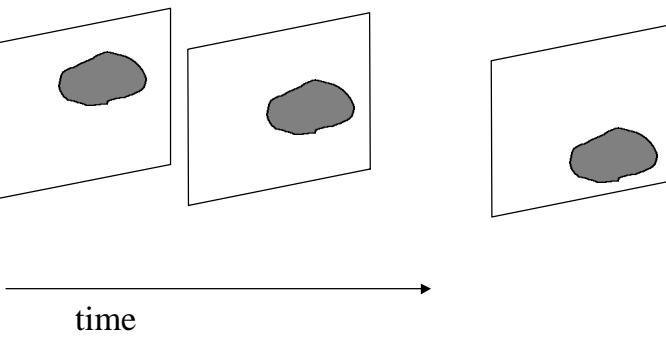


Fundamentals of Lossy Video Compression

1



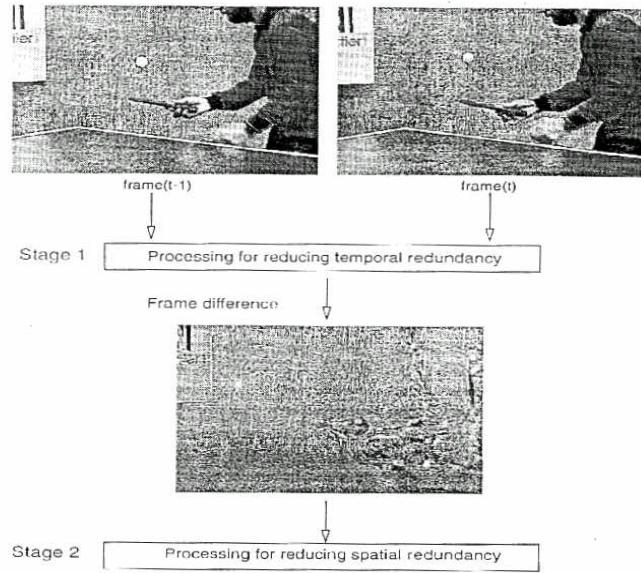
Image Sequence Model



2



Two-stage video coding process



3

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Stage 1 : Reducing Temporal Redundancy

- Segment a frame into macroblocks.
- Output energy is increased with the degree of temporal redundancy.
- Interframe coder .

4

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Stage 2 : Reducing Spatial Redundancy

- Processing the difference frame (spatially correlated) from stage 1.
- Using DCT coding.
- Intraframe coder.
- Hybrid coding method.

5



Motion Compensation

- The process of compensating for the displacement of moving objects from one frame to another.
- It is preceded by motion estimation.
- Similar with DPCM.

6



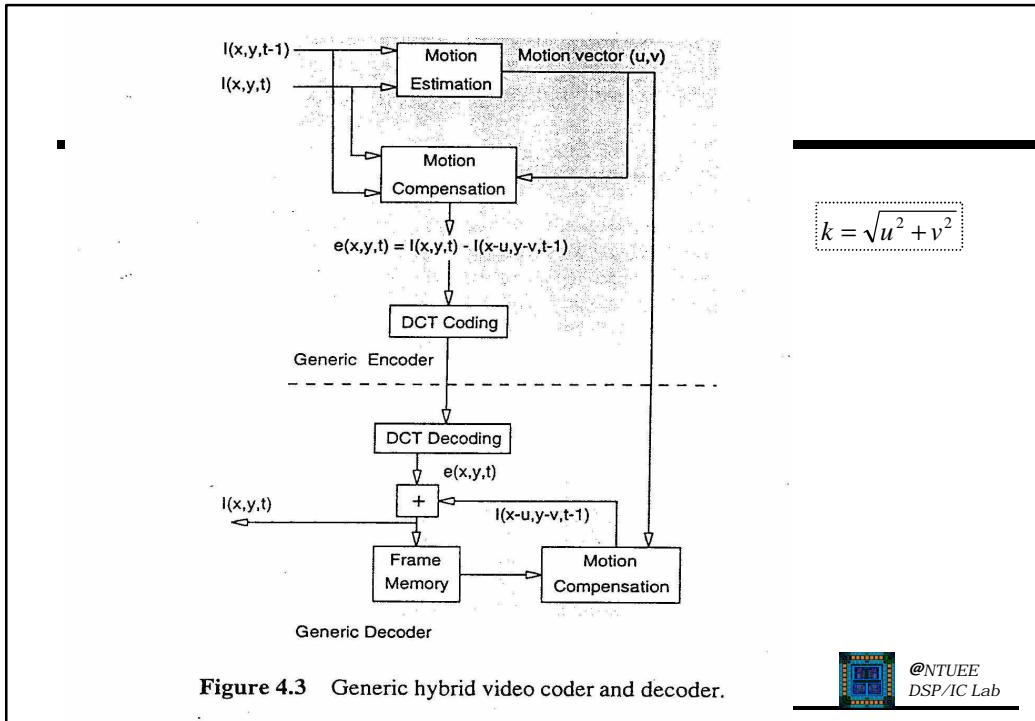


Figure 4.3 Generic hybrid video coder and decoder.



