Lucas Kanade Optical Flow Estimation on the TI C66x Digital Signal Processor

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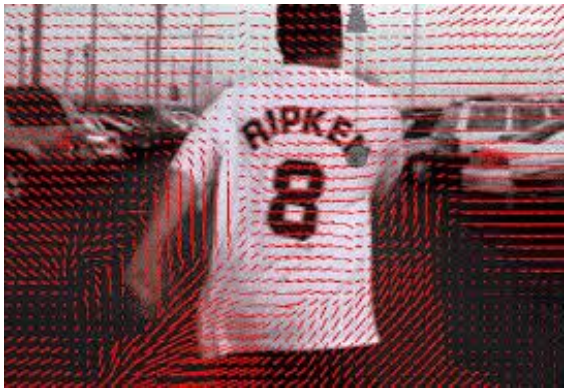
What is Optical Flow

- **Evaluates the pixel movement in video stream**
  - Represented as a dense 2D fields
- **Many applications need to apply real-time optical flow**
  - Robotic vision
  - Augmented reality
- **Computationally intensive**



TI C66x Multicore DSP

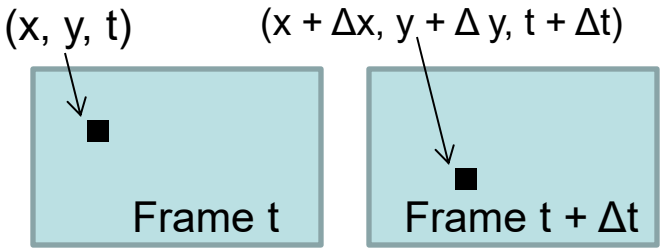
- **Unique architectural features**
  - Eight cores
  - Statically scheduled VLIW/SIMD instructions
  - 2 register files and 8 functional units per core

	Tesla K20X GPU	Intel i7 Ivy Bridge	TI C6678 Keystone	NVIDIA Tegra K1
	Server GPU	Server CPU	**Embedded**	Embedded
Peak single precision throughput	3.95 Tflops	448 Gflops	**160 Gflops**	327 Gflops
Peak Power	225 W	77 W	**<10 W**	<20 W
DRAM bandwidth	250 GB/s	25.6 GB/s	**12.8 GB/s**	17.1 GB/s

Why using DSP?

- Low power consumption
- High performance floating point arithmetic
- Strong potential for computer vision tasks
  - 1D vs 2D (signal processing vs image processing)

Gradient-based Optical Flow Solver



- Optical flow evaluation

$$f(x, y, t) = f(x + \Delta x, y + \Delta y, t + \Delta t)$$

- First-order approximation

$$f(x, y, t) = f(x, y, t) + \frac{\partial f}{\partial x}\Delta x + \frac{\partial f}{\partial y}\Delta y + \frac{\partial f}{\partial t}\Delta t$$

Gradient of pixel in x, y and t direction, known

$$\frac{\partial f}{\partial x}v_x + \frac{\partial f}{\partial y}v_y = -\frac{\partial f}{\partial t}$$

Optical flow, unknown

One formula with two unknowns

Lucas Kanade Method

If we assume the pixel adjacent to the center has the same optical flow as the center

x-1,y-1	**x,y-1**	**x+1,y-1**
x-1,y	**x,y**	**x+1,y**
x-1,y+1	**x,y+1**	**x+1,y+1**

$$\begin{cases} \dfrac{\partial f(x-1,y-1)}{\partial x}v_x + \dfrac{\partial f(x-1,y-1)}{\partial y}v_y = -\dfrac{\partial f(x-1,y-1)}{\partial t} \\ \cdots \\ \dfrac{\partial f(x+1,y+1)}{\partial x}v_x + \dfrac{\partial f(x+1,y+1)}{\partial y}v_y = -\dfrac{\partial f(x+1,y+1)}{\partial t} \end{cases}$$

