

# FAST PATTERN MATCHING IN 3D IMAGES ON GPUS

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MIT Lincoln Lab



# In Memory of Dennis M. Healy, Jr.



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Contributed by Mary Healy Hambric

# Outline

- LCCs : local correlation coefficients
  - application requirements
  - computational challenges
  - recent progress
- Fast LCC
  - Algorithmic acceleration
  - Architectural acceleration (on GPUs)
- Building blocks
  - In image processing and information processing
- Conclusion

# Fast Convolution or Correlation

## Convolution (Correlation) Theorem

$$F(h * g) = F(h) \cdot F(g)$$

$$h * g = F^{-1}( F(h) \cdot F(g) )$$

### Discrete Version

Equally spaced sampling

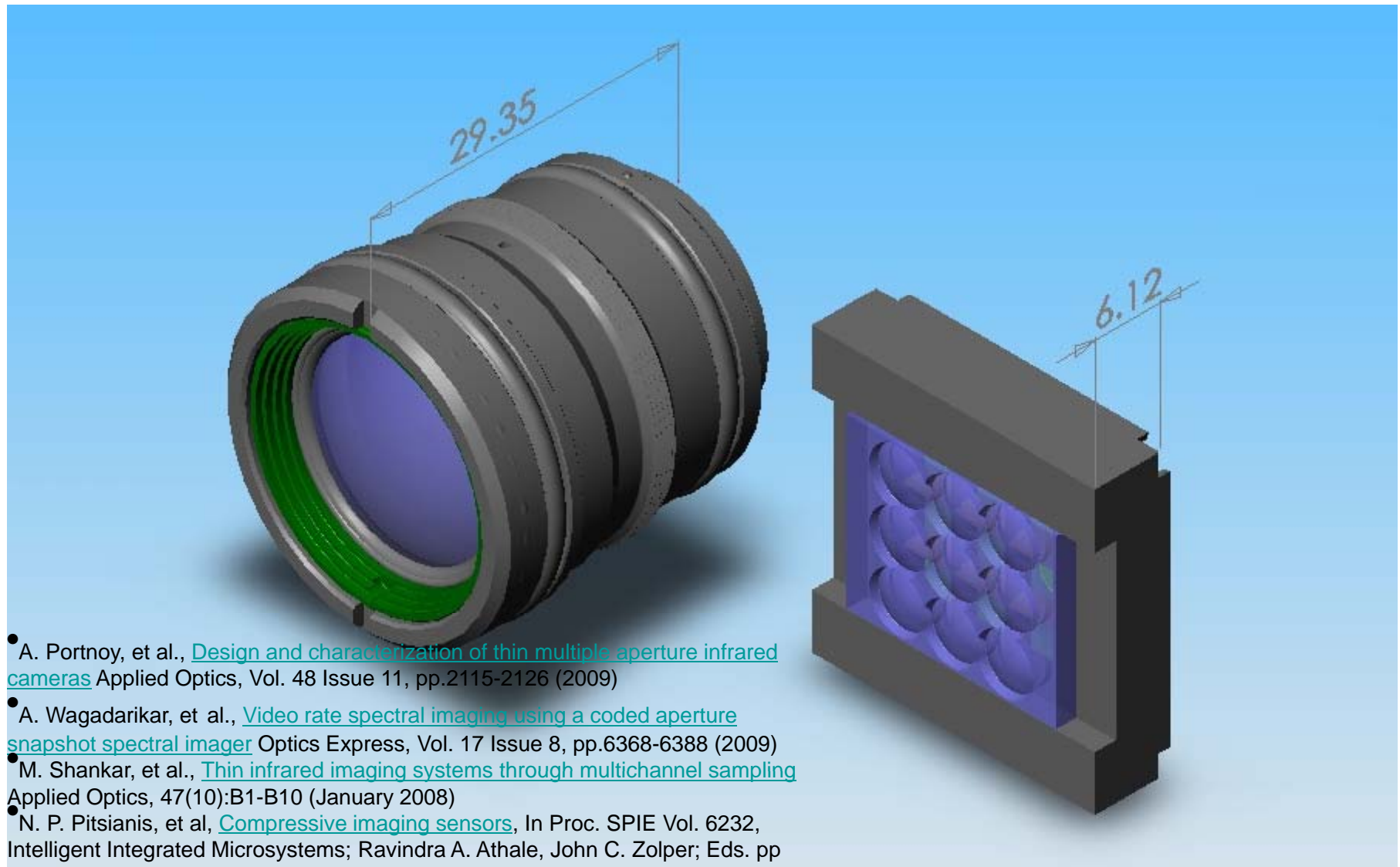
Periodic convolution : padding otherwise