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Performance Evaluation

Questions before using interframe coding:

- How does intraframe coding compare to interframe coding?
- How do hybrid coding schemes compare to intraframe or interframe coding alone?
- Does the added complexity of motion compensation warrant its use
- 2-D correlated (intraframe)
- Differencing (interframe)
- Motion-compensation (interframe)
- Hybrid (interframe /intraframe)

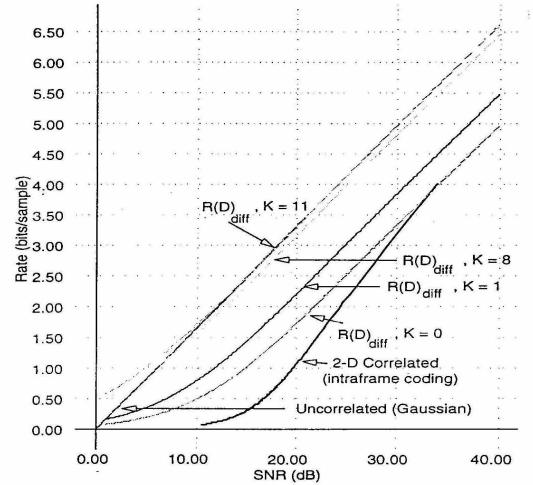


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Frame differencing with no motion compensation

- K is the displacement distance
- K>8 offers no improvement, means no correlation
- All cases show that FD is good enough. Intraframe coding does the job best .

$$k = \sqrt{u^2 + v^2}$$



9

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Motion-compensated prediction

- There are 40% improvement even at high motion-estimation error of +/- 1 pixel.
- Different motion precision achieve different performance.

$$R = \frac{1}{2} \log_2 \frac{S_e^2}{D}$$

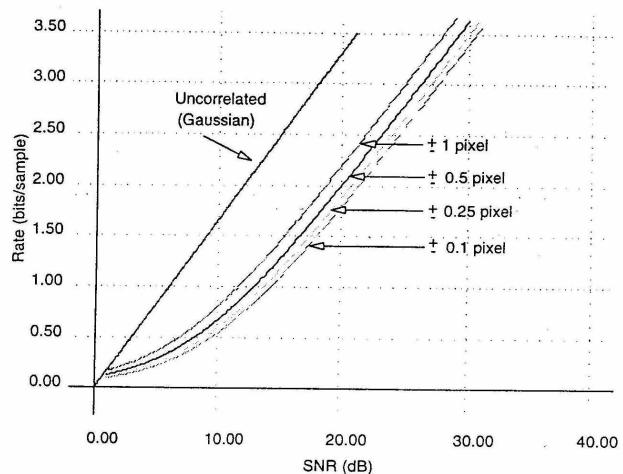


Figure 4.6 Rate-distortion performance for motion-compensated prediction with no intraframe coding.

Motion-compensated prediction v.s. intraframe coding

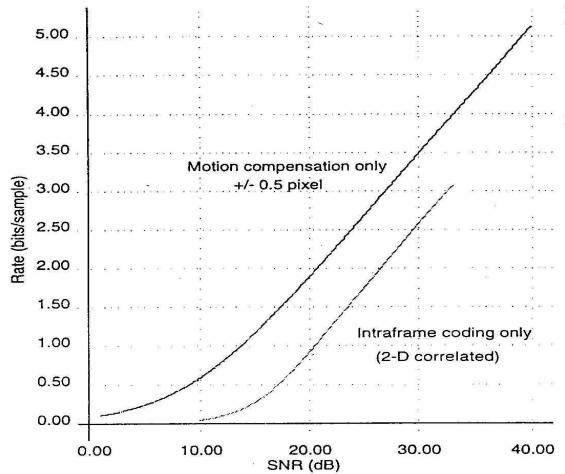


Figure 4.7 Rate-distortion performance for motion-compensated prediction versus intraframe coding.



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Hybrid Coding: Motion-compensated video followed by intraframe coding

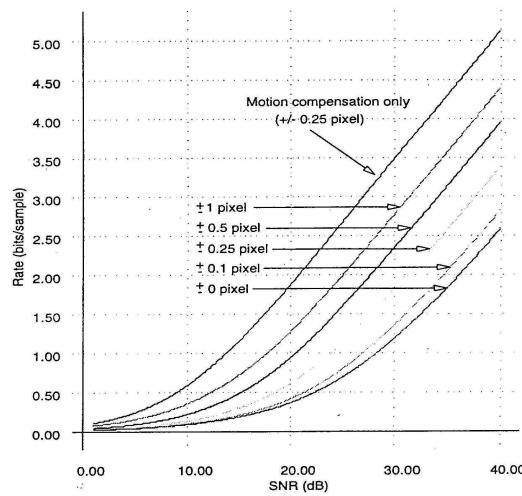
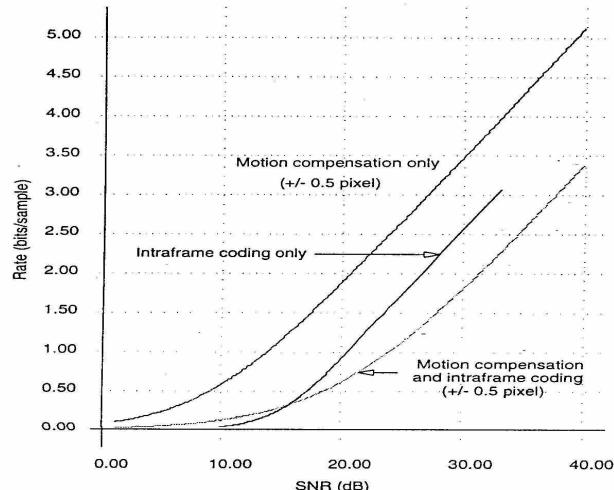


Figure 4.8 Rate-distortion functions for hybrid video coding.

- Hybrid coding can get better results.

Rate-distortion functions for Hybrid, interframe, and intraframe video coding



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R(D) Summary

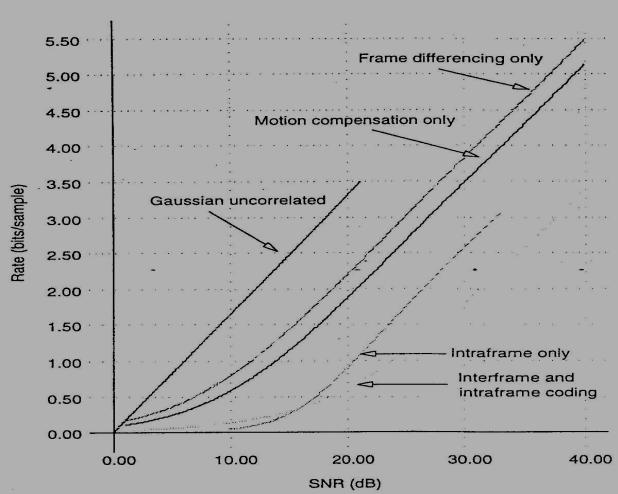


Figure 4.10 Rate-distortion functions for various video coding schemes.



