

# *Intelligent Sensor systems*

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## *Intelligent surveillance system (our old definition)*

- ❑ The system solves different tasks **automatically**;
- ❑ System is **adaptive** to the changes;
- ❑ System allows **fast reorganization** and **tuning**;
- ❑ System doesn't require **permanent human monitoring** and **control**.

## *Open problems to be solved*

1. Unique feature selection.
2. 3D scene reconstruction.
3. Image registration.
4. Extended object tracking.
5. Dynamic camera calibration.
6. Optimal sensor control for multi-target tracking.
7. Face localization in human silhouette.
8. Image and multimedia data bases.
9. Face recognition.
10. Abnormal behavior detection.
11. Optimal resource allocation.
12. Object selection.

## *Open problems (after 3 years)*

**OK** 1. Unique feature selection.

**Near to OK** 2. 3D scene reconstruction.

**Some results** 3. Image registration.

**Some results** 4. Extended object tracking.

**Negative res.** 5. Dynamic calibration.

**Next year** 6. Optimal sensor control for multitarget tracking.

**Several meth.** 7. Face localization in human silhouette.

**Some results** 8. Image and multimedia data bases.

**Some results** 9. Face recognition.

**Next year** 10. Abnormal behavior detection.

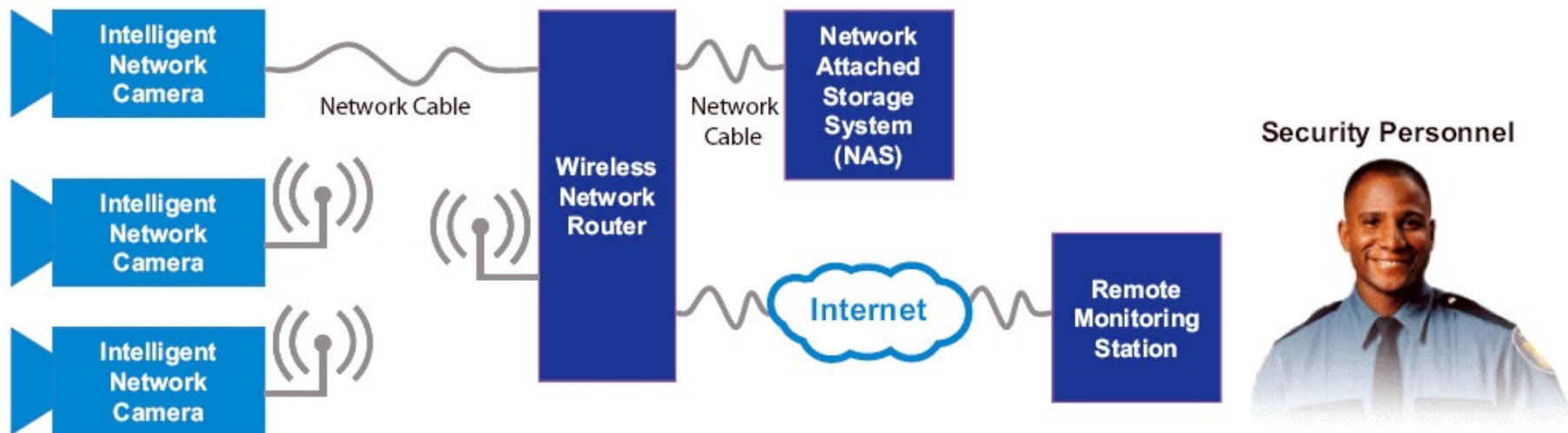
**Some results** 11. Optimal resource allocation.