**FFT :  $O(N \log(N))$**

# Local Correlation Coefficients (LCCs)

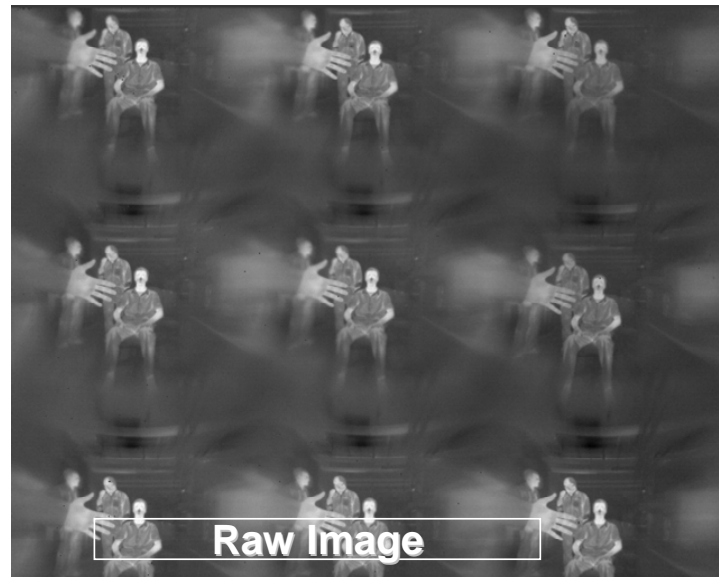
- Calculating the LCCs of a prototype-pattern with all patches in a large image
  - A basic operation in image registration, object classification and recognition, target identification and tracking
  - Statistically robust to local changes and noise
- Fast calculation of LCCs without compromising integrity
  - ❑ in many situations, rapid computation of LCCs was based on relaxed linearized conditions, to avoid local translation in mean and normalization in variance
  - ❑ “Fast LCC with *local* zero-mean translation and unit-variance normalization”, Sun & Pitsianis 2008

# Applications: MONTAGE

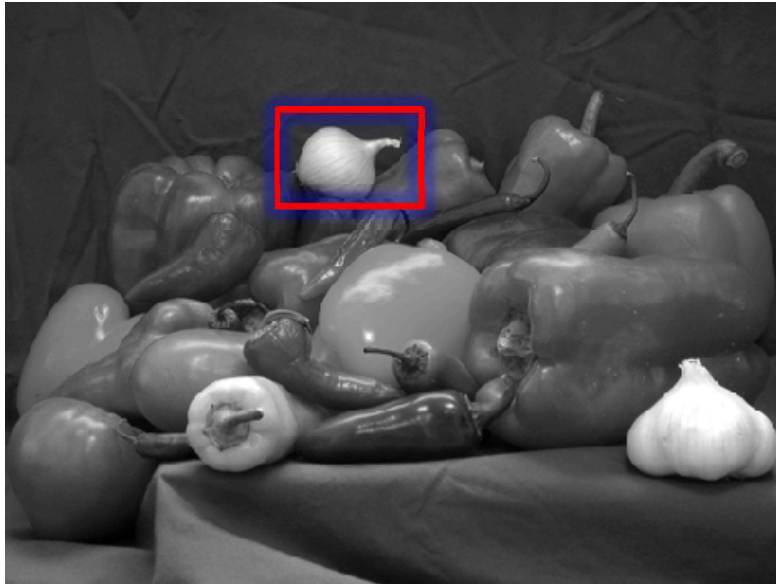


- A. Portnoy, et al., [Design and characterization of thin multiple aperture infrared cameras](#) Applied Optics, Vol. 48 Issue 11, pp.2115-2126 (2009)
- A. Wagadarikar, et al., [Video rate spectral imaging using a coded aperture snapshot spectral imager](#) Optics Express, Vol. 17 Issue 8, pp.6368-6388 (2009)
- M. Shankar, et al., [Thin infrared imaging systems through multichannel sampling](#) Applied Optics, 47(10):B1-B10 (January 2008)
- N. P. Pitsianis, et al, [Compressive imaging sensors](#), In Proc. SPIE Vol. 6232, Intelligent Integrated Microsystems; Ravindra A. Athale, John C. Zolper; Eds. pp 43-51, May 2006

# Sub-pixel Image Registration

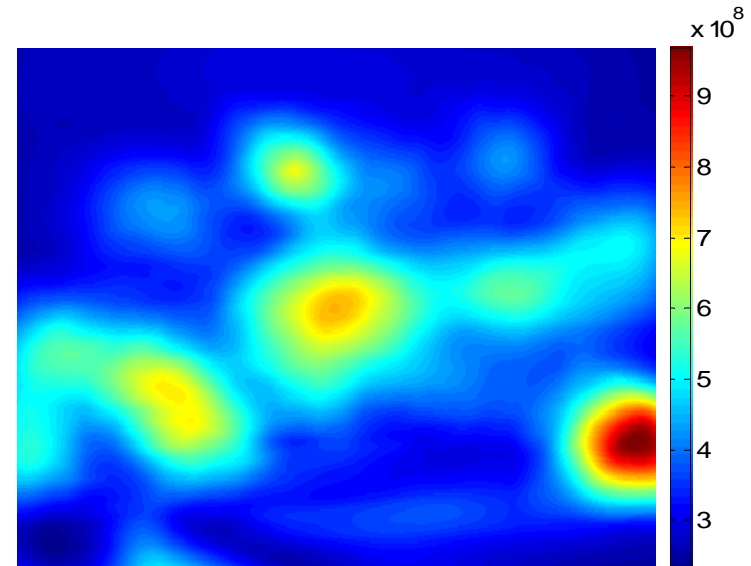
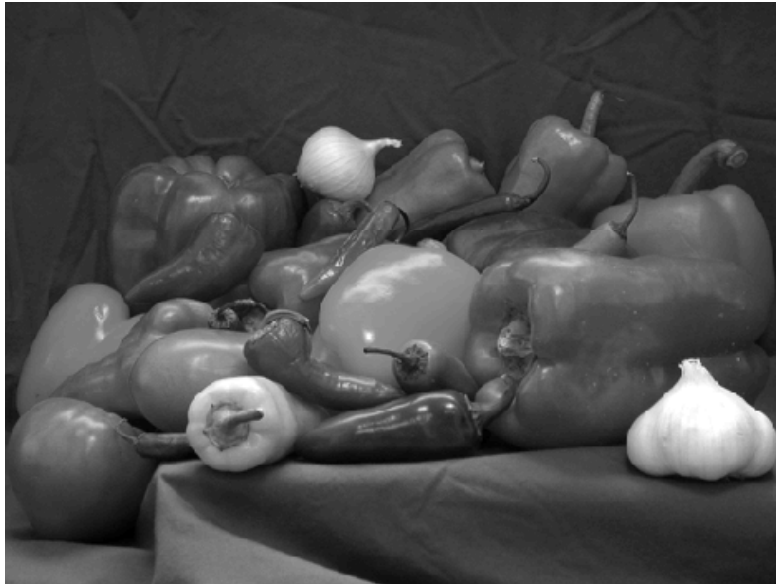