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Motion-compensated prediction

- Hybrid coding method is quite effective.
- In interframe coding , the motion-estimation problem takes an important role.

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Motion Compensation Algorithms in Video Coding

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Motion Estimation

❑ Objective

Predict current frame from neighboring frames

❑ Motion Estimation Algorithm

– Pixel-based method (Pel-Recursive Algorithm)

- Large computation overhead

– Block-based method

- Regularity and simplicity

- Suitable for hardware implementation

– Object-based method (content-based)

- ❖ Crucial to make possible a high degree of video compression

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Block-Matching Motion Estimation

$X_t(p,q)$

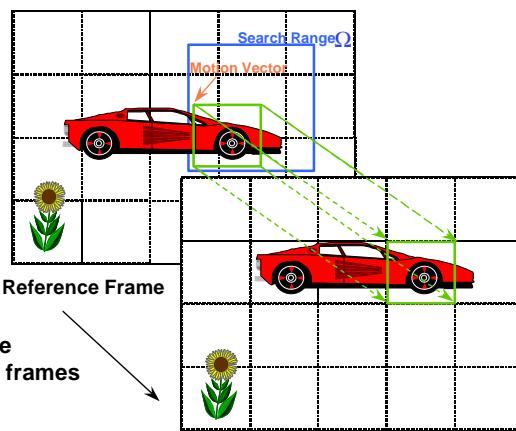
the block at location (p,q) in t -th frame

Motion Vector

$V_t(p,q) = (Vec_i, Vec_j)$

the location in the search range Ω

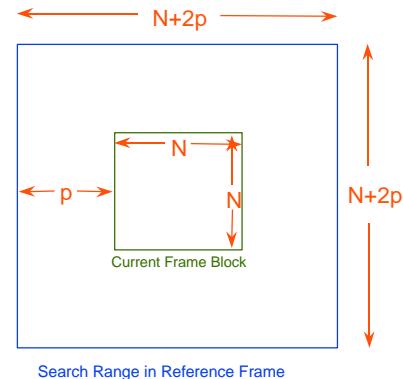
that has the maximum correlation value
between blocks in temporally adjacent frames



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Factors of Affecting Block-Matching Algorithm(BMA)

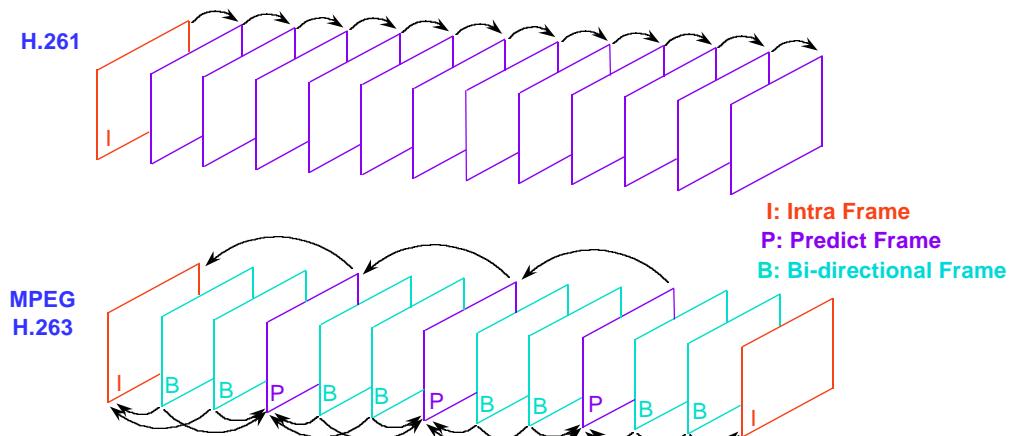
- ☛ **Search Algorithm**
- ☛ **Match Criterion**
- ☛ **Search Range**



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Coding of Moving Pictures



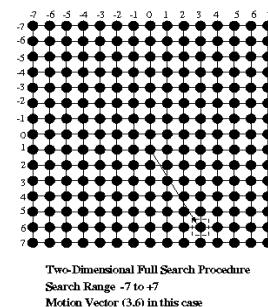
20



Brief Review of Previous Algorithms

Search Algorithms

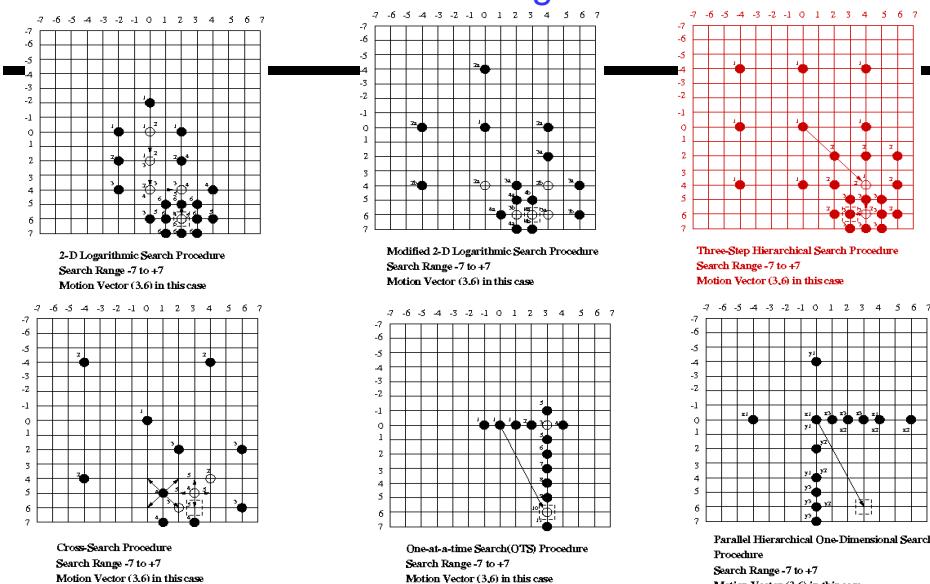
- Two-Dimensional Full Search(2DFS)**
 - *Exhaustive search*
 - *Extremely Large Computation*
- Fast Search**
 - *Assumption: Monotonic Distortion Function*
 - *Reduce computation at the expense of accuracy*
 - 2-D Logarithmic Search**
 - Modified 2-D Logarithmic Search**
 - Three-Step Hierarchical Search**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