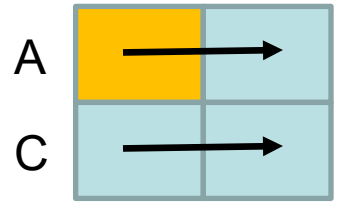
Let $A = \begin{bmatrix} \dfrac{\partial f(x-1,y-1)}{\partial x}, \dfrac{\partial f(x-1,y-1)}{\partial y} \\ \cdots \\ \dfrac{\partial f(x+1,y+1)}{\partial x}, \dfrac{\partial f(x+1,y+1)}{\partial y} \end{bmatrix}$ $b = \begin{bmatrix} \dfrac{\partial f(x-1,y-1)}{\partial t} \\ \cdots \\ \dfrac{\partial f(x+1,y+1)}{\partial t} \end{bmatrix}$

$$\begin{bmatrix} V_x \\ V_y \end{bmatrix} = (A^T A)^{-1} A^T b = \begin{bmatrix} \sum \dfrac{\partial f}{\partial x}^2 & \sum \dfrac{\partial f}{\partial x}\dfrac{\partial f}{\partial y} \\ \sum \dfrac{\partial f}{\partial x}\dfrac{\partial f}{\partial y} & \sum \dfrac{\partial f}{\partial y}^2 \end{bmatrix} \begin{bmatrix} -\sum \dfrac{\partial f}{\partial x}\dfrac{\partial f}{\partial t} \\ -\sum \dfrac{\partial f}{\partial y}\dfrac{\partial f}{\partial t} \end{bmatrix}$$

Least Square Method

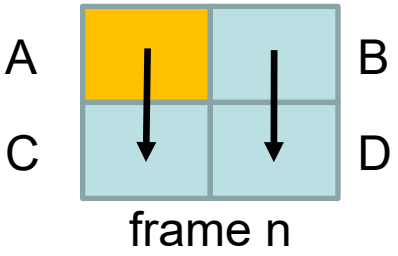
Image Derivative Computation

$$\frac{\partial f}{\partial x} =$$



(A – B + C – D) / 2

$$\frac{\partial f}{\partial y} =$$



(A – C + B – D) / 2

$$\frac{\partial f}{\partial t} =$$

A - B

Lucas Kanade Method

- Input: Frame n, frame n+1, window size w
- Output: Optical flow field F

- For each pixel x, y
- Compute x,y,t derivative matrices Dx, Dy, Dt for its neighbor window
- Compute optical flow by the least square method

Derivative Computation (Example)

Image n

10	10	10	10
10	30	10	10
10	10	10	10
10	10	10	10

Image n + 1

10	10	10	10
10	10	10	10
10	10	30	10
10	10	10	10

-10	10	0
-10	10	0
0	0	0

$$\frac{\partial f}{\partial x}$$

-10	-10	0
10	10	0
0	0	0

$$\frac{\partial f}{\partial y}$$

0	0	0
0	20	0
0	0	-20

$$\frac{\partial f}{\partial t}$$

Least Square Method Example (Neighbor Window Size = 3)

$\frac{\partial f}{\partial x}$

-10	10	0
-10	10	0
0	0	0

$\frac{\partial f}{\partial y}$

-10	-10	0
10	10	0
0	0	0

$\frac{\partial f}{\partial t}$

0	0	0
0	20	0
0	0	-20

$$\sum_W \left(\frac{\partial f}{\partial x}\right)^2 = 400$$

$$\sum_W \left(\frac{\partial f}{\partial y}\frac{\partial f}{\partial t}\right) = 200$$

$$\sum_W \left(\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}\right) = 0$$

$$\sum_W \left(\frac{\partial f}{\partial y}\right)^2 = 400$$

$$\sum_W \left(\frac{\partial f}{\partial x}\frac{\partial f}{\partial t}\right) = 200$$

$$\begin{bmatrix} Vx \\ Vy \end{bmatrix} = \begin{bmatrix} 400 & 0 \\ 0 & 400 \end{bmatrix}^{-1} \begin{bmatrix} -200 \\ -200 \end{bmatrix}$$