# Template Matching

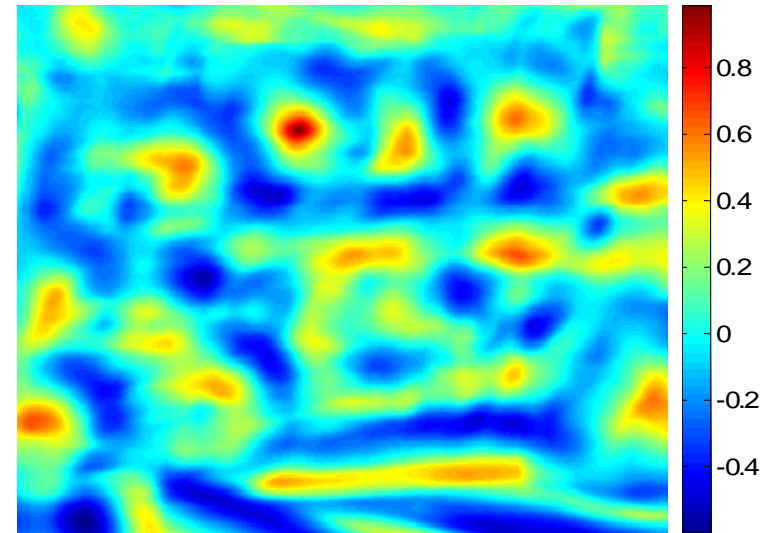
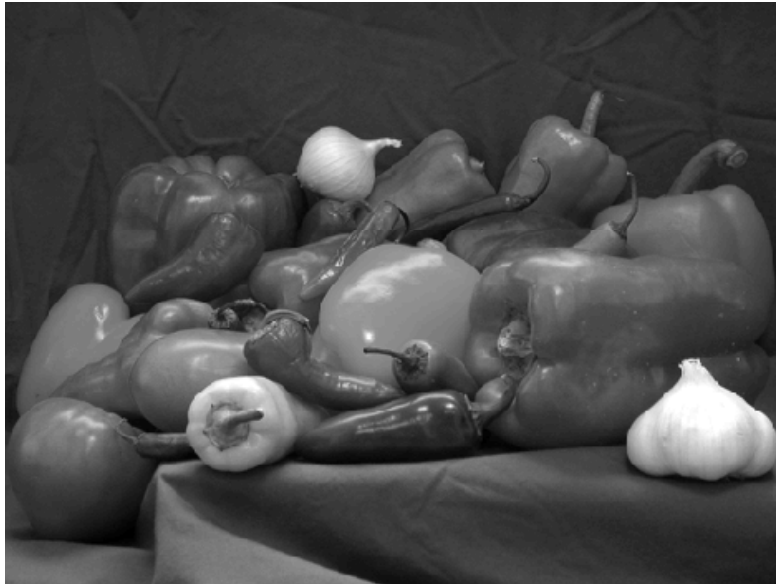




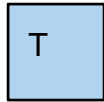
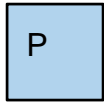
# Without Local Normalization



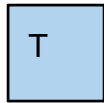
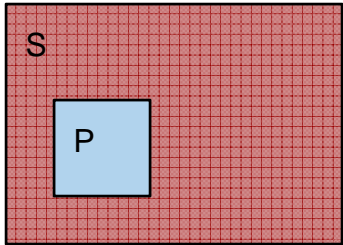
# With Local Normalization



# Local Correlation Coefficients

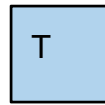
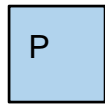


$$\text{corr}(P, T) = \sum_{(x,y)} P(x, y) \cdot T(x, y)$$

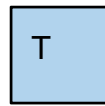
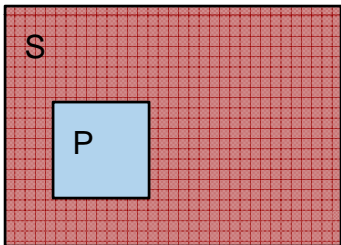


$$\text{corr}(S, T)_{(u,v)} = \sum_{(x,y)} S(x, y; u, v) \cdot T(x, y)$$

# Normalized Local Correlation Coefficients



$$c(P, T) = \sum_{(x,y)} \frac{P(x, y) - \mu_P}{\sigma_P} \cdot \frac{T(x, y) - \mu_T}{\sigma_T}$$



$$c(S, T)_{(u,v)} = \sum_{(x,y)} \frac{S(x, y; u, v) - \mu_{S(u,v)}}{\sigma_{S(u,v)}} \cdot \frac{T(x, y) - \mu_T}{\sigma_T}$$

$$\mu_T = \frac{1}{N_T} \sum_{(x,y)} T(x, y), \quad \sigma_T^2 = \frac{1}{N_T} \sum_{(x,y)} (T(x, y) - \mu_T)^2$$

X. Sun, N. P. Pitsianis, and P. Bientinesi, [Fast computation of local correlation coefficients](#) Proc. SPIE 7074, 707405 (2008)

## **Algorithmic Acceleration**

- 1. Reformulation in term of convolutions**
- 2. Use of Fourier transform identities**