21

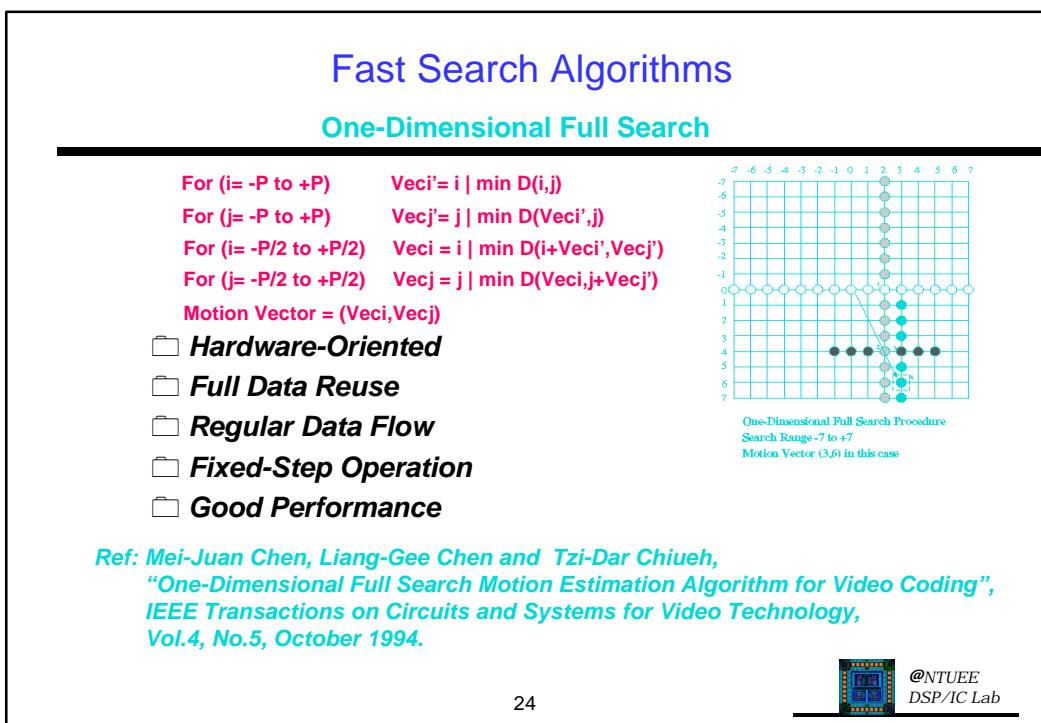
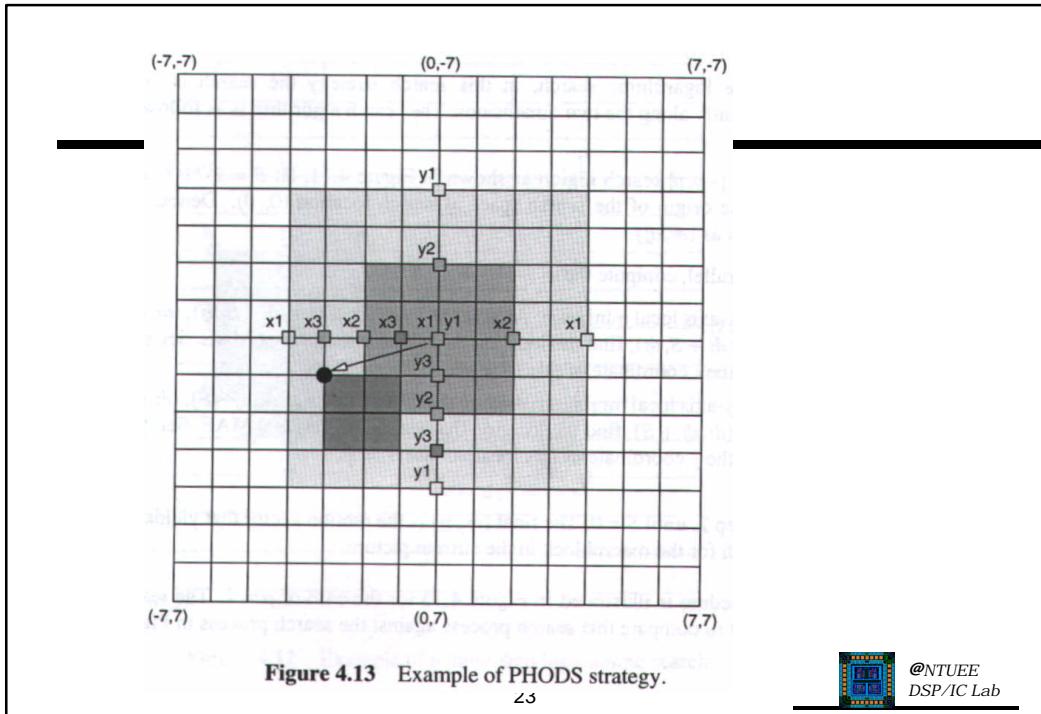


Fast Search Algorithms



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Performance Comparison

	Miss America	Train Calendar	Table Tennis
PSNR (dB)			
2DFS	38.64	19.57	25.48
1DFS	38.39	19.45	24.55
3Step	38.20	19.40	24.06
Entropy (bits/pixel)			
2D FS	3.49	5.93	5.27
1DFS	3.52	5.94	5.39
3Step	3.56	5.94	5.47