Optimize Lucas Kanade Method on DSP

- **Derivative computation**
  - SIMD arithmetic
  - Data interleaving

- **Least square method**
  - Loop unrolling
  - SIMD load & arithmetic

Derivative Computation

10	10	10	10
10	30	10	10
10	10	10	10
10	10	10	10

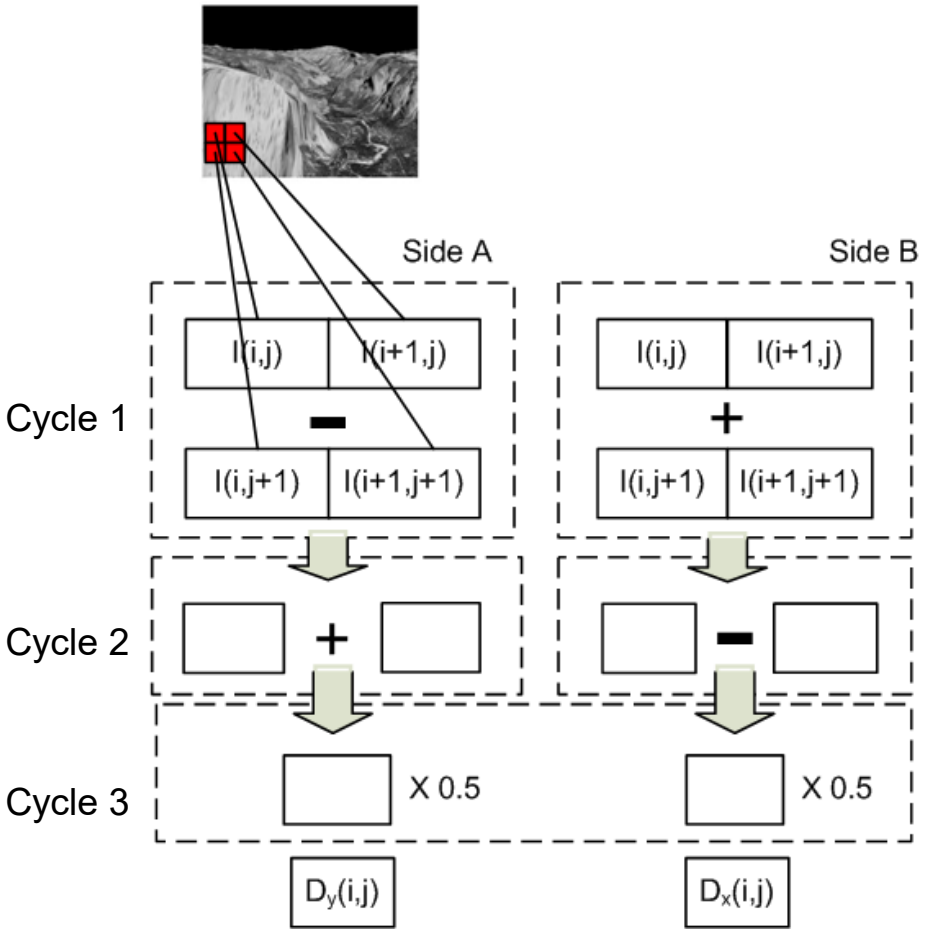
Derivative Computation (Dx, Dy)