# Reformulation in Terms of Convolutions

$$\sum_{x,y} [S(x, y; u, v) - \mu_S(u, v)] T(x, y) = \begin{matrix} \downarrow & & \downarrow & & \downarrow \\ \{S * T\}(u, v) - \frac{1}{N_T} \{S * B_T\}(u, v) \cdot \{B_S * T\}(u, v) \end{matrix}$$

$$\longrightarrow \quad \{S * T\}(u, v) = \sum_{(x,y)} S(x, y; u, v) T(x, y)$$

$$\longrightarrow \quad \{S * B_T\}(u, v) = N_T \mu_S(u, v)$$

$$\longrightarrow \quad \{B_S * T\}(u, v) = \sum_{(x,y)} B_S(x, y; u, v) T(x, y)$$

$$\longrightarrow \quad \sigma_S = \sqrt{S^2 * B_T - N_T \mu_S^2}$$

# Fast LCC in the Fourier Domain

A.  $F(B_T), F(B_S), F(T), F^{-1}(F(T) \cdot F(B_S))$   
 % pre-calculated

B.  $F(S + i \cdot S^2)$   
 % to obtain  $F(S), F(S^2)$

C.  $F^{-1}(F(S) \cdot F(B_T) + i \cdot F(S^2) \cdot F(B_T))$   
 % to obtain  $S * B_T$  and  $S^2 * B_T$

D.  $F^{-1}(F(S) \cdot F(T))$   
 % to obtain  $S * T$ .

**2.5 FFTs per image**

# DFT Identity with real data : **Two by one**

Let  $\hat{z} = F(x + i y)$  then

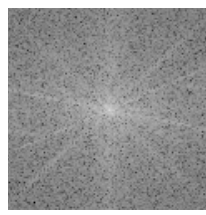
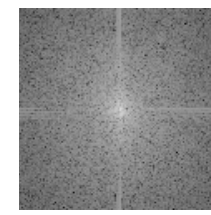
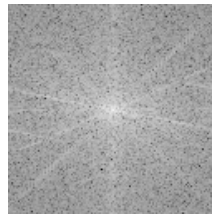
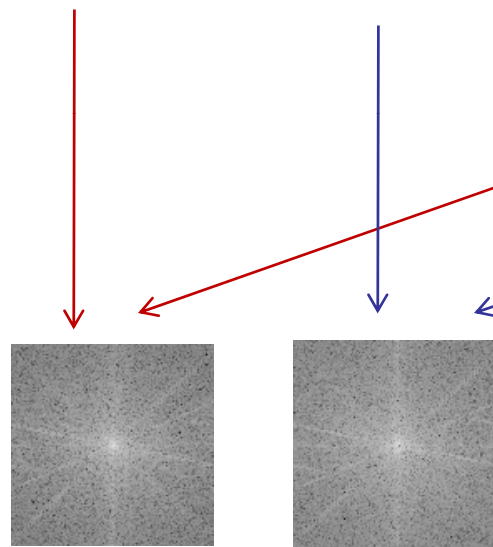
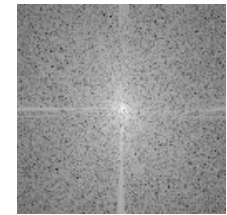
$$2\hat{x} = (I + J)\hat{z}_R + i(I - J)\hat{z}_I$$

$$2\hat{y} = (I + J)\hat{z}_I - i(I - J)\hat{z}_R$$

$$x + i y = F^{-1}(\hat{x} + i \hat{y})$$



# Illustration of **Two-by-One** identity


 $\hat{x}$ 

 $\hat{y}$ 

 $\hat{x} + i \hat{y}$ 

 $x + i y = F^{-1}(\hat{x} + i \hat{y})$

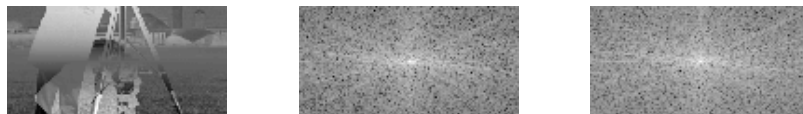
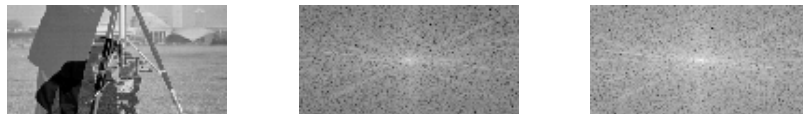
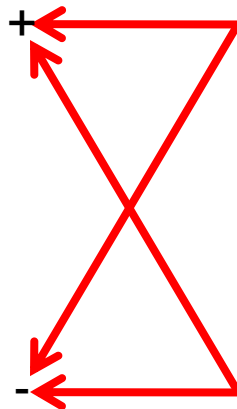
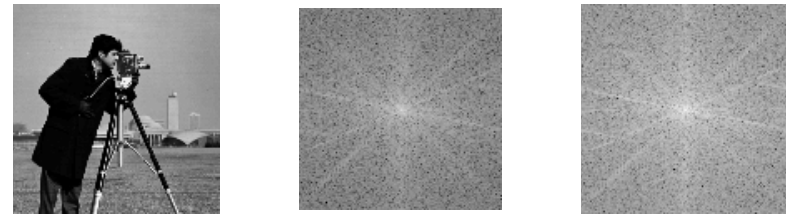
# DFT Identity : **One-by-Half**

$$w = \omega_n^{(0:\frac{n}{2}-1)}$$

$$\begin{bmatrix} \hat{x}_T \\ \hat{x}_B \end{bmatrix} = \begin{bmatrix} Fx_E + w \odot Fx_O \\ Fx_E - w \odot Fx_O \end{bmatrix}$$

$$\begin{bmatrix} x_T \\ x_B \end{bmatrix} = \begin{bmatrix} F^{-1}\hat{x}_E + \bar{w} \odot F^{-1}\hat{x}_O \\ F^{-1}\hat{x}_E - \bar{w} \odot F^{-1}\hat{x}_O \end{bmatrix}$$