30 frames/sec Sequences

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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

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Matching Criteria

Cross-Correlation Function(CCF)

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

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

Mean Squared Error(MSE) --> most widely used in software

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

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

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Matching Criteria

Mean Absolute Error(MAE) → Most Widely Used in hardware

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

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

Pel Difference Classification(PDC)

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

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

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

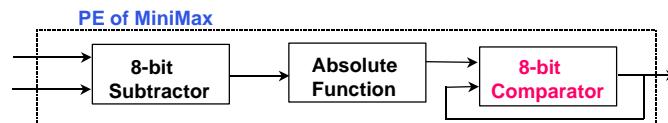
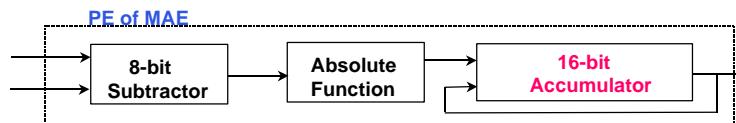
28



Matching Criteria

Minimized Maximum Error (MinMax) → Hardware Reduction

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

$$(\text{Veci}, \text{Vecj}) = (i, j) | \min G(i, j)$$


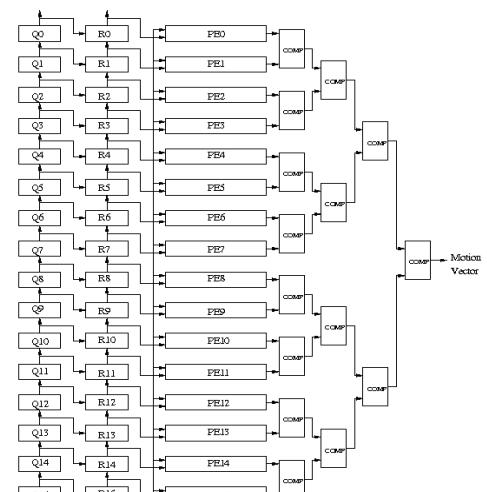
29



Architecture Design and Chip Implementation

- One-Dimensional Full Search
- MinMax Criterion

Technology	0.8 um CMOS
Chip Size	6.5 mm x 5.3 mm
Number of Transistors	48170
Chip Clock	43 MHz
Number of Pads	61
Power Dissipation	383 mW



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Subjective Quality

1DFS'

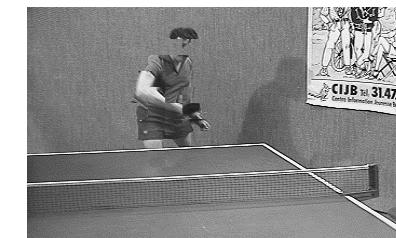
Table Tennis I



Min-max

MAE

Table Tennis II



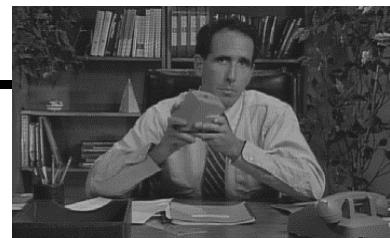
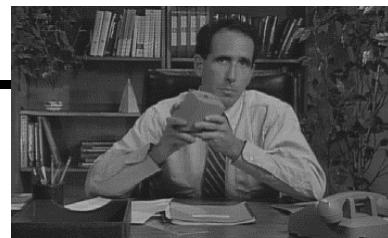
Min-max

MAE

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Salesman



Min-max

MAE

Train & Calendar



Min-max

MAE

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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

Figure 4.15 Pixel decimation for block matching in an 8×8 block.

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Pixel Subsampling for MAE calculations

- For each MAE value , we 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 .

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Projections for MAE calculations

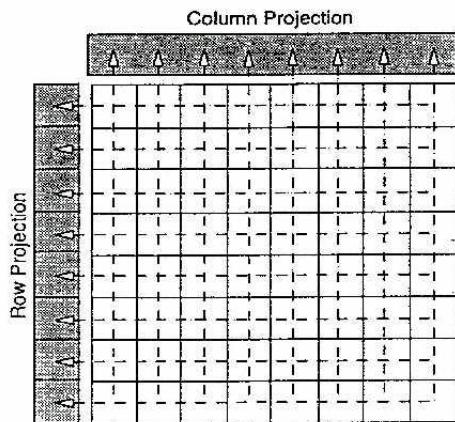


Figure 4.16 Row and column projection of pixels in an 8×8 block.

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Predictive Motion Estimation Using Boundary/Side Match

Motivation

- Relieve huge computation complexity imposed on full search for large search range motion estimation
- MPEG and HDTV applications
- Little attention paid in the past

Goal

- Provide solutions for the computation reduction of increasing search area
- Object-based concept

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Predictive Motion Estimation Algorithms

$$V_t(p, q) = E[V_t(p, q)] + dV_t(p, q), \quad |dV_t(p, q)| \leq W$$

$E[V_t(p, q)]$:Predicted Motion Vector

Temporal Prediction

Inter-Frame Prediction

$dV_t(p, q)$:Refined Displacement

Spatial Prediction

Inter-Block Prediction

W :Reduced Search Range

Median Vector Prediction

(e.g. one-quarter of search range Ω)

