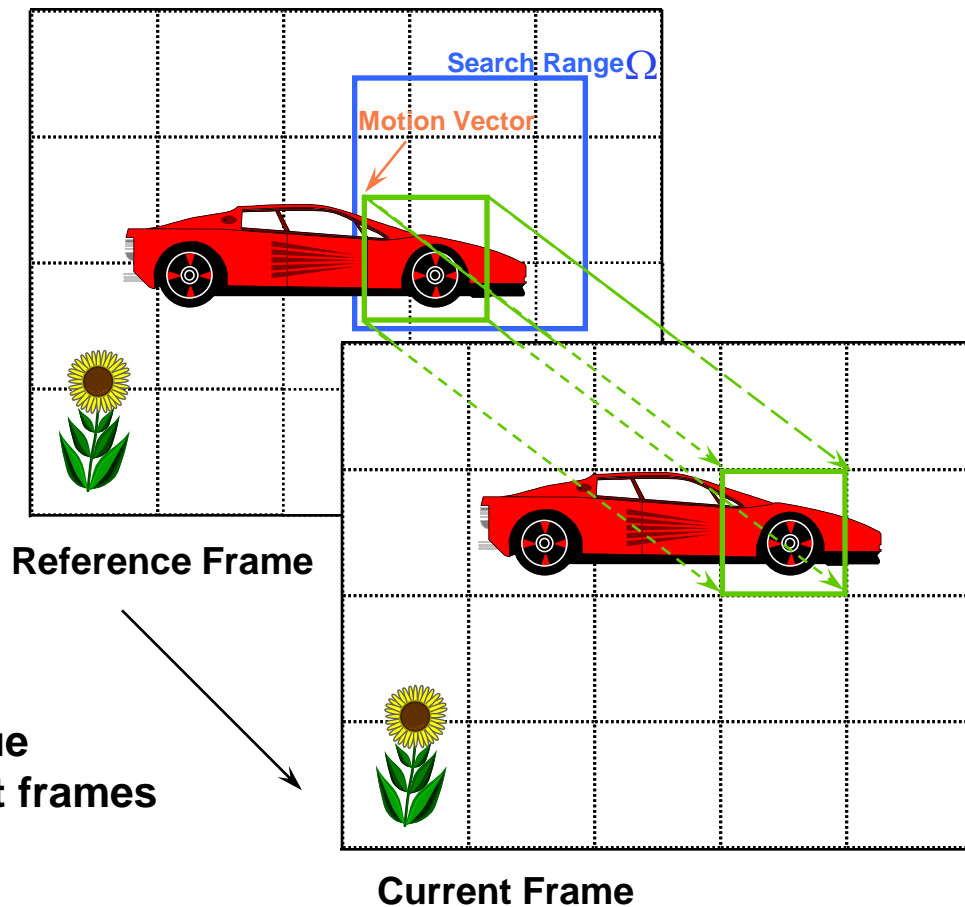


Motion Estimation

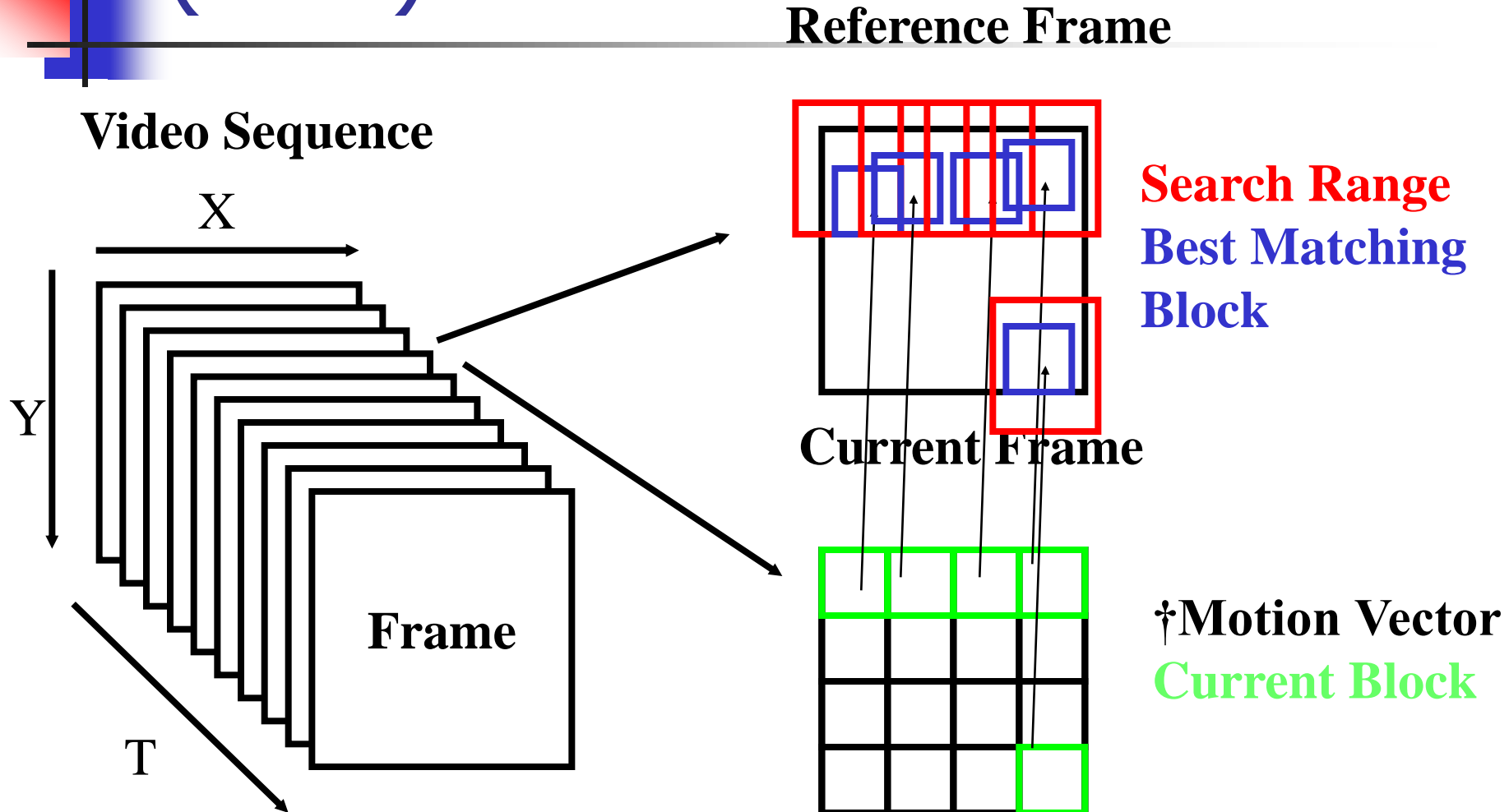
- Pixel-based method
 - Pel-recursive algorithm
 - Optical flow
- Block-based method
 - Full-search block matching algorithm
 - Fast motion estimation
 - More improvements on motion estimation

Block-Matching Motion Estimation

Motion Vector
 $V_t(p,q) = (Vec_i, Vec_j)$
the location in the **search range** Ω
that has the maximum correlation value
between blocks in temporally adjacent frames

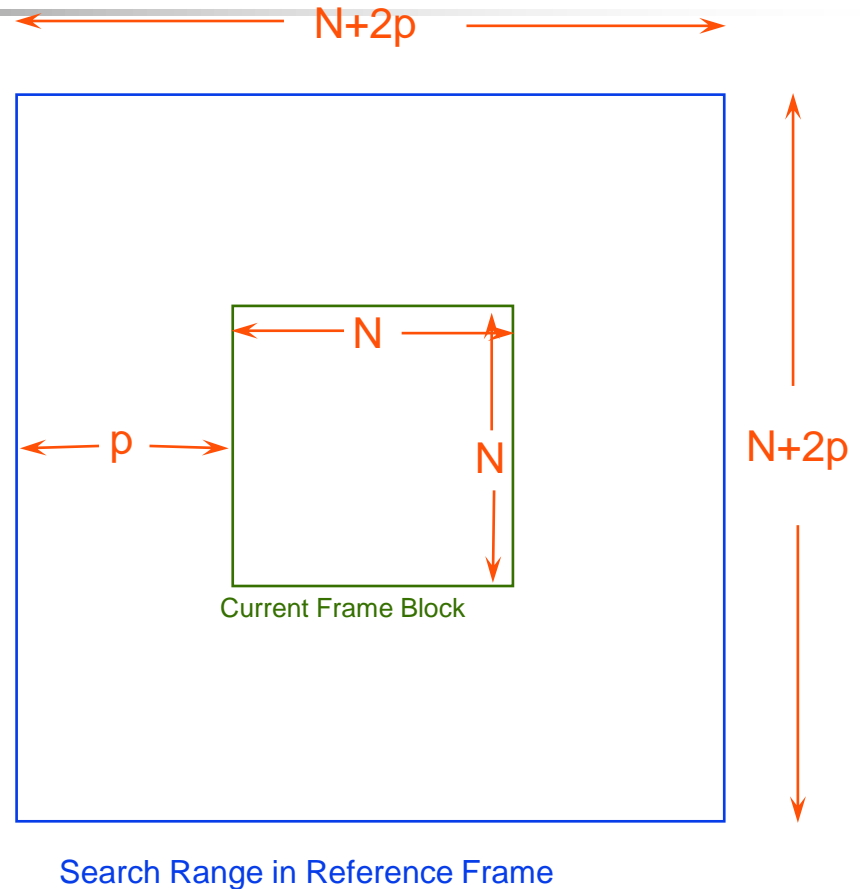


Block Matching Algorithm (BMA)

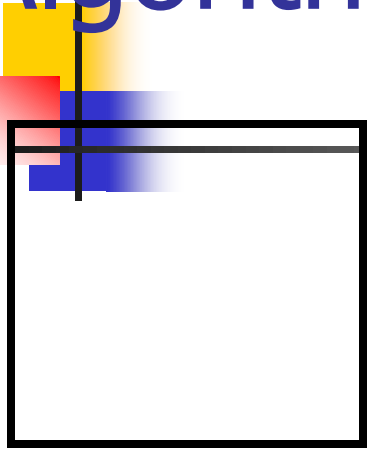


Factors of Affecting BMA

- Search algorithm
- Matching criterion
 - SSD (sum of squared pixel difference, mostly used in software)
 - SAD (sum of absolute pixel difference, mostly used in hardware)
- Search range $[-p, +p]$