# Illustration of **One-by-Half**



## Architectural Acceleration

1. **Necessary complement of fast algorithms in real-time image processing or massive data processing**
  
2. **The use of GPUs in particular**
  - **omnipresent in desktops, laptops**
  - **a prototype of parallel architecture**
    - ❖ many-core
    - ❖ memory hierarchy
    - ❖ bandwidth
    - ❖ programming model
    - ❖ 3D image processing

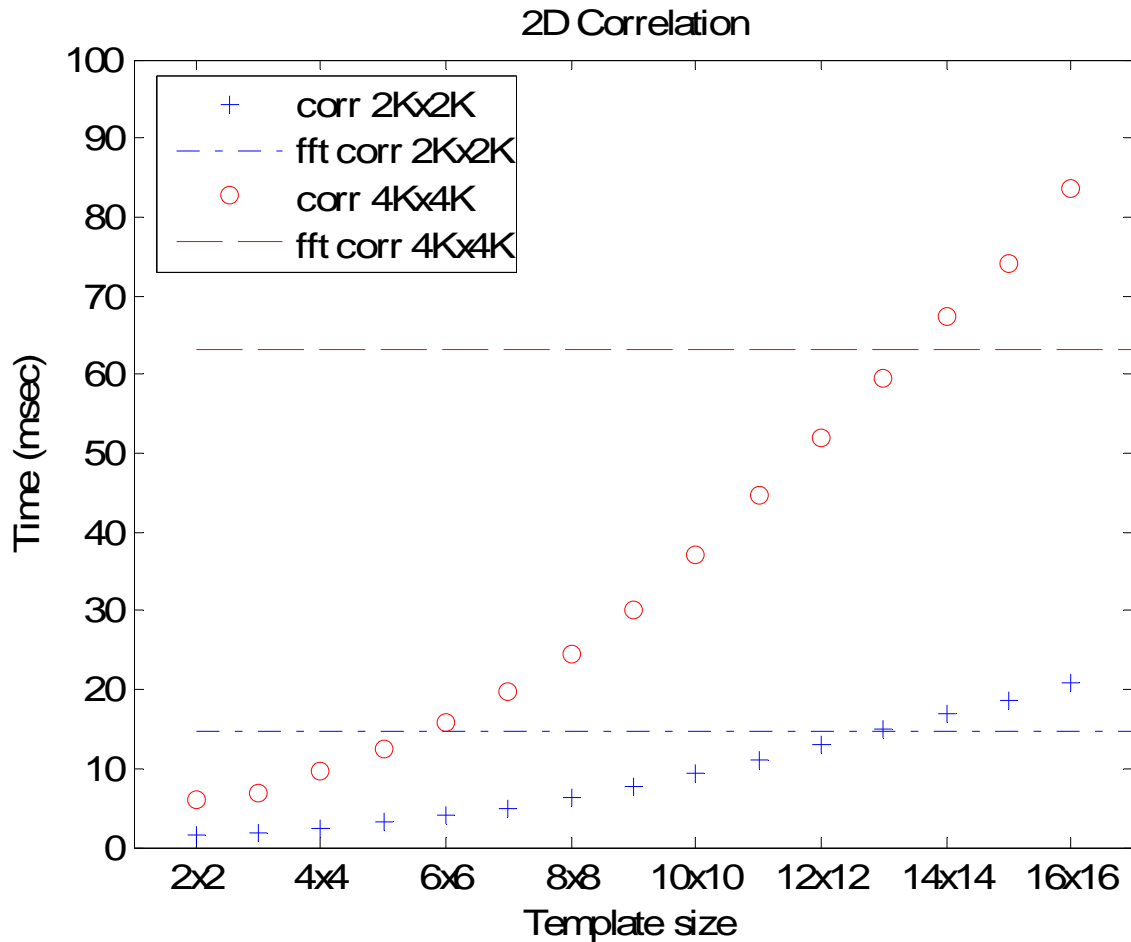
# 2D Convolution on CPU and GPU

Data Size	Xeon 1 core @ 1.86GHz		C1060 @ 1.35 GHz
	double	float	float
$2K \times 2K$	931	674	14
$4K \times 4K$	4,223	3,210	63