**Next year** 12. Object selection.

# Where we are?

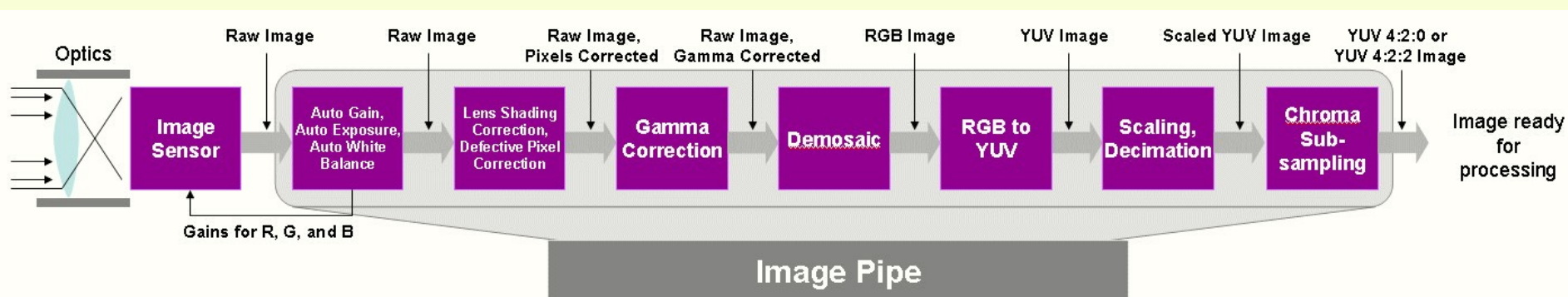
## John Weber, Avnet Classical security systems

**Intelligent Network Security System**



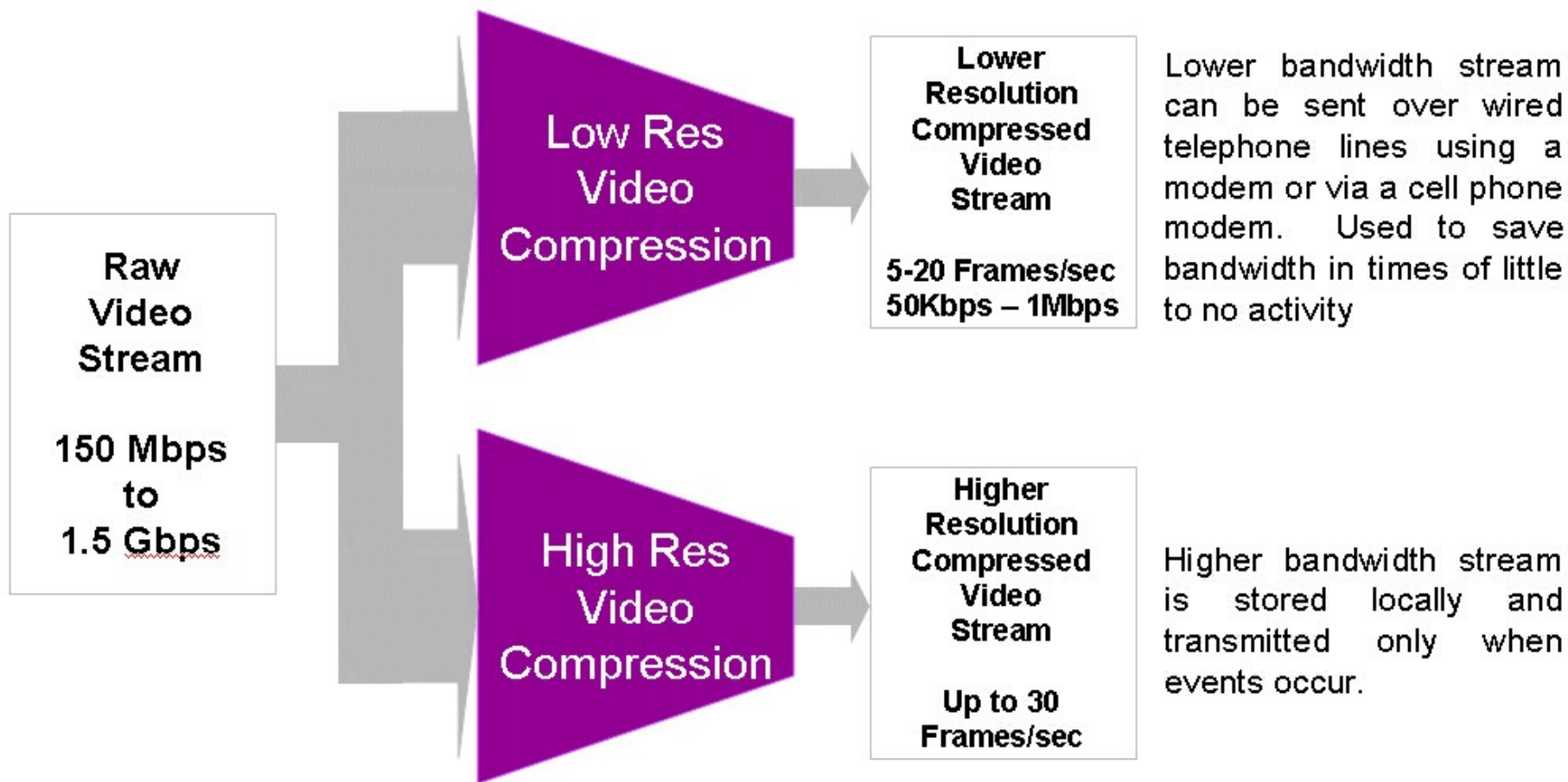
# John Weber, Avnet , Smart camera basics