-10	10	0
-10	10	0
0	0	0

-10	-10	0
10	10	0
0	0	0

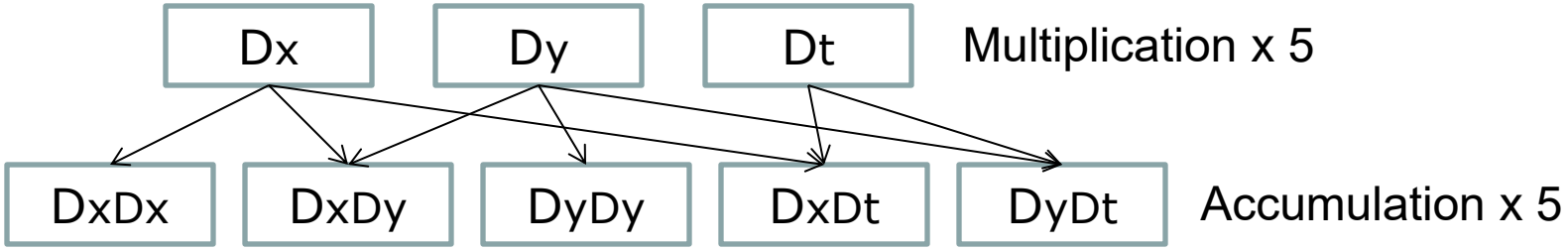
Interleave

-10	-10	10	-10	0	0
-10	10	10	10	0	0
0	0	0	0	0	0

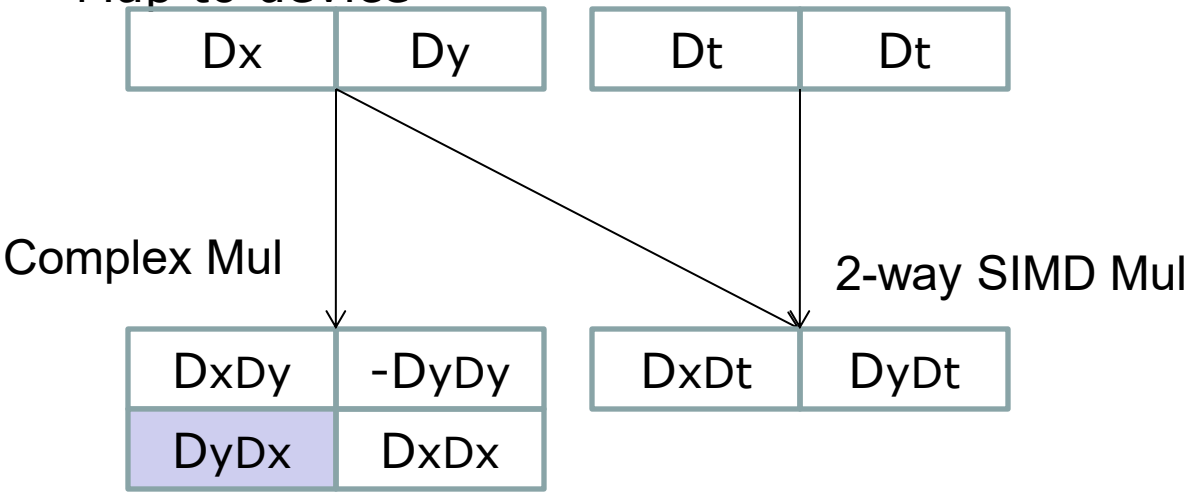


Least Square Method

- Required computations



- Map to device



(a+bj)(c+dj) = (ac-bd) + (ad+bc)j

Least Square Method

- Unrolled 2x
  - Group up loads into SIMD operation

Load DxDy Load Dt Complex MUL SIMD MUL SIMD ADD

DxDy

-10	-10	10	-10	0	0
-10	10	10	10	0	0
0	0	0	0	0	0

Dt

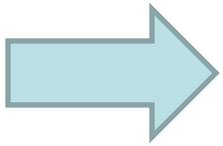
0	0	0
0	20	0
0	0	-20

(Dx,Dy,Dt)

-10	-10	0

(Dx,Dy,Dt)

10	-10	0



(DxDx,DxDy,DyDy,DxDt,DyDt)

100	100	100	0	0

(DxDx,DxDy,DyDy,DxDt,DyDt)