Full-Search Block Matching Algorithm

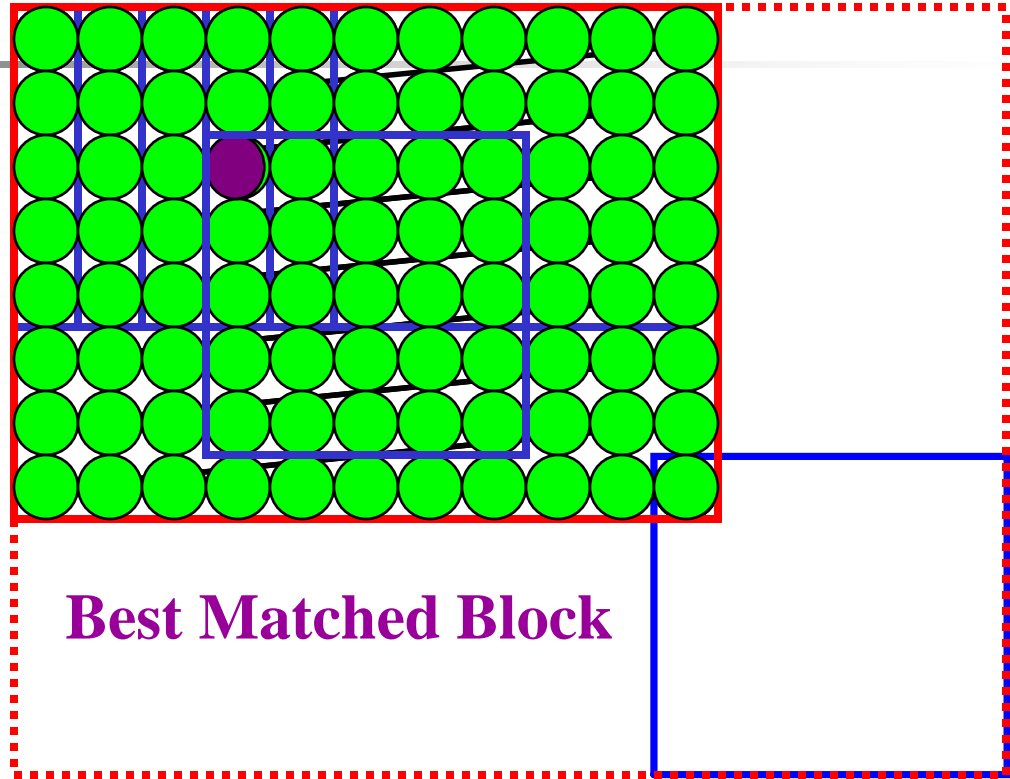


Current Block

Search Range

**Reference Block
(Candidate Block)**

**Candidate Search
Position
(Search Location)**



$$SAD(i, j) = \sum_{k=1}^N \sum_{l=1}^N |x_t(k, l) - x_{t-1}(k + i, l + j)|$$



Computation Complexity

```
Loop 1: For m= 0 to (width/blocksize)-1
Loop 2:   For n= 0 to (height/blocksize)-1
Loop 3:     For i = -d to d-1
Loop 4:       For j = -d to d-1
Loop 5:         For k = 0 to N-1
Loop 6:           For l = 0 to N-1
                  SAD(i,j) = SAD(i,j) + |X(k,l)-Y(k+i,l+j)|
            End (Loop 6)
        End (Loop 5)
    End (Loop 4)
End (Loop 3)
End (Loop 2)
End (Loop 1)
```

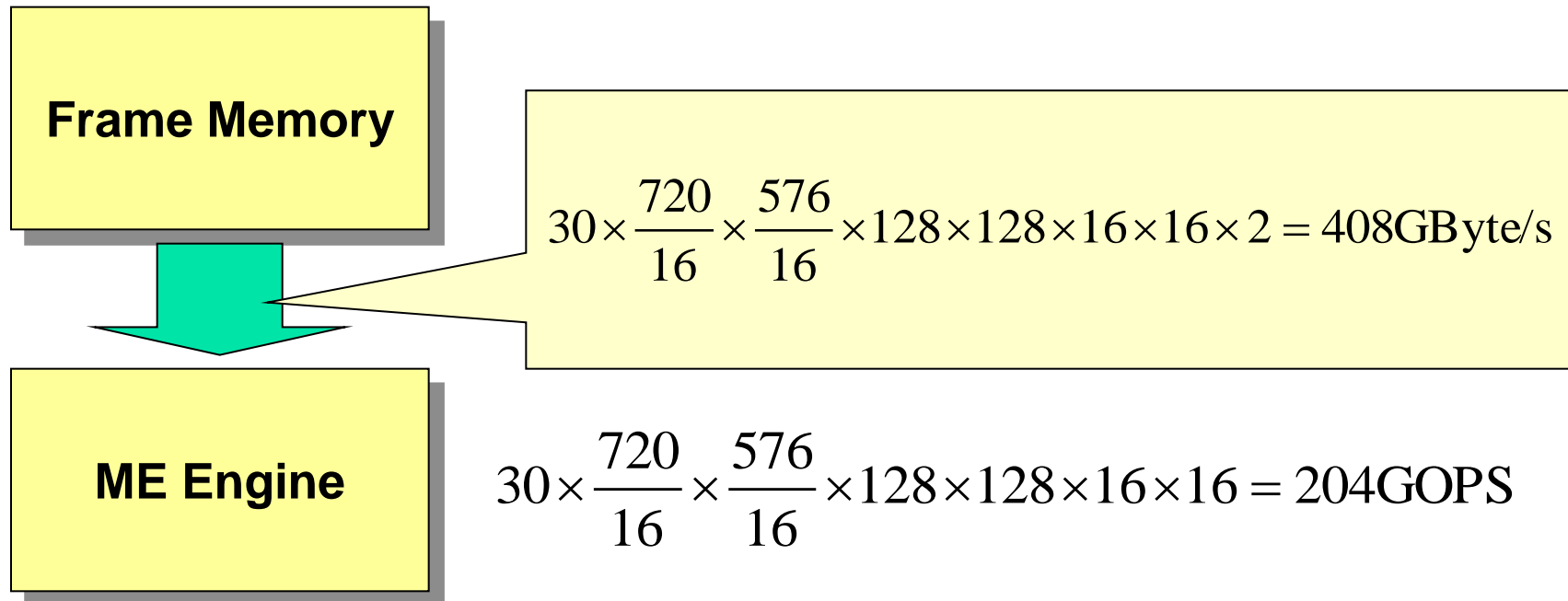
For each macroblock

For each candidate search position

Calculate the distortion, and chose the smallest one

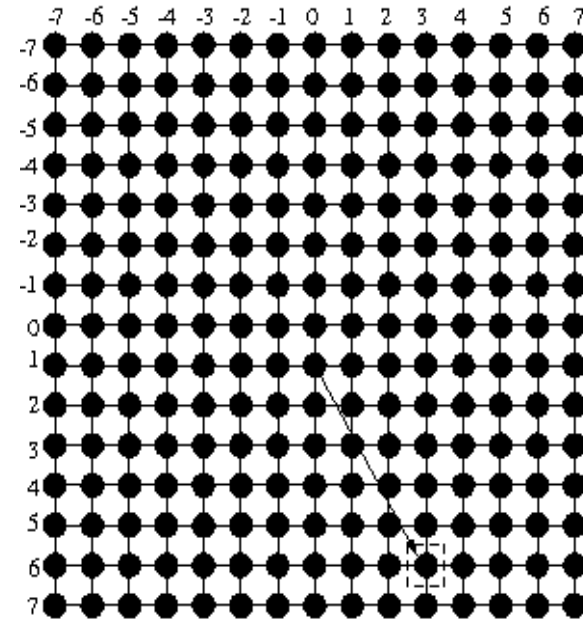
Ultra Large Complexity and Memory Bandwidth

- For example, for a 720x576 30fps video, block size=16x16, SR=[-64, 63]



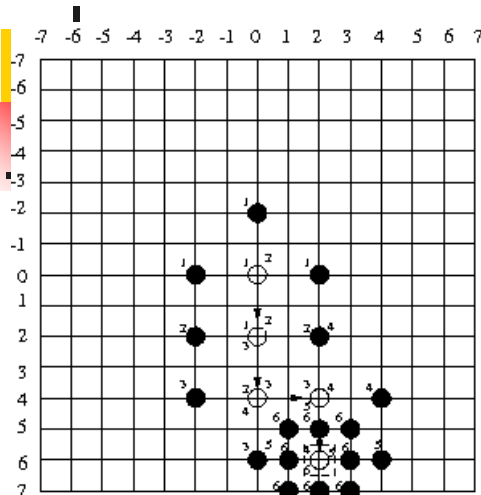
Review of Block Matching Algorithms

- Two-Dimensional Full Search(2DFS) (FSBMA)
 - Exhaustive search
 - Extremely Large Computation
- Fast Search
 - Assumption: Monotonic Distortion Function
 - Reduce computation at the expense of accuracy
 - 2-D Logarithmic Search
 - Modified 2-D Logarithmic Search
 - Three-Step Hierarchical Search
 - Cross Search
 - One-at-a-time Search
 - Parallel Hierarchical One-Dimensional Search
 - One-Dimensional Full Search

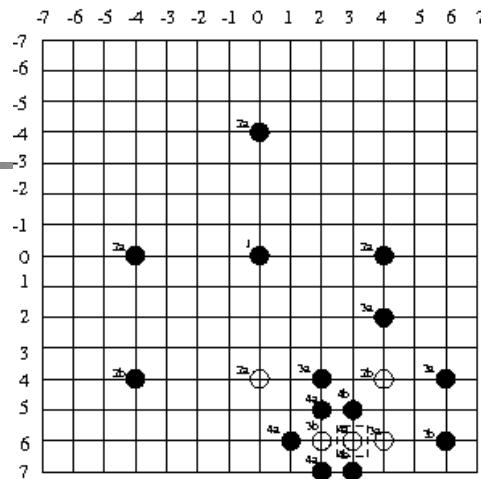


Two-Dimensional Full Search Procedure
Search Range -7 to +7
Motion Vector (3,6) in this case