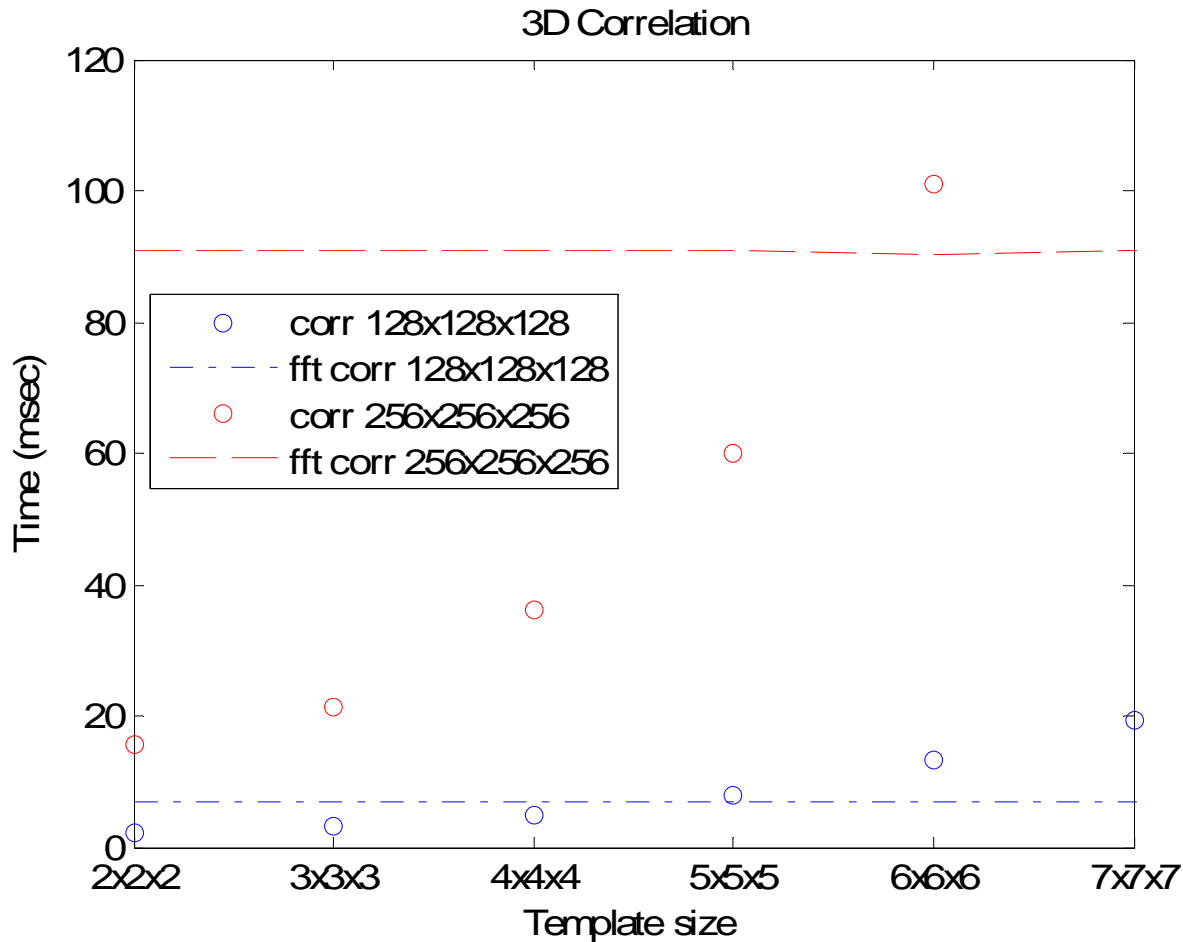
Execution time (msec)

FFTW 3.1.2 on Xeon  
 CUDA SDK 2.3 CUFFT on GPU

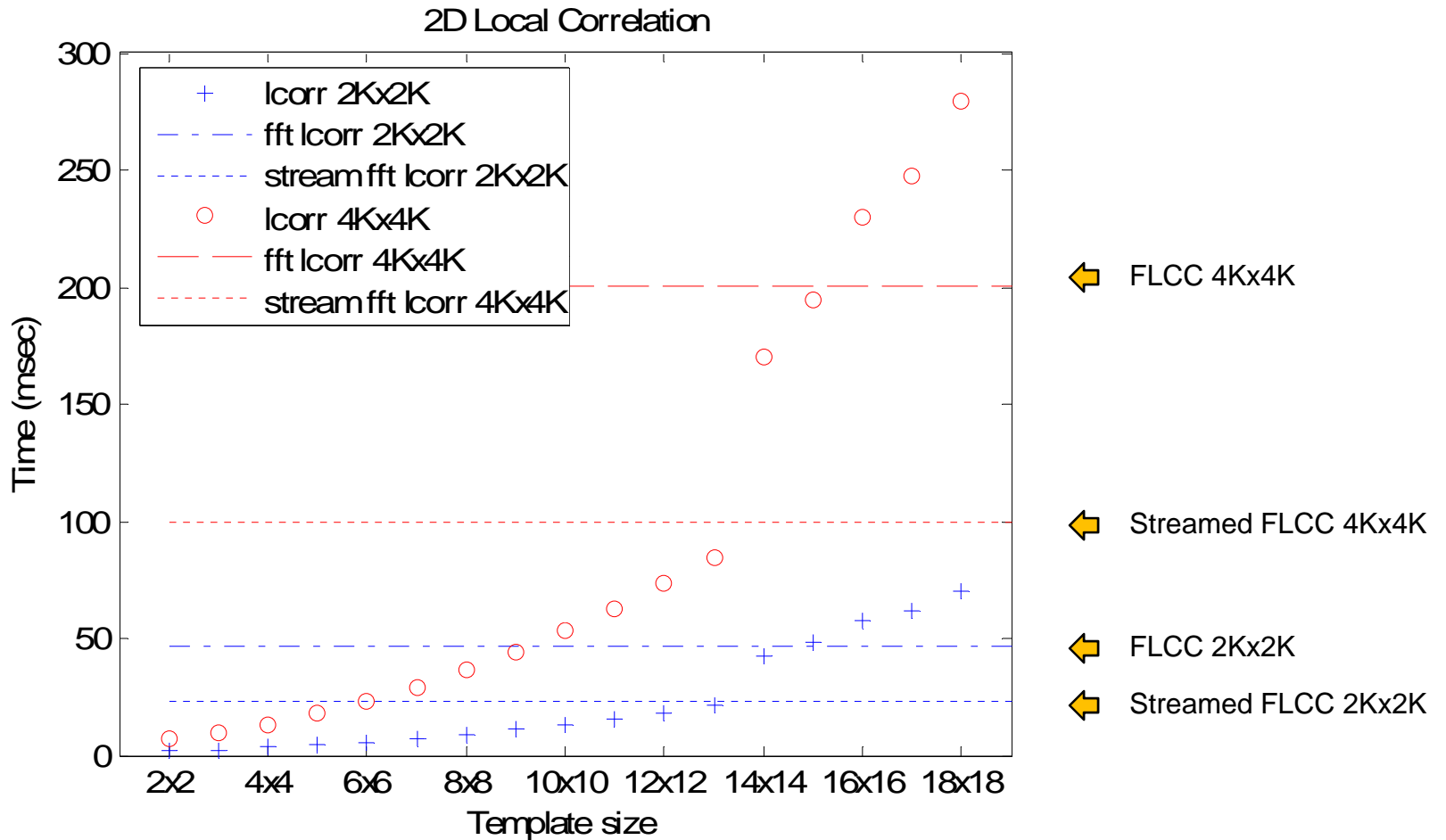
# Algorithmic Acceleration of 2D Convolution