100	-100	100	0	0

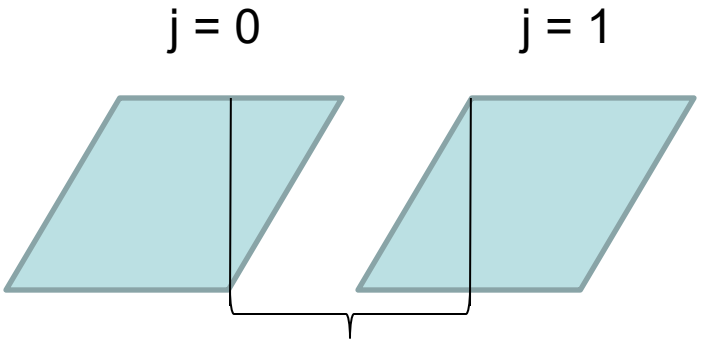
+

200
0
200
0
0

Loop Flattening

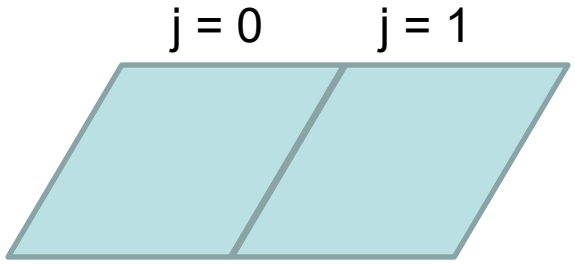
- Software Pipelining
  - TI's compiler technique to allow independent loop iterations be executed in parallel
  - The consecutive iterations are packed and executed together so that the arithmetic functional units are fully utilized

```
for (i = 0; i < m; ++i)
  for (j = 0; j < n; ++j)
```