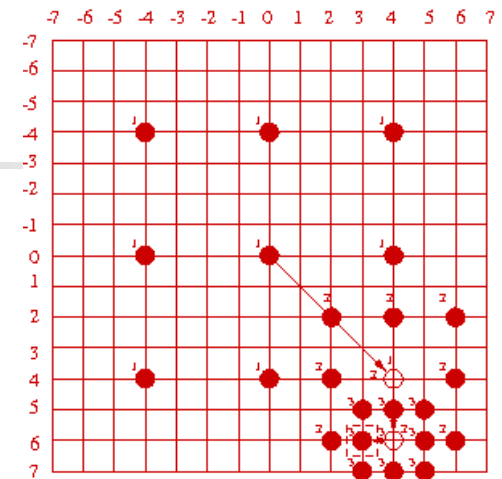
Fast Search Algorithms



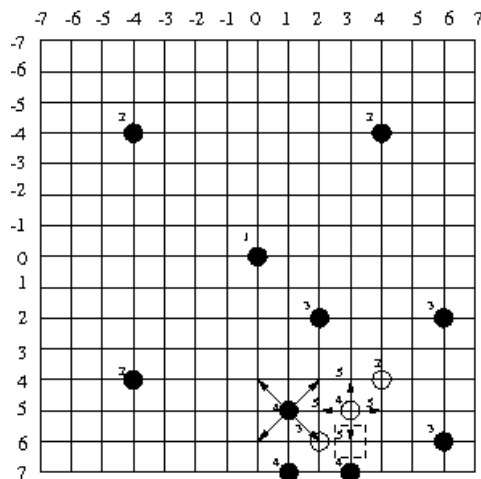
2-D Logarithmic Search Procedure
Search Range -7 to +7
Motion Vector (3,6) in this case



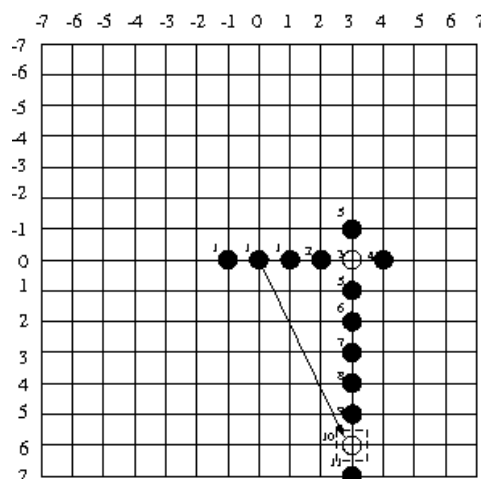
Modified 2-D Logarithmic Search Procedure
Search Range -7 to +7
Motion Vector (3,6) in this case



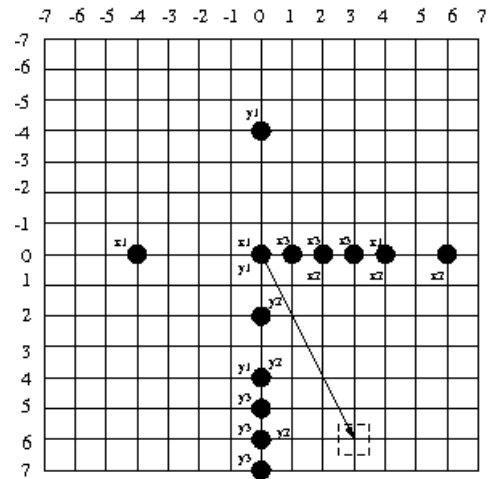
Three-Step Hierarchical Search Procedure
Search Range -7 to +7
Motion Vector (3,6) in this case



Cross-Search Procedure
Search Range -7 to +7
Motion Vector (3,6) in this case



One-at-a-time Search(OTS) Procedure
Search Range -7 to +7
Motion Vector (3,6) in this case



Parallel Hierarchical One-Dimensional Search Procedure
Search Range -7 to +7
Motion Vector (3,6) in this case

Fast Search Algorithms

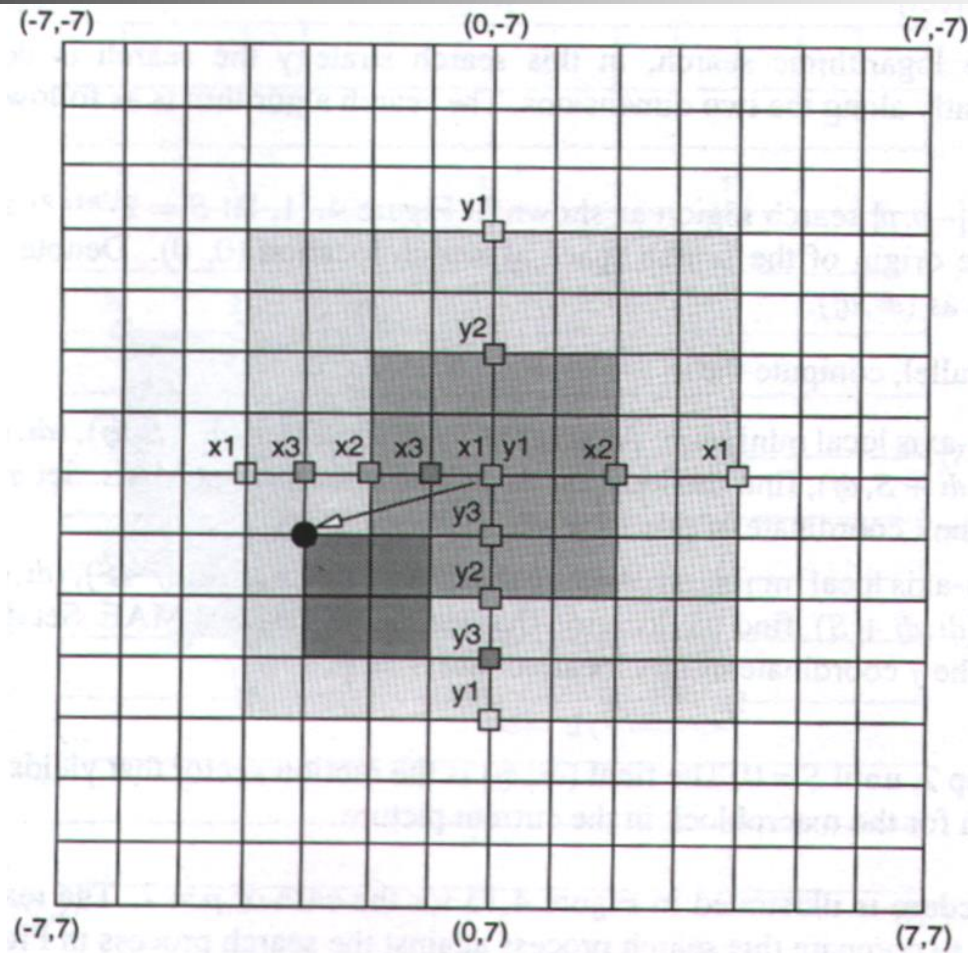


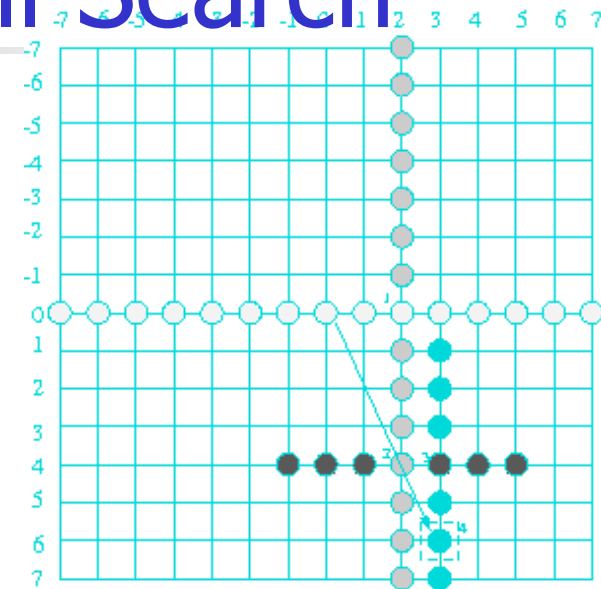
Figure 4.13 Example of PHODS strategy.

Fast Search Algorithms

- One-Dimensional Full Search

For (i= -P to +P) Veci' = i | min D(i,j)
For (j= -P to +P) Vecj' = j | min D(Veci',j)
For (i= -P/2 to +P/2) Veci = i | min D(i+Veci',Vecj')
For (j= -P/2 to +P/2) Vecj = j | min D(Veci,j+Vecj')
Motion Vector = (Veci,Vecj)

- ❏ **Hardware-Oriented**
- ❏ **Full Data Reuse**
- ❏ **Regular Data Flow**
- ❏ **Fixed-Step Operation**
- ❏ **Good Performance**

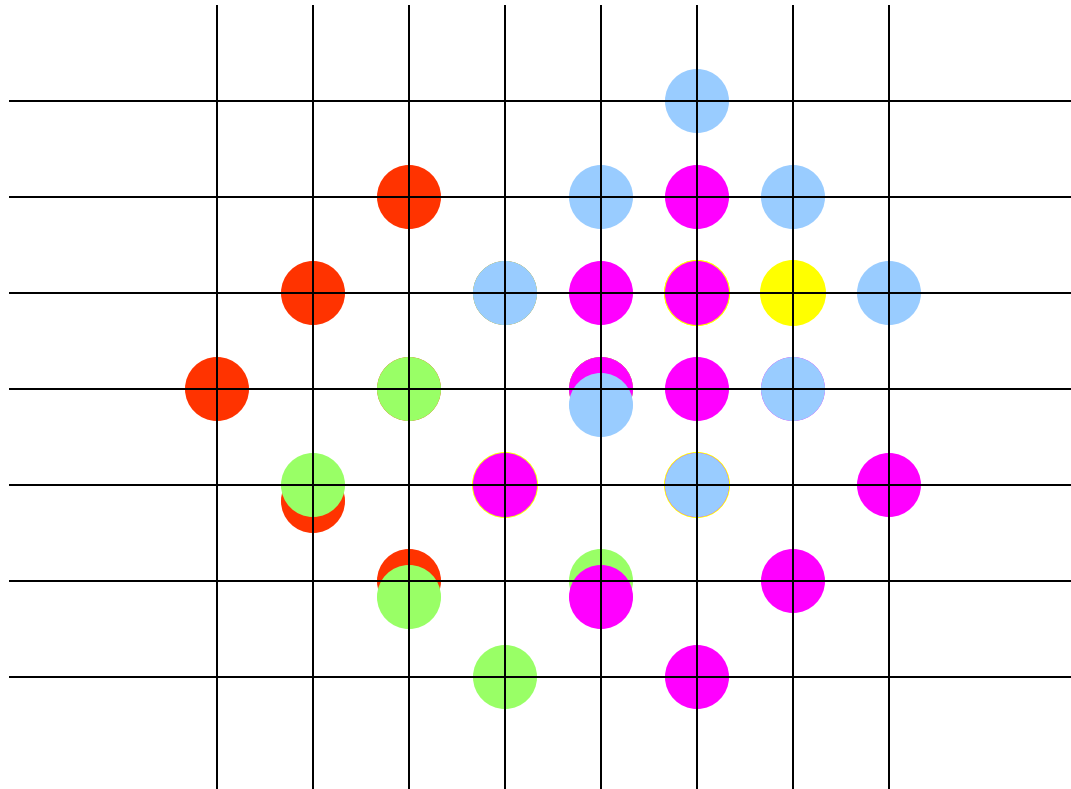


One-Dimensional Full Search Procedure
Search Range -7 to +7
Motion Vector (3,6) in this case

Ref: Mei-Juan Chen, Liang-Gee Chen and Tzi-Dar Chiueh,
“One-Dimensional Full Search Motion Estimation Algorithm for Video Coding”,
IEEE Transactions on Circuits and Systems for Video Technology,
Vol.4, No.5, October 1994.