## The image pipe



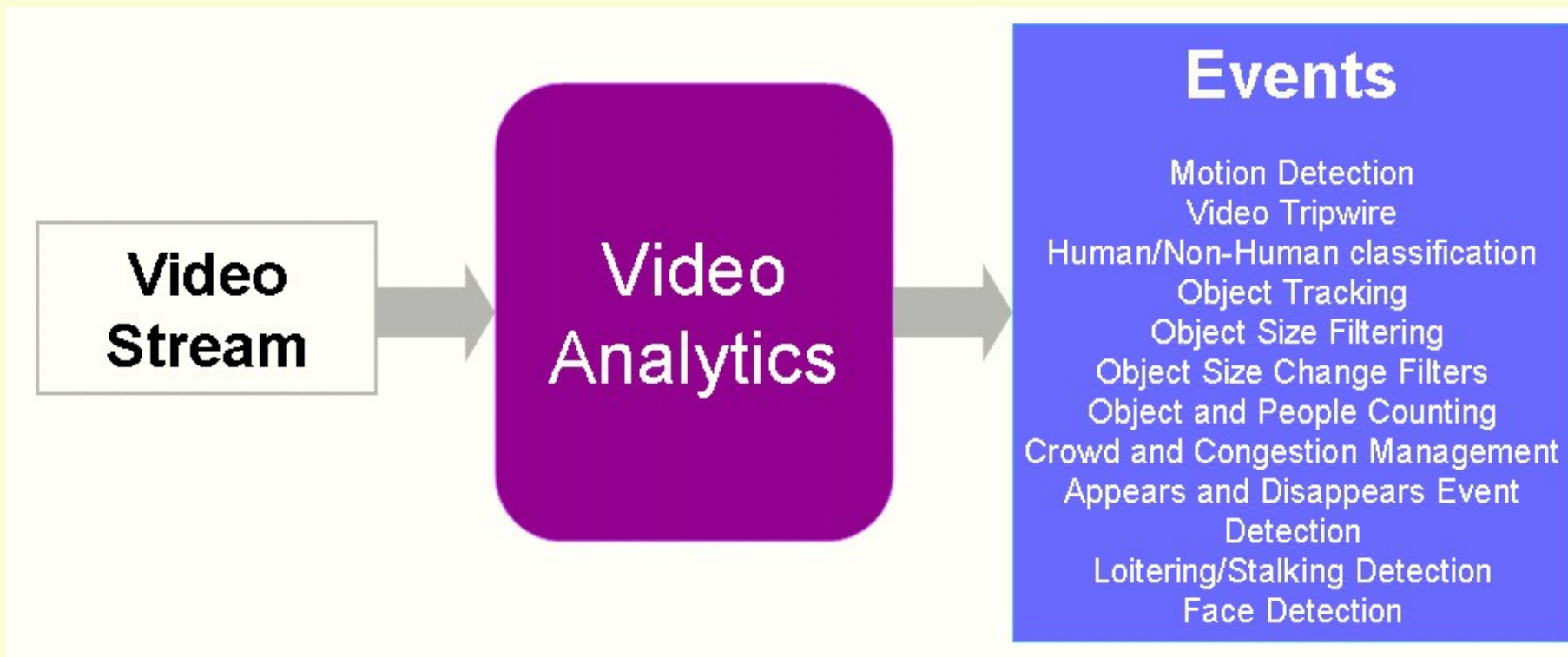
# John Weber, Avnet , Smart camera basics