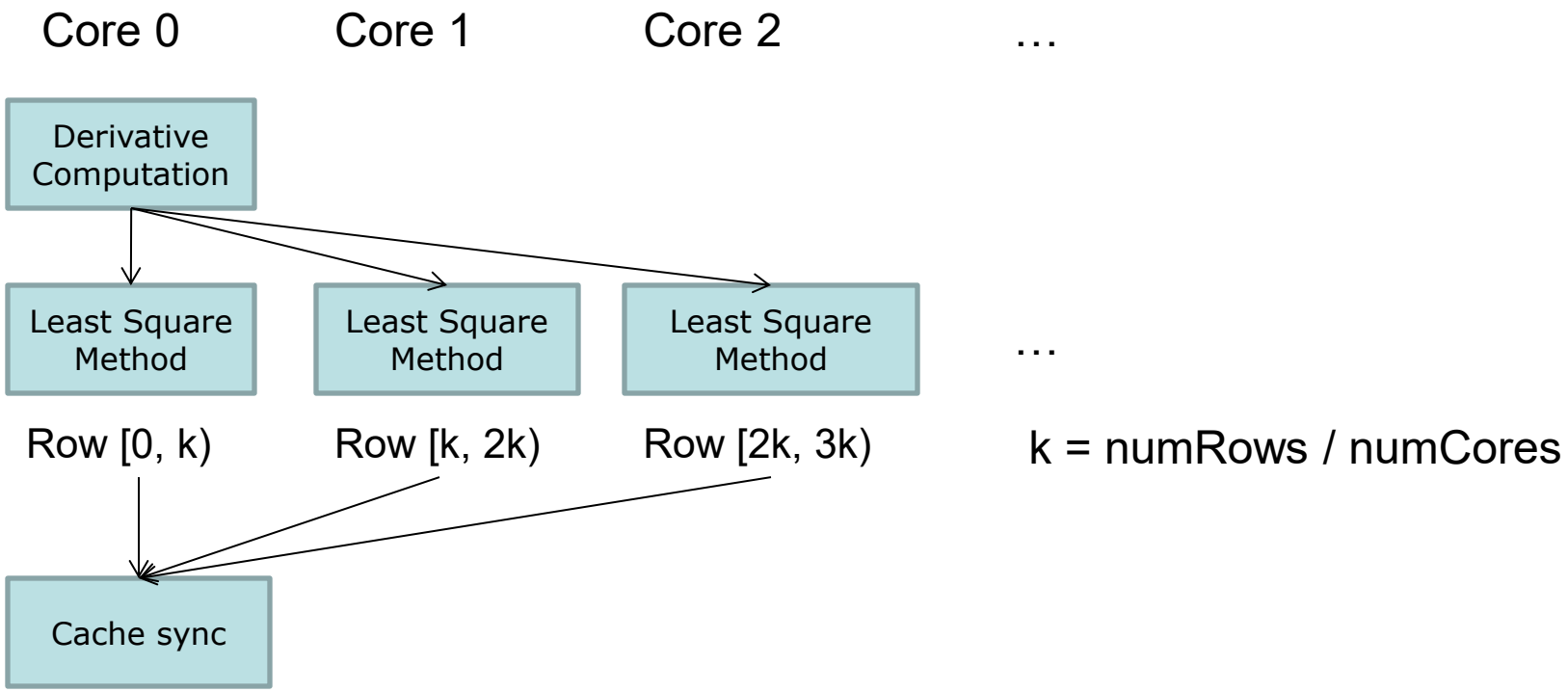


Pipeline prologue/epilogue overhead

```
for (k = 0; k < m * n; ++k)
  …
  Update i, j;
```



Multicore Utilization



Accuracy Improvement

- **Cannot catch movement larger than window size**
  - Gaussian Pyramid
    - A coarse to fine strategy for optical flow computation
    - Catches large movements

- **First order approximation may not be accurate**
  - Iterative refinement
    - Iteratively process and offset pixels until the computed optical flow is converged
    - Introduce data random access

Experiment Setup

Platform	#Cores	Implementation	Power Measurement
TI C6678 DSP	8	Our Implementation	TI GPIO-USB Module
ARM Cortex A9	2	Our Implementation	YOKOGAWA WT500 Power Analyzer
Intel i7-2600	4	Our Implementation	Intel RAPL
Tesla K20 GPU	2688	OpenCV	NVIDIA SMI

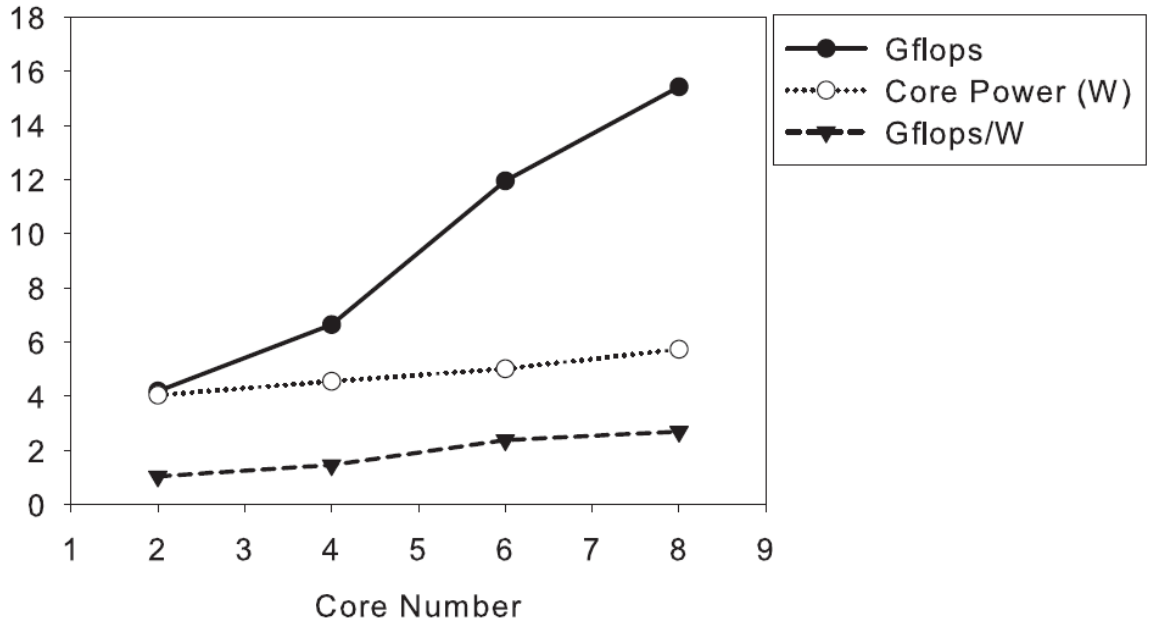
Results and Analysis

- Highest Performance
  - Tesla K20
- Lowest Power
  - Cortex A9
- Best Power Efficiency
  - TI C66x DSP