Proposed Boundary Match Prediction

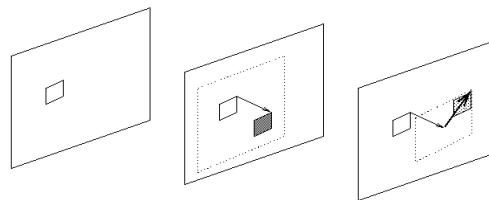
Proposed Side Match Prediction

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Inter-Frame Prediction

$$E[V_t(p, q)] = V_{t-1}(p, q)$$

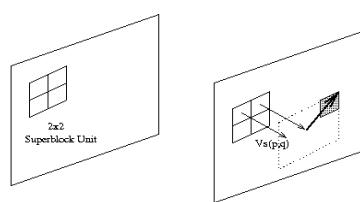


Frame t-1

Frame t

Inter-Block Prediction

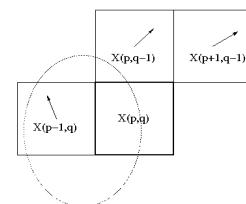
$$E[V_t(p, q)] = V_s(p, q)$$



Median Vector Prediction

$$E[V_t(p, q)] = \arg \underset{v \in V_{cs}}{\text{Median}} v$$

$$V_{cs} = \{V_t(p, q-1), V_t(p-1, q), V_t(p+1, q-1)\}$$



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Boundary/Side Match

- ❑ A motion object often covers many small blocks
- ❑ Blocks in the same object have similar motion vectors
- ❑ Spatial Neighboring Blocks
 - Very likely move in the same direction with similar velocities
 - Highly correlated or dependent
- ❑ Utilize the **high spatial correlation** between the **boundary pixels of adjacent blocks** to determine a more accurate initial motion estimation center
- ❑ Other applications
 - Vector quantization (VQ)
 - Recovery of lost vector or channel error
 - Transform coded image reconstruction



Boundary Match

$$[X(p,q)]^c_i = (x_{1i}, x_{2i}, \dots, x_{ni})^T \quad \text{column vector}$$

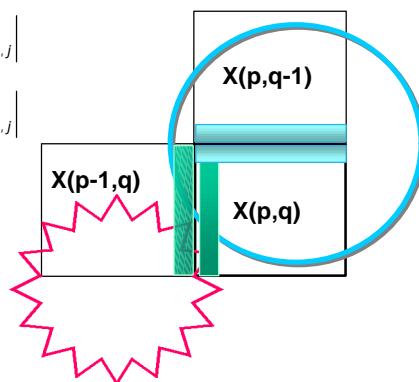
$$[X(p,q)]^r_i = (x_{1i}, x_{2i}, \dots, x_{ni}) \quad \text{row vector}$$

$$d_{bm, V_t(p, q-1)} = \sum_{j=1}^n |[X(p, q)]^r_{1,j} - [X(p, q-1)]^r_{n,j}|$$

$$d_{bm, V_t(p-1, q)} = \sum_{j=1}^n |[X(p, q)]^c_{1,j} - [X(p-1, q)]^c_{n,j}|$$

$$E[V_t(p, q)] = \arg \min_{v \in V_{cs}} d_{bm, v}$$

$$V_{cs} = \{V_t(p, q-1), V_t(p-1, q)\}$$



Side Match

$$d_{smU} = \sum_{j=1}^n | [X_{MC}(p, q)]_{1,j}^r - [X(p, q-1)]_{n,j}^r |$$

$$d_{smL} = \sum_{j=1}^n | [X_{MC}(p, q)]_{1,j}^c - [X(p-1, q)]_{n,j}^c |$$

$$d_{smR} = \sum_{j=1}^n | [X_{MC}(p, q)]_{n,j}^c - [X(p+1, q)]_{1,j}^c |$$

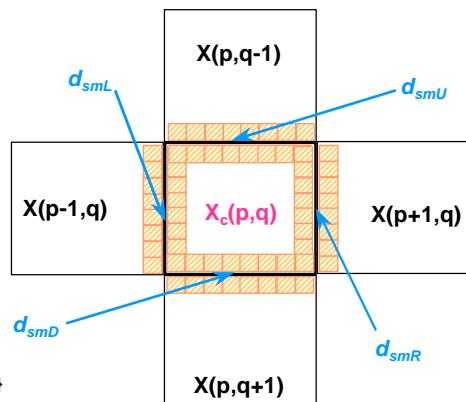
$$d_{smD} = \sum_{j=1}^n | [X_{MC}(p, q)]_{n,j}^r - [X(p, q+1)]_{1,j}^r |$$

$$d_{sm} = d_{smU} + d_{smL} + d_{smR} + d_{smD}$$

$$E[V_t(p, q)] = \arg \min_{v \in V_{cs}} d_{sm,v}$$

$$V_{cs} = \{V_t(p, q-1), V_t(p-1, q), V_t(p+1, q-1)\}$$

minimum gray-level transition
across four boundaries



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Computation Comparison

Algorithms	Search Range	Computation Complexity (SD/block)
Full Search	-p ~ p	$(2p+1)^2 \times m \times n$
Inter- Frame	-p/2 ~ p/2	$(p+1)^2 \times m \times n$
Inter- Block	-p ~ p -p/2 ~ p/2	$[1/4(2p+1)^2 + 3/4(p+1)^2] \times m \times n$
Median	- p/2 ~ p/2	$(p+1)^2 \times m \times n + 6$
Boundary Match	- p/2 ~ p/2	$(p+1)^2 \times m \times n + m + n$
Side Match	- p/2 ~ p/2	$(p+1)^2 \times m \times n + 6(m + n)$

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Objective Performance Measurement

PSNR: Peak-to-Peak Signal-to-Noise Ratio

predicted image compared to the original image

$$PSNR = 10 \times \log_{10} \frac{255^2}{MSE} \quad (\text{dB})$$

Entropy of Prediction Error (bits/pixel)

$$Entropy = - \sum_i p(e_i) \cdot \log_2 p(e_i) = \sum_i p(e_i) \cdot \log_2 \frac{1}{p(e_i)}$$