## Compression



# John Weber, Smart camera basics

## Information processing





- 1. Super-resolution**
- 2. Depth recovery**

**N.B. Using one only controllable IP camera**

Let denote signal by  $f \in R_n$  . This signal can be decomposed in an arbitrary orthonormal basis

$$\Psi = [\psi_1 \psi_2 \dots \psi_n]$$

as follow:

$$f(t) = \sum_{i=1}^n x_i \psi_i(t)$$

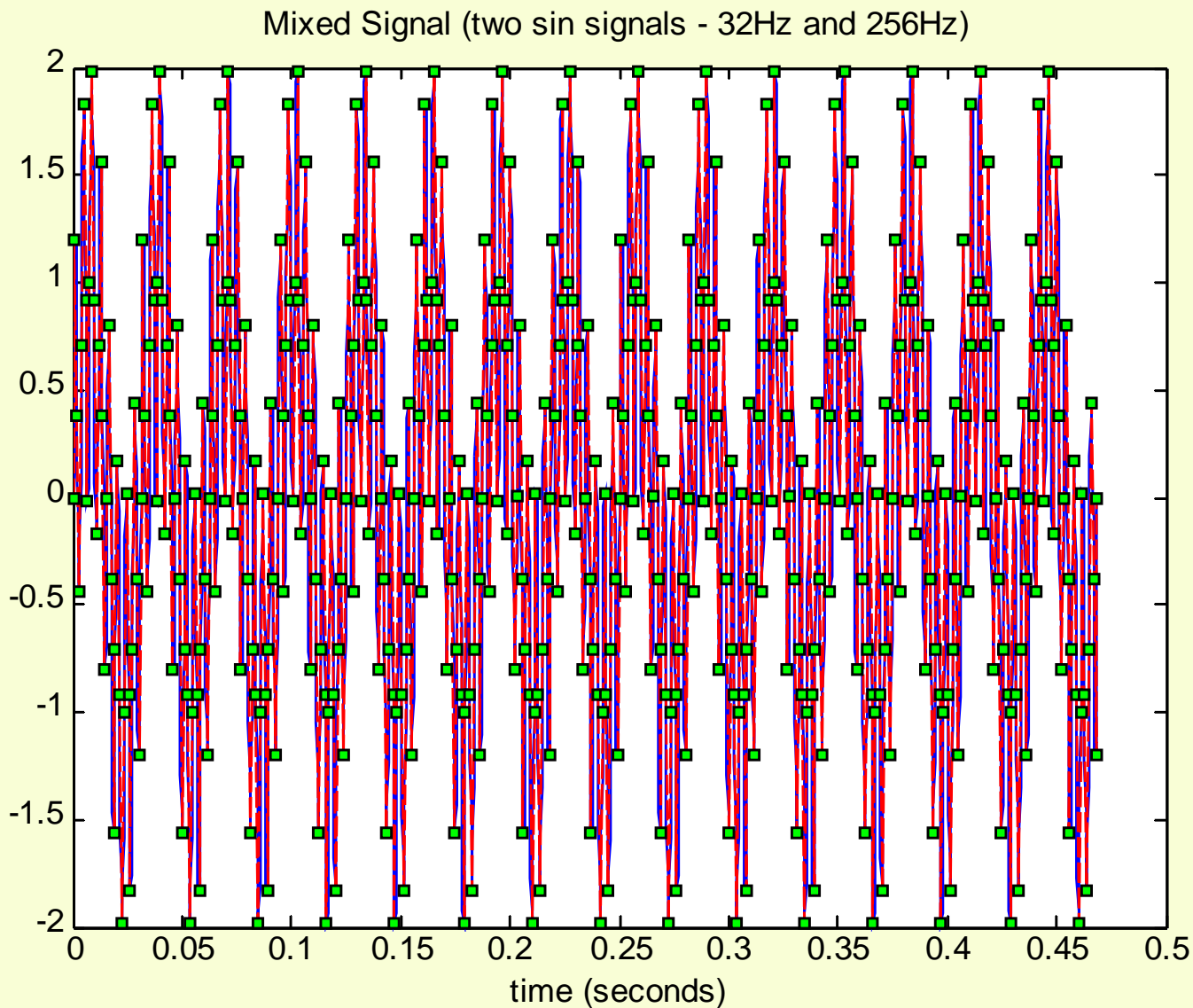
$$x_i = \langle f, \psi_i \rangle$$

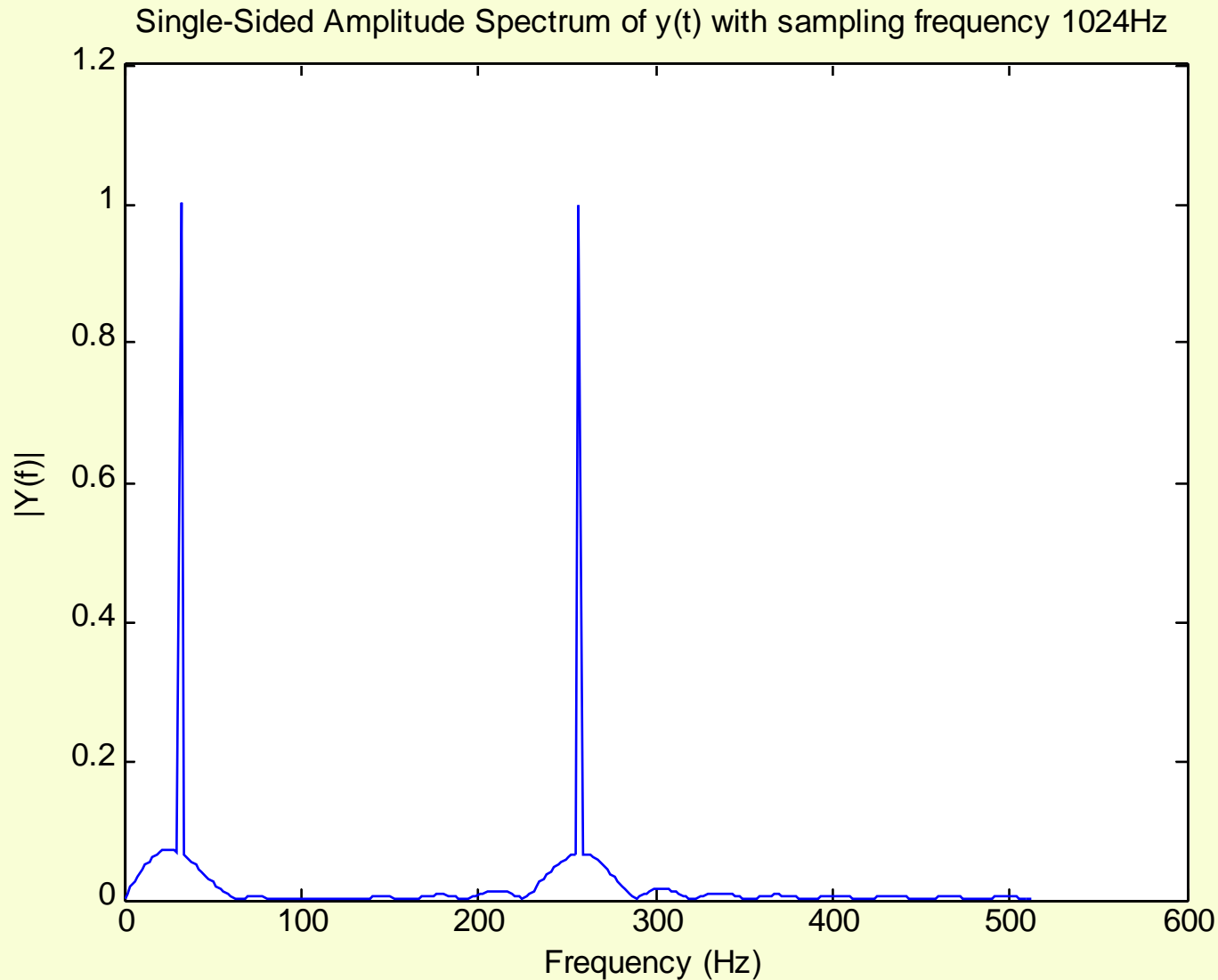
where  $x_i$  are the coefficients of the corresponding orthonormal functions.