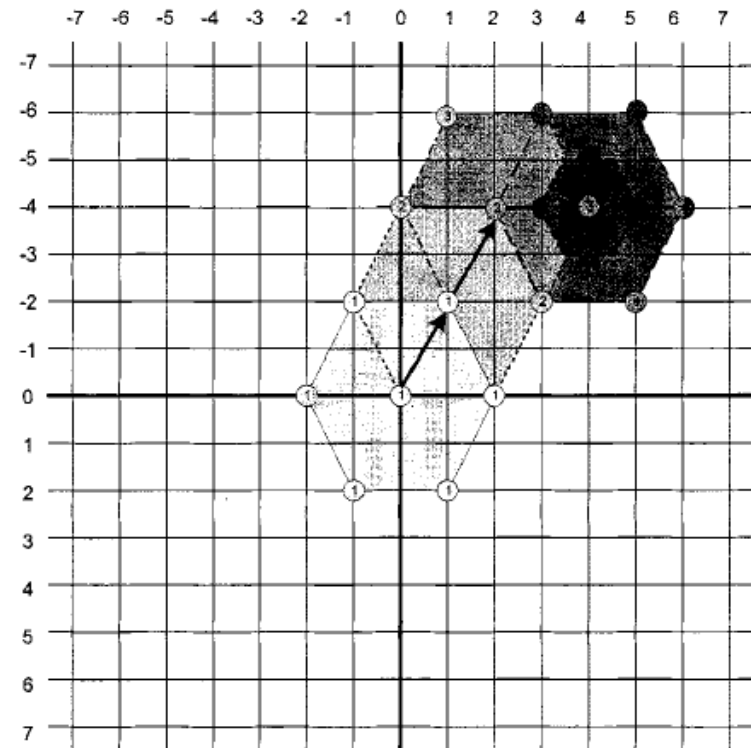
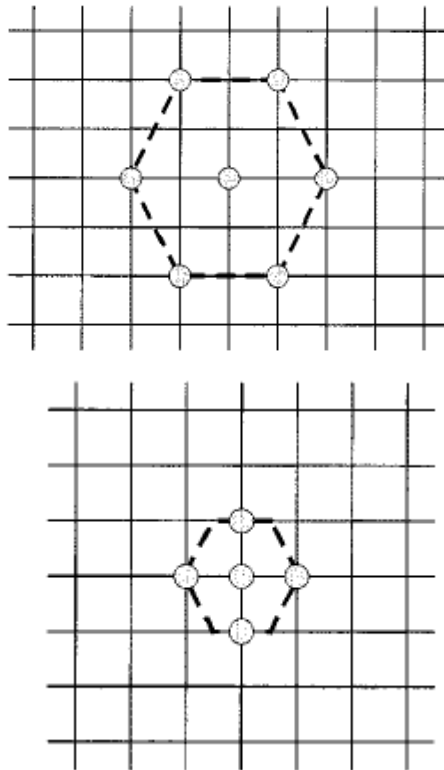
Diamond Search



MV

Ref: Shan Zhu and Kai-Kuang Ma, "A new diamond search algorithm for fast block matching motion estimation," *Proceedings of ICICS, 1997 International Conference on Information, Communications and Signal Processing*.

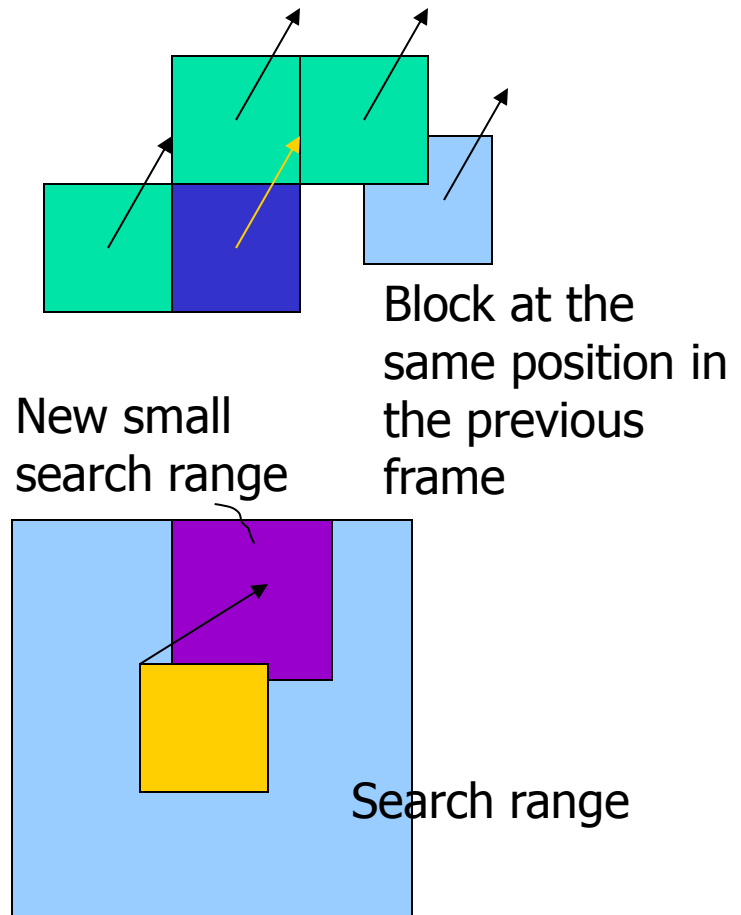
Hexagon-Based Search (HEXBS)



Ce Zhu, Xiao Lin, and Lap-Pui Chau, "Hexagon-based search pattern for fast block motion estimation," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 12, no. 5, pp. 349--355, May 2002.

Motion Vector Prediction

- Prediction: guess the motion vector of the current block from the neighbors
- Good prediction can
 - Improve the performance of fast motion estimation
 - Can achieve similar quality with smaller search range





Matching Criteria

- Cross-Correlation Function (CCF)
- Mean Squared Error (MSE)
- Mean Absolute Error (MAE)
- Pel Difference Classification (PDC)
- Minimized Maximum Error (MiniMax)

$x_t(k,l)$: luminance for the location (k,l) in $X_t(p,q)$

$x_{t-1}(k+i,l+j)$: luminance for the shifted location
by i pels and j lines within the search range



Matching Criteria

Cross-Correlation Function(CCF)

$$\text{CCF}(i,j) = \frac{\sum_{k=1}^N \sum_{l=1}^N x_t(k,l) \cdot x_{t-1}(k+i,l+j)}{\left[\sum_{k=1}^N \sum_{l=1}^N x_t^2(k,l) \right]^{\frac{1}{2}} \left[\sum_{k=1}^N \sum_{l=1}^N x_{t-1}^2(k+i,l+j) \right]^{\frac{1}{2}}}$$

$$(\text{Vec}i, \text{Vec}j) = (i,j) \mid \max \text{CCF}(i,j)$$

Mean Squared Error(MSE)

$$\text{MSE}(i,j) = \frac{1}{N^2} \sum_{k=1}^N \sum_{l=1}^N [x_t(k,l) - x_{t-1}(k+i,l+j)]^2$$

$$(\text{Vec}i, \text{Vec}j) = (i,j) \mid \min \text{MSE}(i,j)$$



Matching Criteria

Mean Absolute Error(MAE)



Most Widely Used in hardware

$$\text{MAE}(i,j) = \frac{1}{N^2} \sum_{k=1}^N \sum_{l=1}^N |x_t(k,l) - x_{t-1}(k+i, l+j)|$$

$$(\text{Vec}i, \text{Vec}j) = (i,j) \mid \min \text{MAE}(i,j)$$

Pel Difference Classification(PDC)

$$T(k,l,i,j) = \begin{cases} 1, & |x_t(k,l) - x_{t-1}(k+i, l+j)| \leq \textit{Threshold} \\ 0, & \textit{otherwise} \end{cases}$$

$$G(i,j) = \sum_{k=1}^N \sum_{l=1}^N T(k,l,i,j)$$

$$(\text{Vec}i, \text{Vec}j) = (i,j) \mid \max G(i,j)$$

Matching Criteria

Minimized Maximum Error (MiniMax)

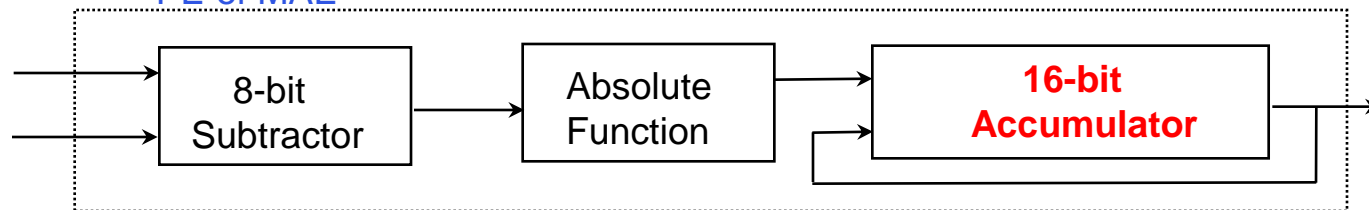


Hardware Reduction

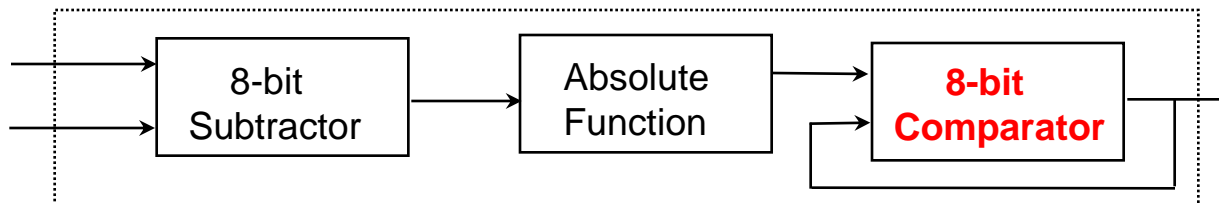
$$G(i,j) = \max_l |x_t(k,l) - x_{t-1}(k+i, l+j)|$$

$$(Vec_i, Vec_j) = (i,j) \mid \min G(i,j)$$

PE of MAE



PE of MiniMax



Subjective Quality

Min-max

MAE

1DFS'