$p(e_i)$: probability of occurrence of prediction error pattern

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PSNR Comparison

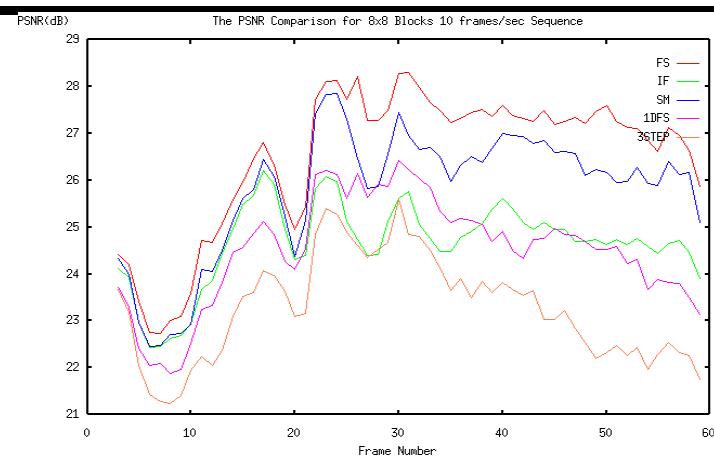
Algorithms	30 frames/sec	15 frames/sec	10 frames/sec
Full Search	27.33	26.90	26.49
Inter-Frame	25.73	25.23	24.66
Inter-Block	26.09	25.52	25.22
Median	25.57	24.93	24.23
Boundary Match	26.40	26.03	25.68
Side Match	26.52	26.17	25.77
IDFS	26.23	25.09	24.49
3-Step	24.94	23.06	23.26

Block size 8x8 60 frames Table Tennis Sequence

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vs Frame Number

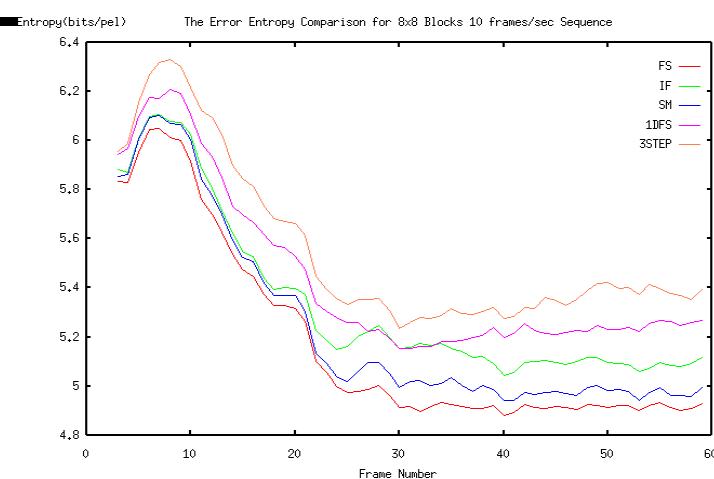


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Error Entropy vs Frame Number



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Motion Vector Characteristics

MV Euclidean Distance(ED) $(V_x - V_{x'})^2 + (V_y - V_{y'})^2$

Hit Ratio(HR)

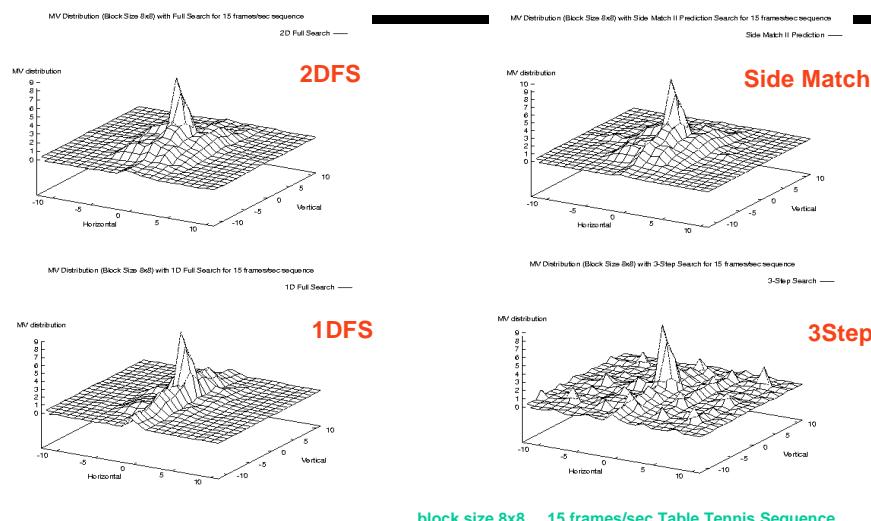
Criterion: $|V_x - V_{x'}| \leq 2$ and $|V_y - V_{y'}| \leq 2$

Frame Rate	30 frames/sec		15 frames/sec		10 frames/sec	
Algorithms	ED	HR	ED	HR	ED	HR
Inter-Frame	23.52	72.92%	60.05	67.50%	74.67	62.46%
Inter-Block	13.05	76.88%	54.54	71.37%	72.82	67.55%
Median	20.63	73.33%	57.15	66.98%	82.41	60.64%
Boundary Match	10.08	79.70%	47.88	74.76%	66.91	70.73%
Side Match	9.97	80.93%	46.08	75.72%	65.18	71.86%
IDFS	26.71	61.97%	95.13	41.74%	132.27	31.55%
3-Step	23.14	50.81%	100.92	30.39%	144.47	23.80%

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Motion Vector Distribution

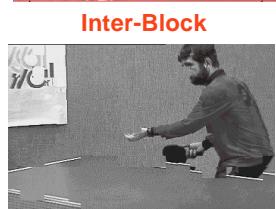
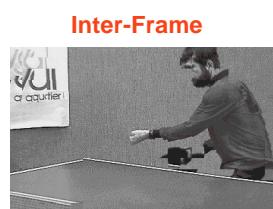
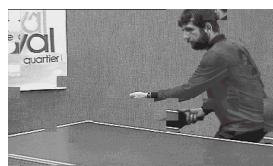
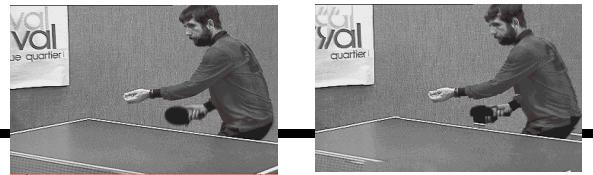