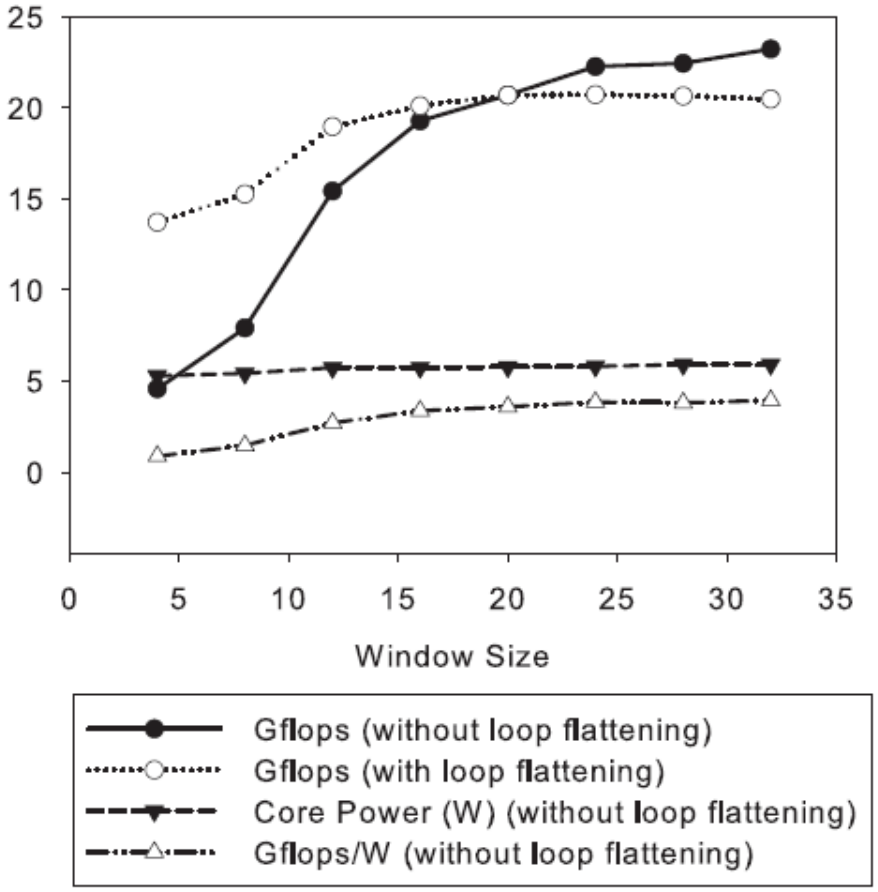
Platform	C66x	CortexA9	Intel i7-2600	K20
Actual Gflops/ Peak Gflops	**12%**	7%	4%	3%
Gflops	15.4	0.7	17.1	**108.6**
Power (W)	5.7	**4.8**	52.5	79.0
Gflops/W	**2.69**	0.2	0.3	1.4

Results and Analysis

- We achieve linear scalability on multi-cores
- The power efficiency of the DSP is low when its cores are partially utilized
  - Static power consumption



Results and Analysis



- Performance are related with window size
  - Software pipeline performance
- Loop flattening is able to improve performance significantly on small window size

Conclusion

- First research work on DPS accelerated Lucas Kanade method
- Achieve higher energy efficiency and device utilization than GPU and CPU

Q & A

Kernels of Pyramidal Lucas Kanade Method

- Gaussian Blur — 28 flop/pixel
- Derivative Computation — 8 flop/pixel
- Least Square Method — 10^5 flop/pixel
- Flow Field Bilinear Interpolation — 3 flop/pixel