Table Tennis I

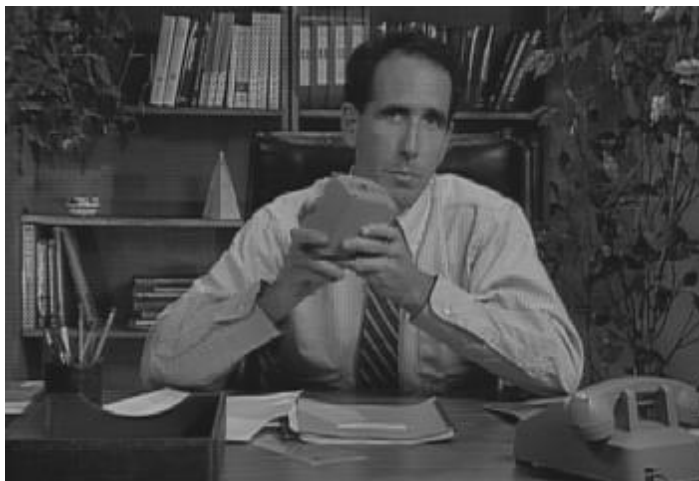


Table Tennis II

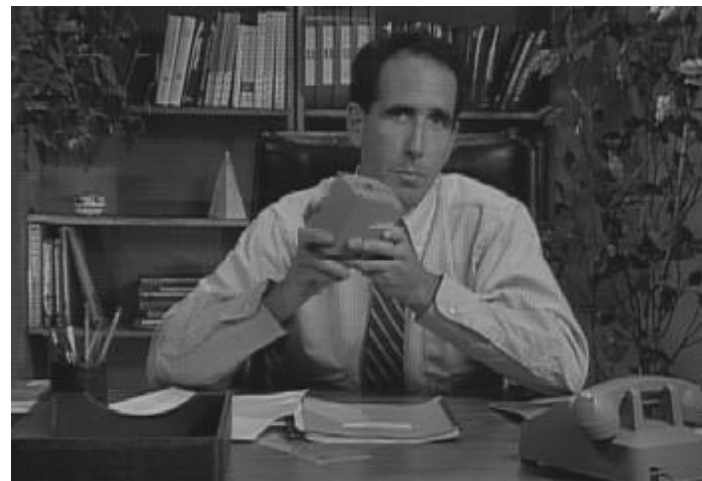


Subjective Quality

Min-max



MAE



Salesman



Train & Calendar



Other Approaches

- Pixel Subsampling for MAE calculations

1	2	1	2	1	2	1	2
3	4	3	4	3	4	3	4
1	2	1	2	1	2	1	2
3	4	3	4	3	4	3	4
1	2	1	2	1	2	1	2
3	4	3	4	3	4	3	4
1	2	1	2	1	2	1	2
3	4	3	4	3	4	3	4

- For each MAE value , use only 1/4 of the pixels.
- But every pixel in the block will be used.
- It minimizes the possibility of not considering one-pixel-wide horizontal , vertical and diagonal lines .

Matching block size 16x16 \rightarrow 8x8
Pixel decimation for block matching
in an 8x8 block.

Projections for MAE calculations

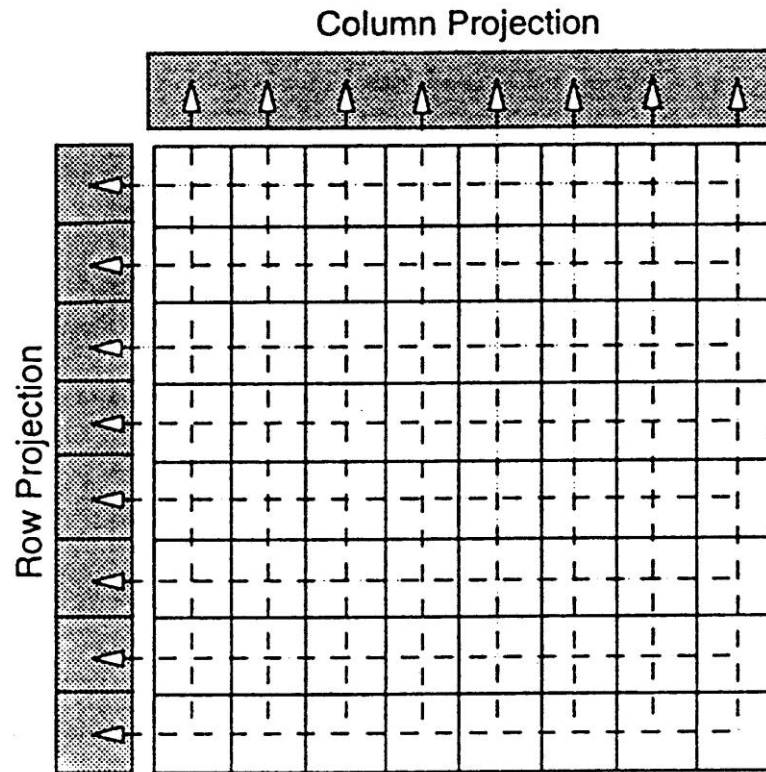


Figure 4.16 Row and column projection of pixels in an 8×8 block.

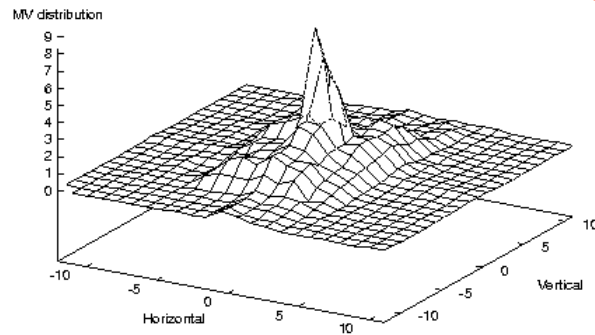
Motion Vector Distribution

block size 8x8 15 frames/sec
Table Tennis Sequence

MV Distribution (Block Size 8x8) with Full Search for 15 frames/sec sequence

2D Full Search —

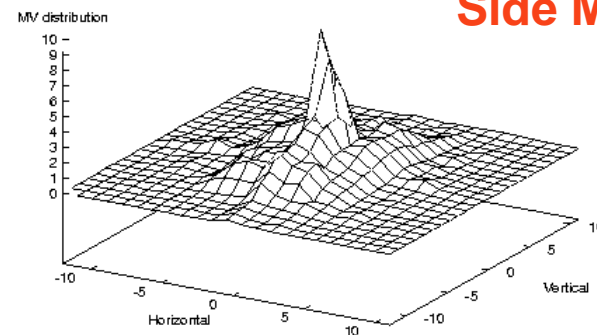
2DFS



MV Distribution (Block Size 8x8) with Side Match II Prediction Search for 15 frames/sec sequence

Side Match II Prediction —

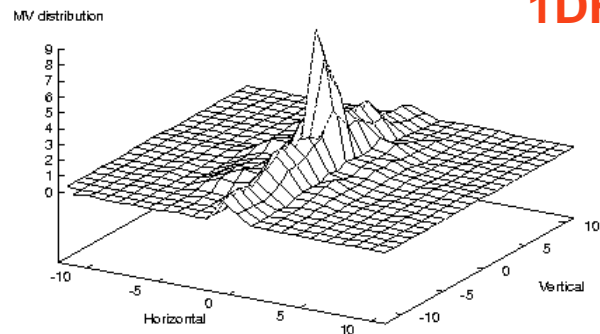
Side Match



MV Distribution (Block Size 8x8) with 1D Full Search for 15 frames/sec sequence

1D Full Search —

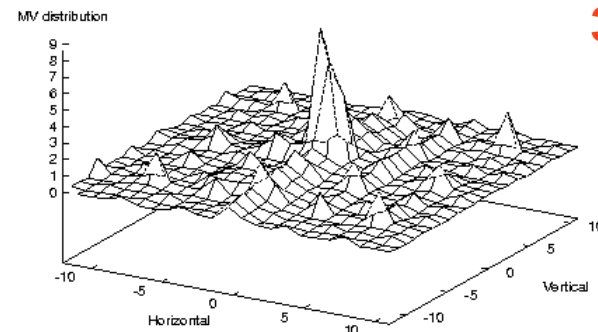
1DFS



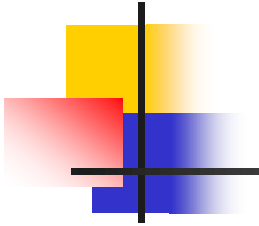
MV Distribution (Block Size 8x8) with 3-Step Search for 15 frames/sec sequence