block size 8x8 15 frames/sec Table Tennis Sequence



Subjective Quality

16x16 blocks
15 frames/sec Table Tennis Sequence



1DFS

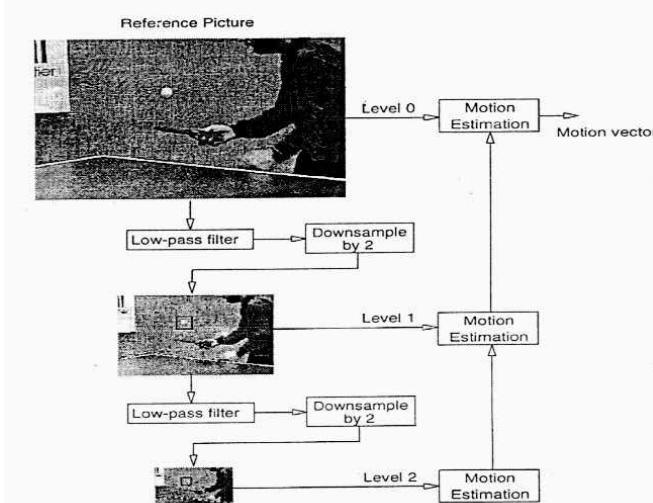
3Step

Side Match

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Hierarchical Motion Estimation



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Hierarchical Motion Estimation

1. Level 2

- Picture size = 180×120 , and macroblock size = 4×4 .
- Number of macroblocks = $\frac{\text{Picture size}}{\text{Macroblock size}} = \frac{180 \times 120}{4 \times 4} = 1,350$. At 30 fps, we have 40,500 macroblocks.
- Search parameter = $\lceil \frac{P}{4} \rceil = 4$.
- Number of search locations = $(2 \times 4 + 1)^2 = 81$.
- Number of operations per search location = macroblock size $\times 3 = 48$.

Complexity for Level 2 = $40,500 \times 81 \times 48 = 157.46$ MOPS.

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Hierarchical Motion Estimation

2. Level 1

- Picture size = 360×240 , and macroblock size = 8×8 .
- Number of macroblocks = $1,350$. At 30 fps, we have 40,500 macroblocks.
- Search parameter = 1.
- Number of search locations = 9.
- Number of operations per search location = macroblock size $\times 3 = 192$.

Complexity for Level 1 = $40,500 \times 9 \times 192 = 69.98$ MOPS.

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3. Level 0

- Picture size = 720×480 , and macroblock size = 16×16 .
- Number of macroblocks = 1,350. At 30 fps, we have 40,500 macroblocks.
- Search parameter = 1..
- Number of search locations = 9.
- Number of operations per search location = macroblock size \times 3 = 768.

Complexity for Level 0 = $40,500 \times 72 \times 48 = 279.9$ MOPS.

Hierarchical Motion Estimation

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

Operations Comparison of Motion-Estimation Methods

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

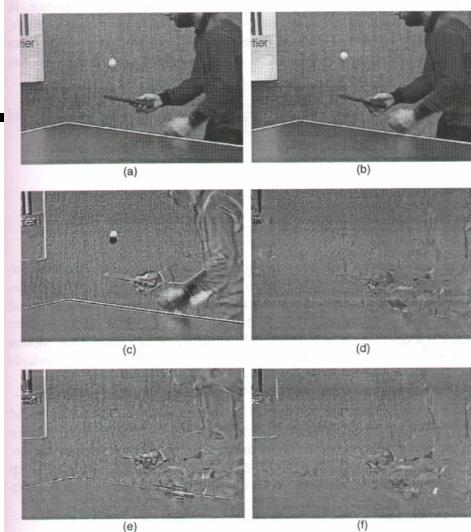


Figure 4.18 Performance comparison of motion-estimation methods. (a) Reference picture; (b) current picture; (c) simple frame differencing; (d) full-search; (e) logarithmic search; (f) three-level hierarchical search.

Sub-pixel-accurate motion estimation

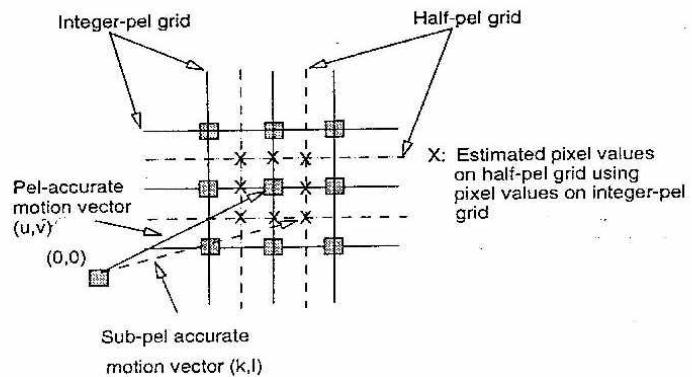


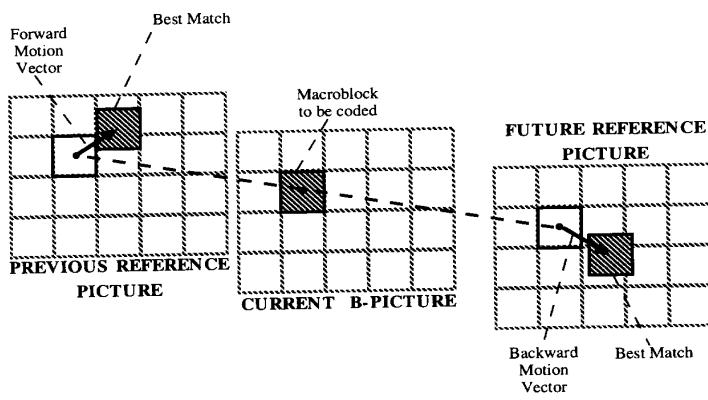
Figure 4.19 Half-pel accurate motion vector estimation.

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Bidirectional Temporal Prediction for Progressive Video

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



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