# Algorithmic Acceleration of 3D Convolution

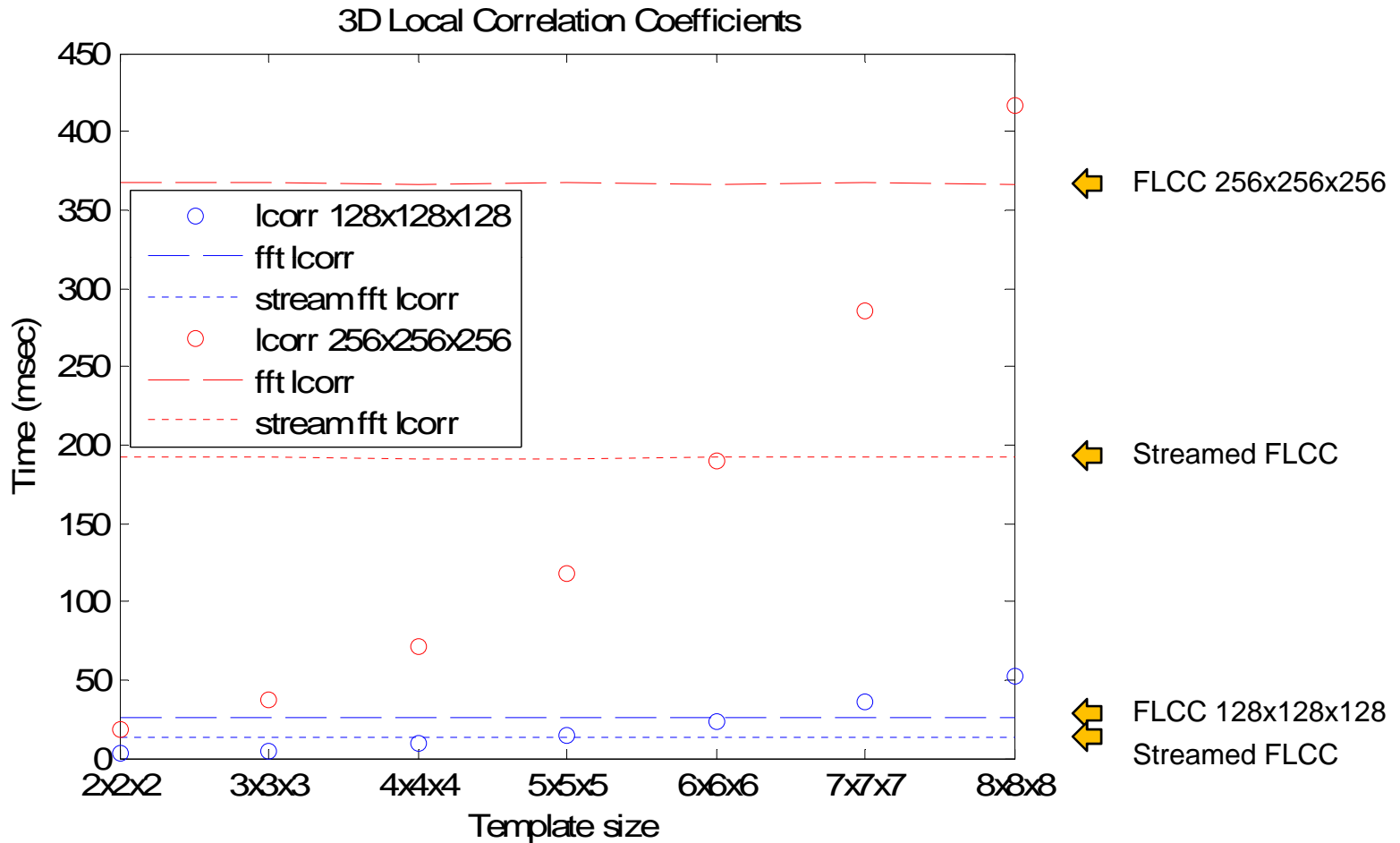


# GPU Acceleration of 2D LCCs





# GPU Acceleration of 3D LCCs

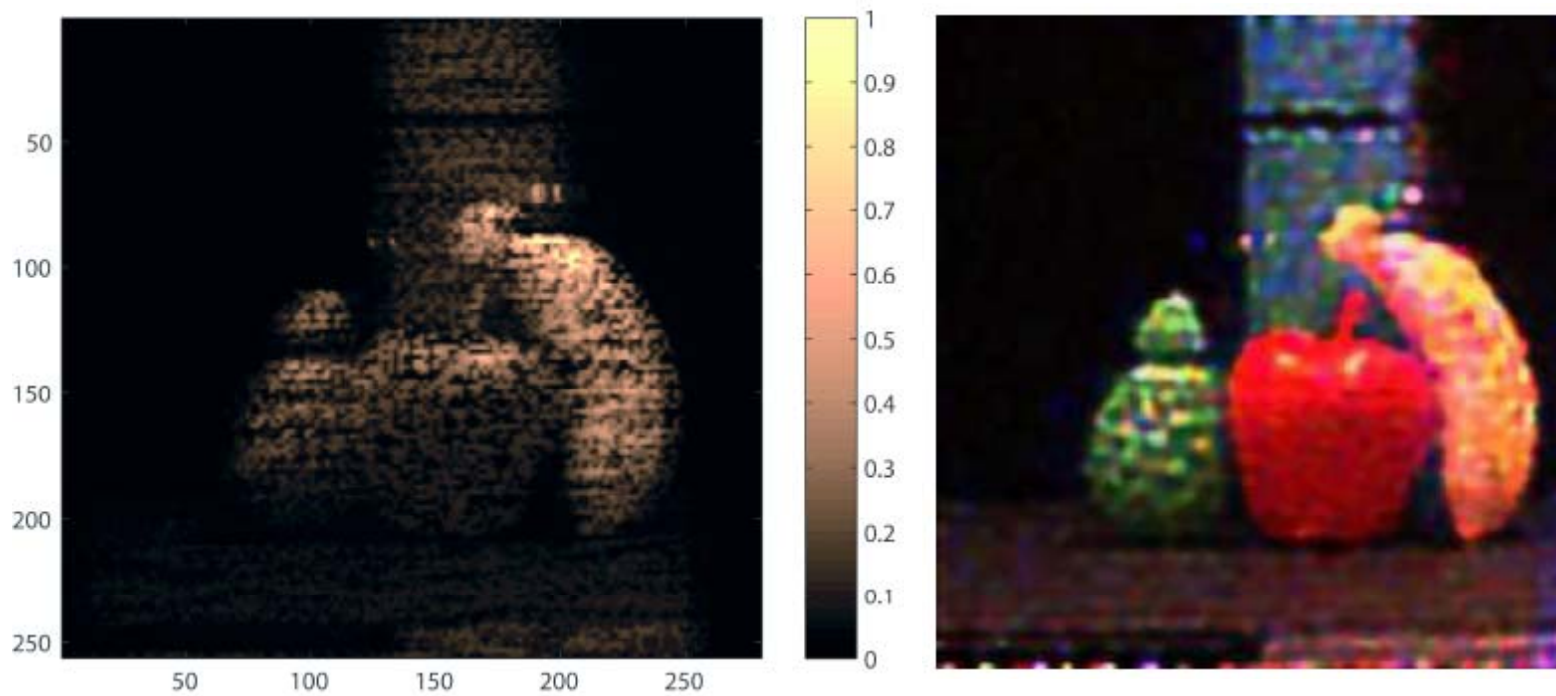


## Building Blocks

1. In image processing
2. In data modeling & information processing

# Fast Deconvolution with Incomplete Data

Construction of spectral images from coded intensity data

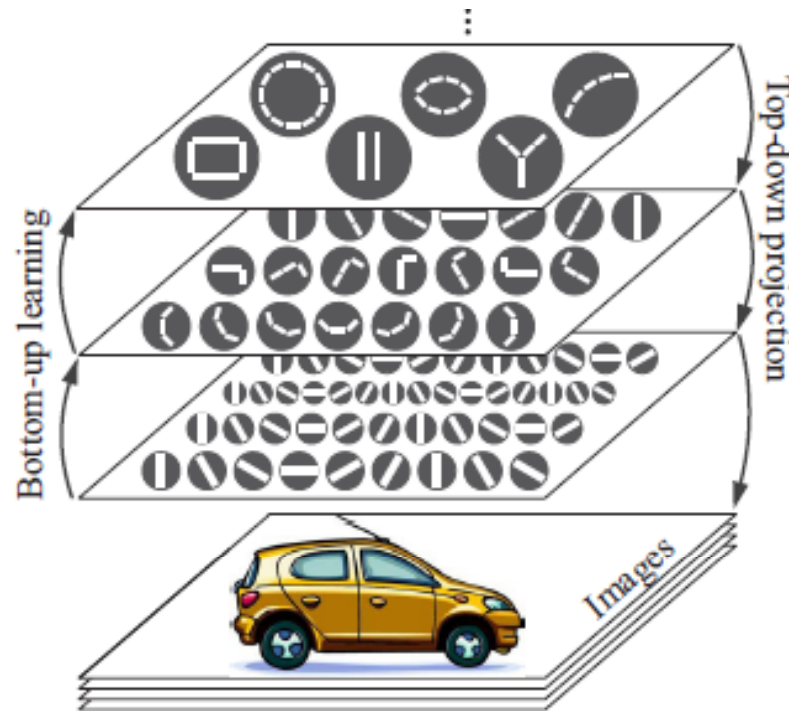


X. Sun and N. P. Pitsianis (2008)

# Hierarchical Data Indexing & Fast Feature Matching

## Object Feature Extraction in Multiple Layers

- *Simple and densely populated* features at lower layers
- *Complex but sparse* features at higher layers



S. Fidler, G. Berginc, A. Leonardis, Proc IEEE CVPR (2006)

# Conclusions

- Convolution/correlation, LCCs important in new and conventional applications
- Reformulation critical in designing fast algorithms without compromising quality
- Joint algorithmic and architectural accelerations
- Efficient implementation of fast algorithms on modern parallel architectures

# Acknowledgments

- **FANTOM** : Algorithm-Architecture Co-design
  - Supported in part by DARPA MTO
- AutoGPU
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