3-Step Search —

3Step



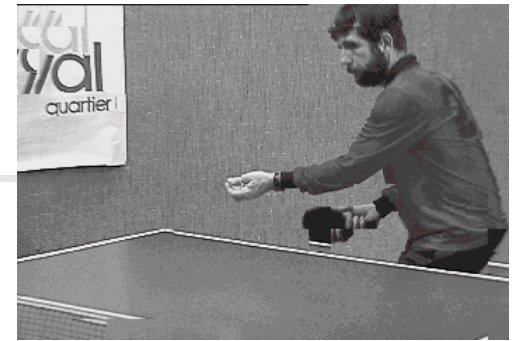
Subjective Quality



16x16 blocks
15 frames/sec Table Tennis Sequence



Original



2DFS



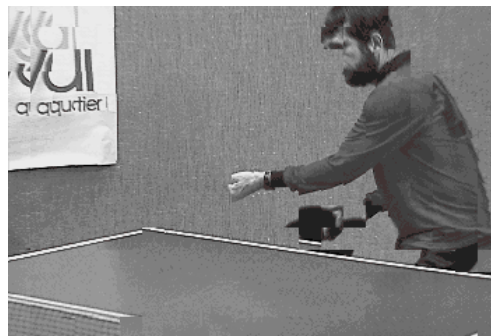
Inter-Frame



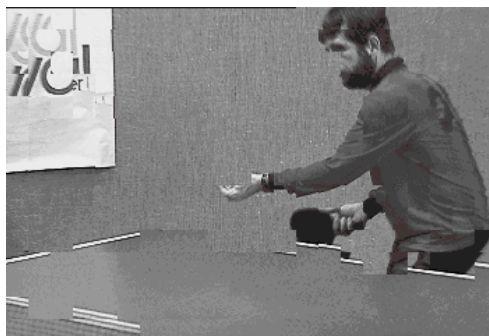
Inter-Block



Boundary Match



1DFS



3Step



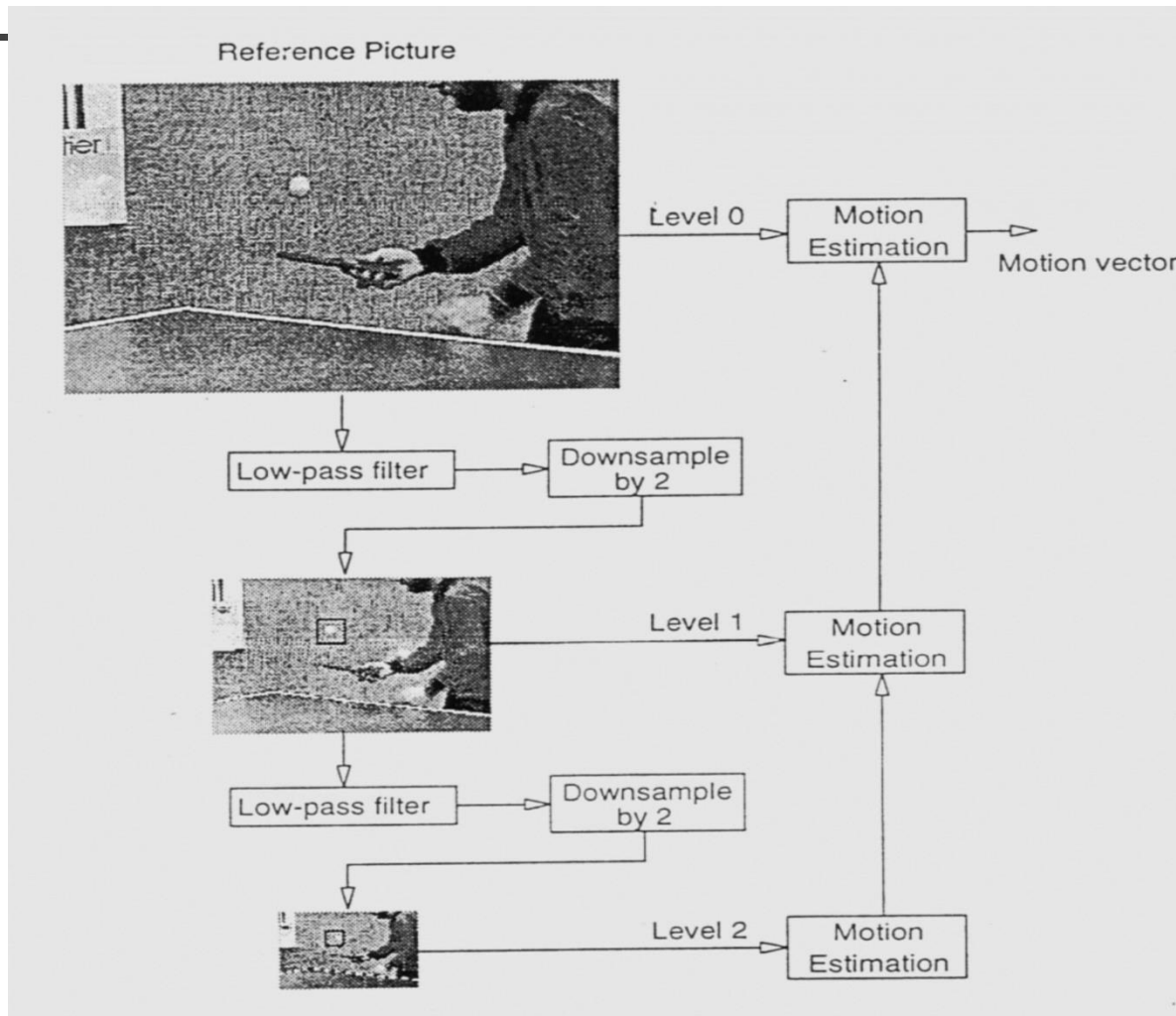
Side Match



Improvements of Motion Estimation

- Hierarchical motion estimation
- Multigrid block matching
- Overlapped block matching
- Motion estimation with fractional precision
- Bidirectional prediction
- Lossless motion estimation

Hierarchical Motion Estimation



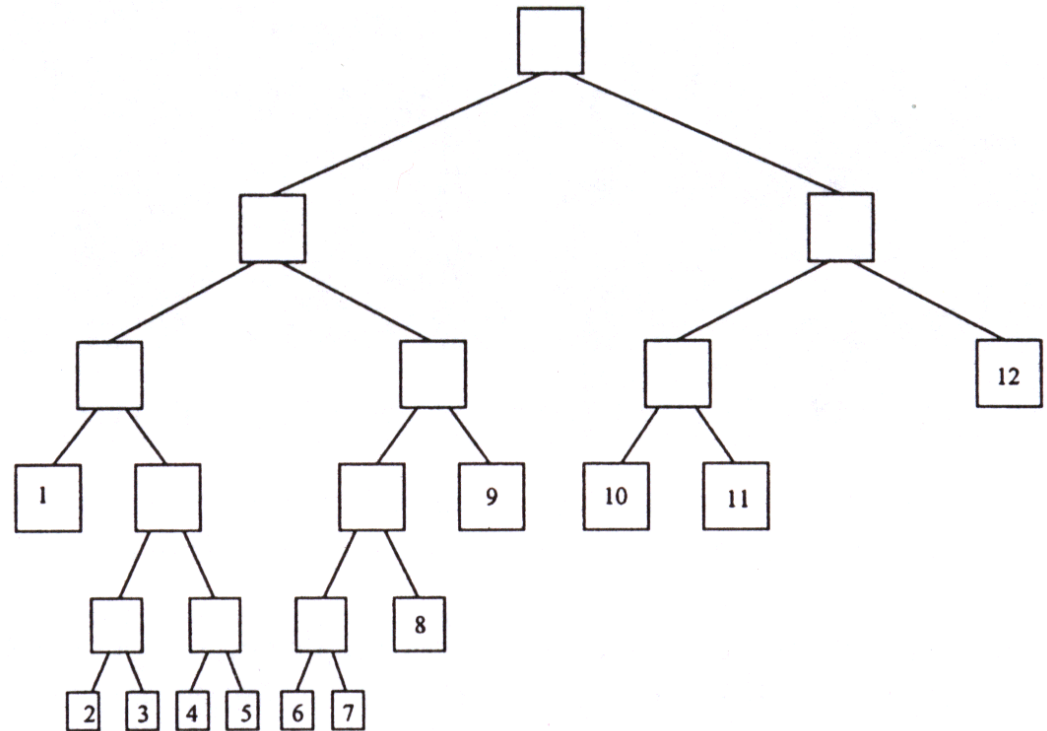
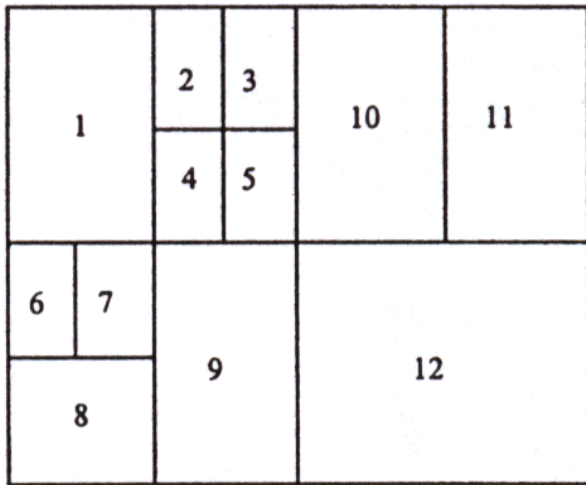
Hierarchical Motion Estimation

- Summary:
 - It requires increased storage to keep pictures at different resolutions.
 - Motion vector may be inaccurate for regions containing small objects .
 - Low-pass filter may be necessary to reduce noise.

Search Method	Operations per Macroblock	Operations for pictures 720 x 40 at 30 fps	
		$p = 15$	$p = 7$
Full-search	$(2p + 1)^2 NM3$	29.89 GOPS	6.99 GOPS
Logarithmic	$(8\lceil \log_2 p \rceil + 1)NM3$	1.02 GOPS	777.60 MOPS
PHODS	$(4\lceil \log_2 p \rceil + 1)NM3$	528.76 MOPS	404.35 MOPS
Hierarchical	$[(2\lceil \frac{p}{4} \rceil + 1)^2 + 180] \frac{NM}{16}3$	507.38 MOPS	398.52 MOPS

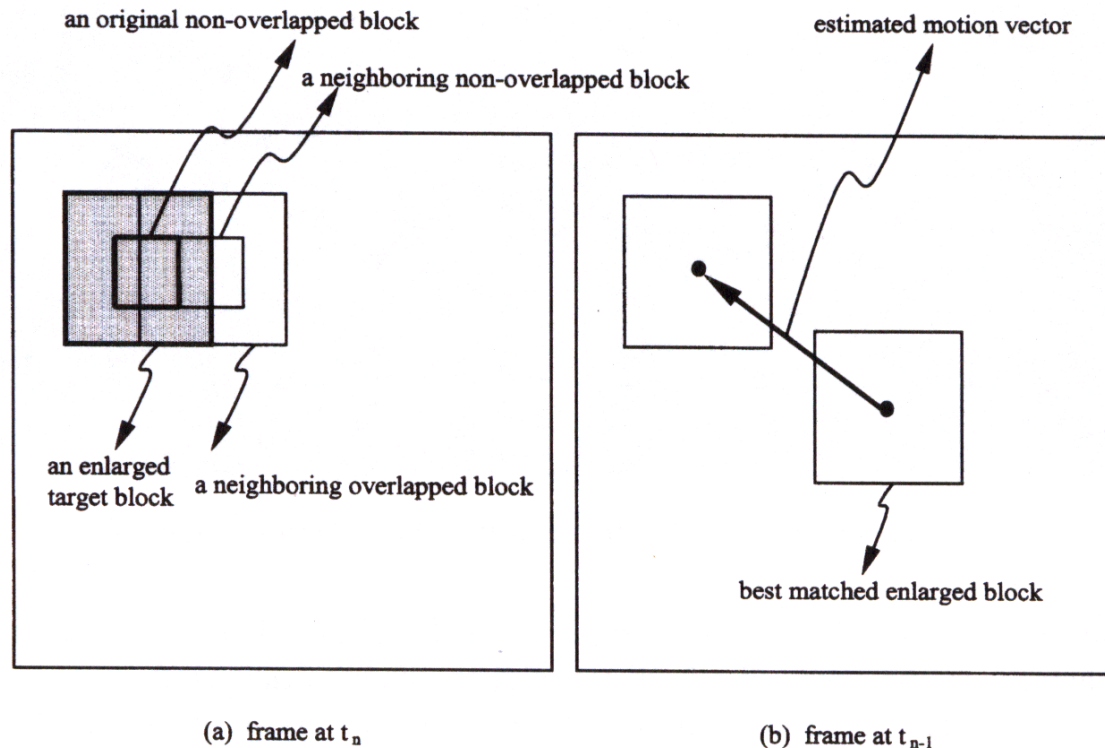
Table 4.1 Computational complexity and MOPS requirements for various motion-estimation algorithms using the MAE criterion and a $[-p, p]$ search range.

Multigrid Block Matching



Overlapped Block Matching (1)

- Relax the restriction of a non-overlapped block partition



The motion estimation procedure is the same except for using **enlarge blocks** and a **window function**



Overlapped Block Matching (2)

- Overlapped block motion estimation

$$E_{v_i}(x, y) = P_{v_i}(x, y) - T(x, y)$$

$$WE_{v_i}(x, y) = E_{v_i}(x, y) \times W(x, y)$$

$$\text{Block matching : to minimize } MAD = \frac{1}{l^2} \sum_{x=1}^l \sum_{y=1}^l |WE_{v_i}(x, y)|$$

$T(x, y)$: enlarged current block

$P_{v_i}(x, y)$: corresponding block in reference with motion vector v_i

$W(x, y)$: window function

- Overlapped block motion compensation (OBMC)

$$WP_{v_i}(x, y) = P_{v_i}(x, y) \times W(x, y)$$

Sub-Pixel-Accurate Motion Estimation (Fractional Precision)

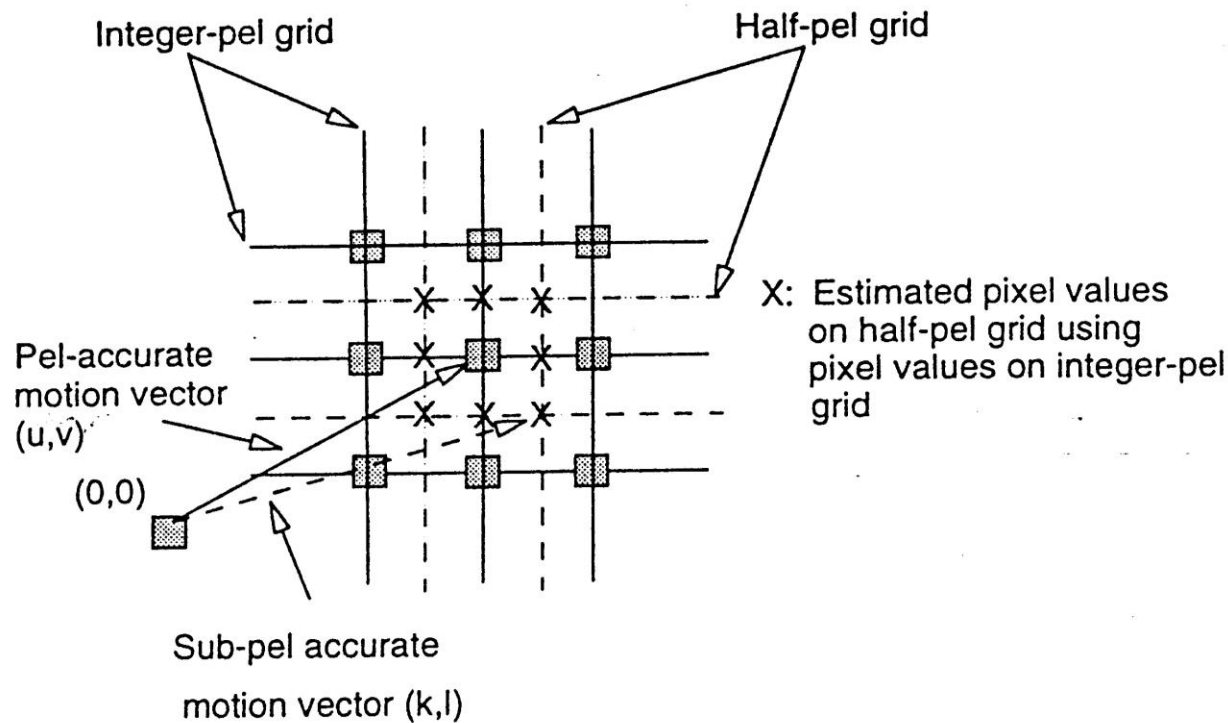
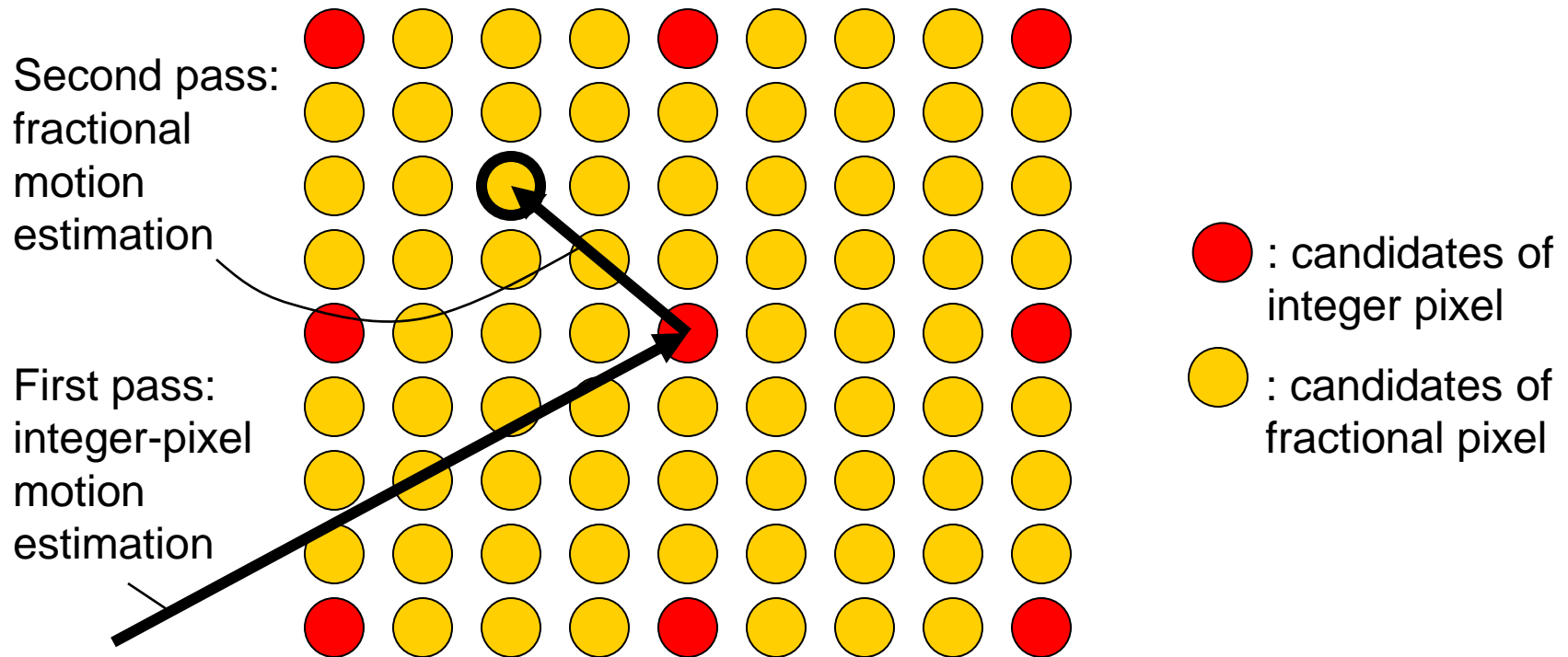


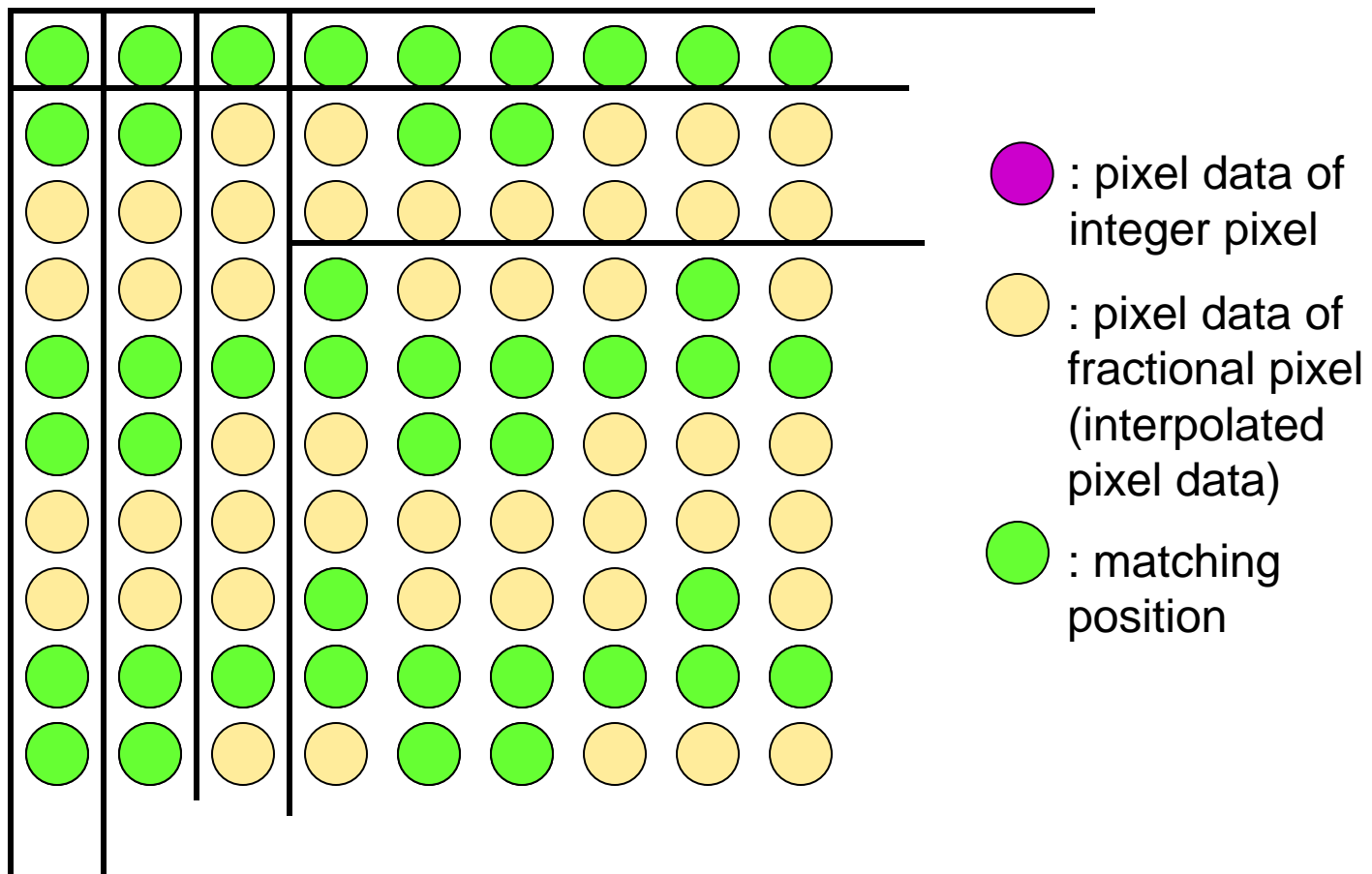
Figure 4.19 Half-pel accurate motion vector estimation.

Motion Estimation with Fractional Precision (1/2)

■ Quarter-pel precision

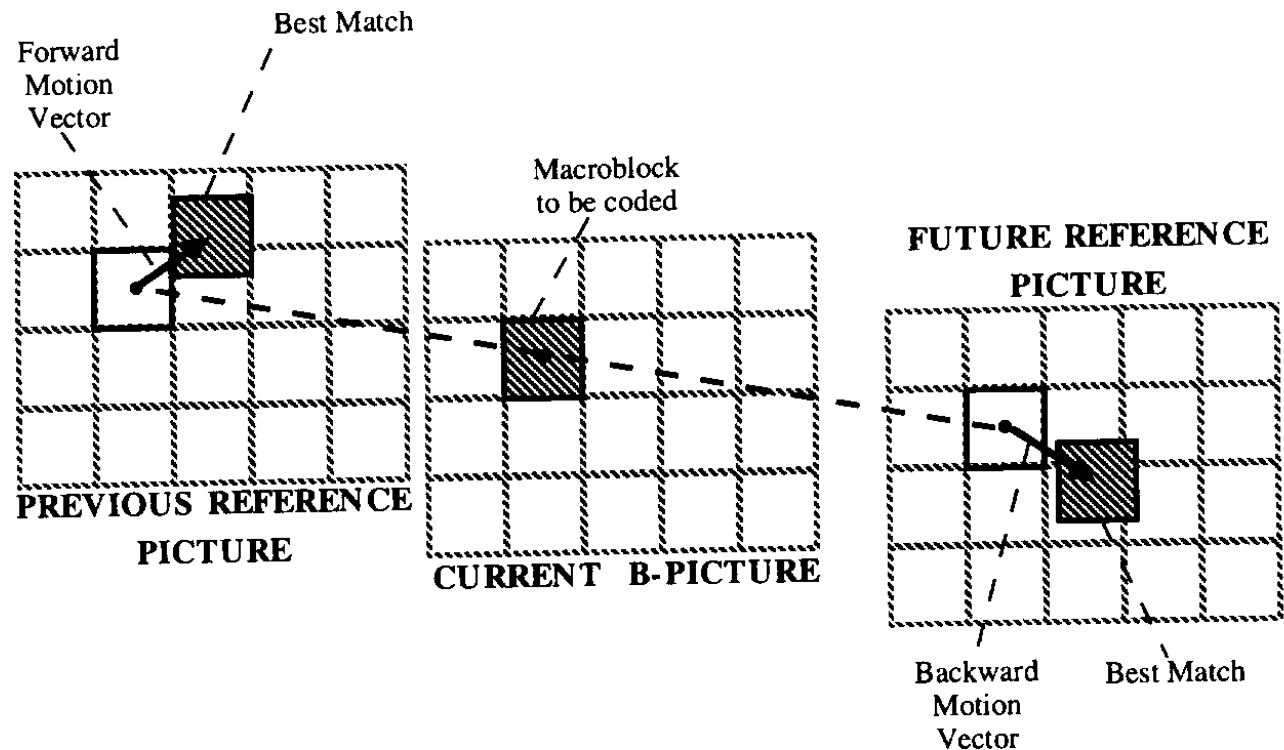


Motion Estimation with Fractional Precision (2/2)



Bidirectional Temporal Prediction for Progressive Video

- Reference frame must be I or P-frame
- B-picture
- 2 MV



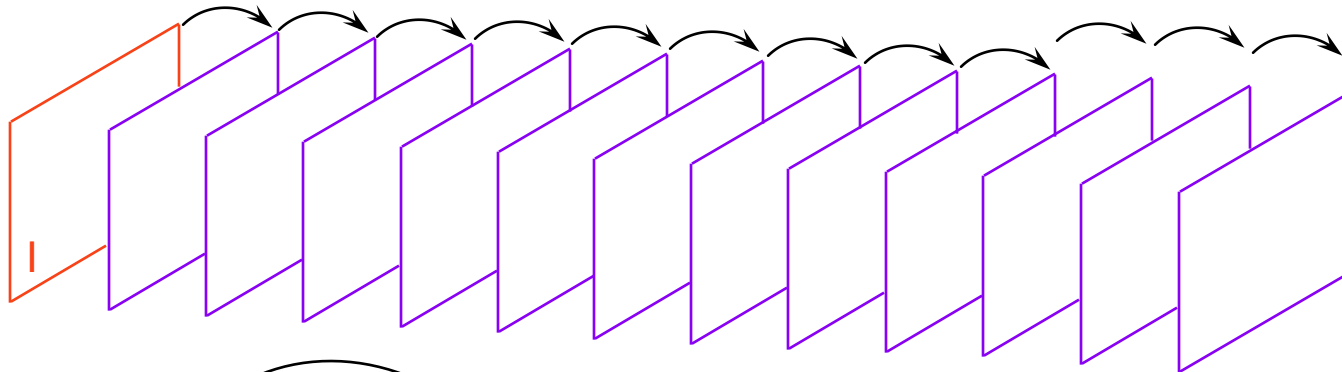
Coding of Moving Pictures

I: Intra Frame

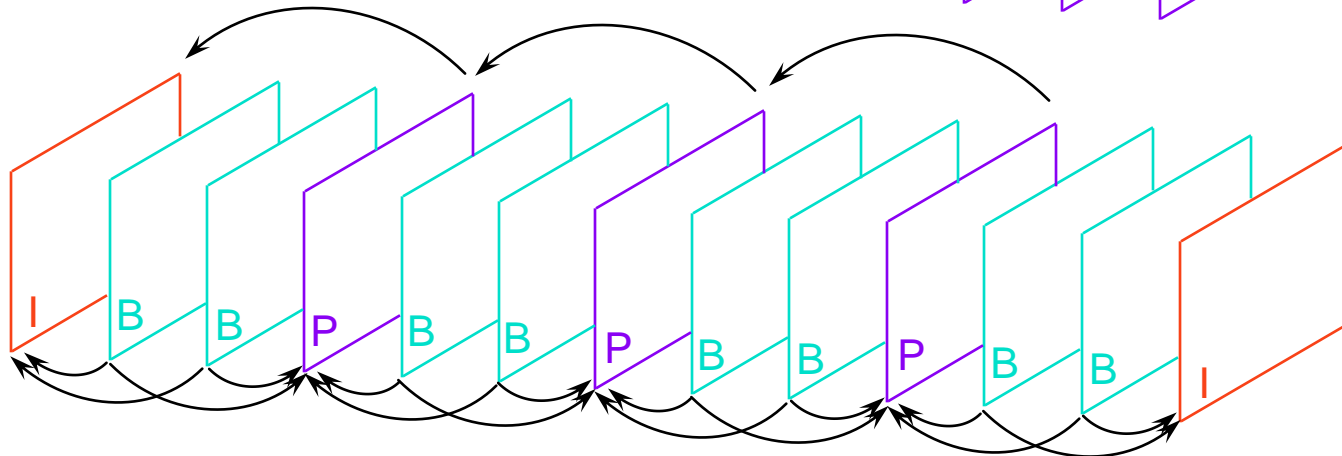
P: Predict Frame

B: Bi-directional Frame

H.261



MPEG
H.263





Lossless Motion Estimation

- Partial Distortion Elimination (PDE)
 - In the loop of calculating SAD, if the current SAD is larger than the minimum SAD value, then quit the loop.
- Successive Elimination Algorithm (SEA)

By the following inequality:

$$\sum |A - B| \geq \sum |A| - \sum |B|$$

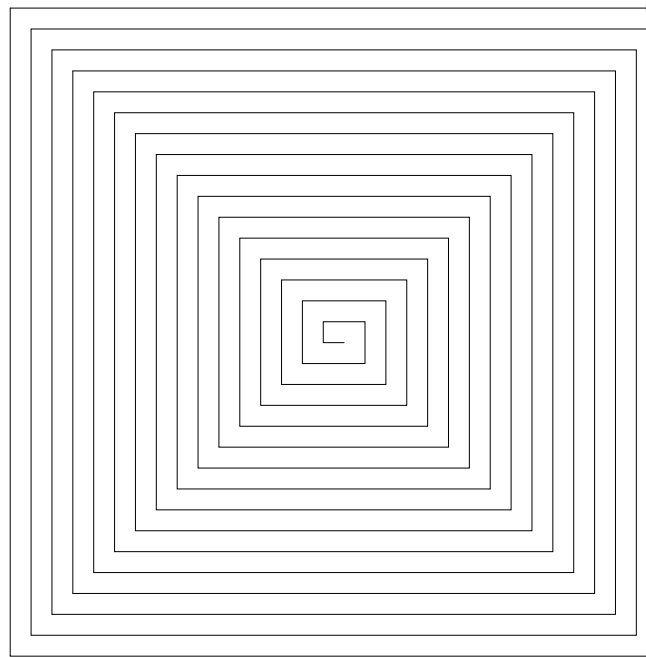
So

$$\sum_{j=0}^{N-1} \sum_{i=0}^{N-1} |c(i, j) - p(i+u, j+v)| \geq \sum_{j=0}^{N-1} \sum_{i=0}^{N-1} |c(i, j)| - \sum_{j=0}^{N-1} \sum_{i=0}^{N-1} |p(i+u, j+v)| = C - \sum_{j=0}^{N-1} \sum_{i=0}^{N-1} |p(i+u, j+b)| = K$$

if $K >$ current minimum SAD then skip this reference point

Spiral Scan

- Provide a good initial guess for PDE and SEA





Lossy Motion Estimation

- Variable/Dynamic Search Range Techniques
- Half-stop Techniques Using Threshold of Matching Distortion
- Lower Bit-resolution Techniques (Using Quantization)
 - Pixel-truncation
- Subsampling Techniques of Matching Block