„Sparse” signals are signals for which almost all coefficients are small or zero and relatively small quantity of coefficients may restore almost ideally the signal. Let the restored signal is presented as a sum of the  $S$  biggest coefficients in decomposition:

$$f_S(t) = \sum_{i \in S} x_i \psi_i(t)$$

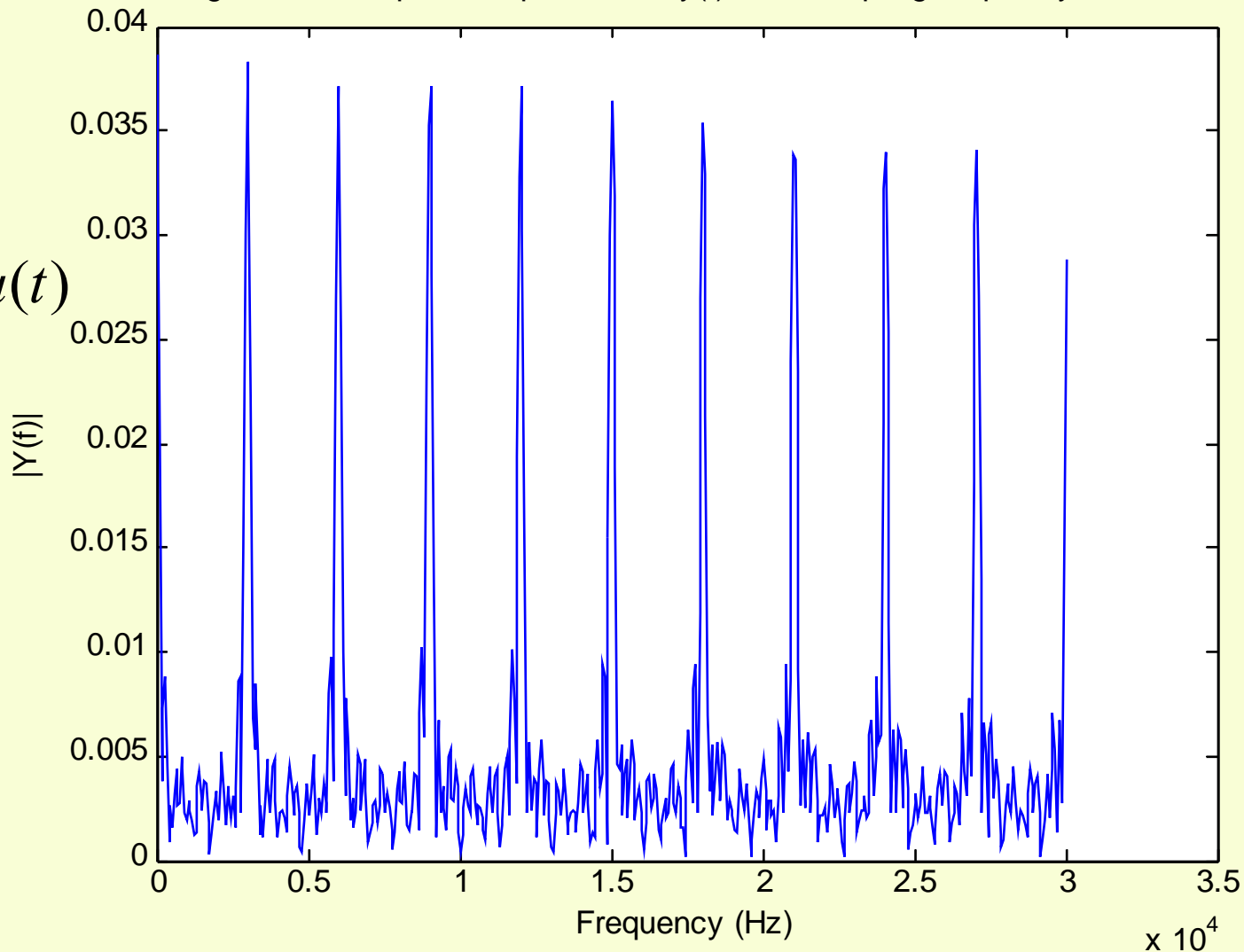
The signal  $f \in R_n$  will be called  $S$  sparse, if  $f_S$  approximate very good  $f$  and the approximation error  $\varepsilon = \|f - f_S\|_{l_2}$  is small enough. For audio- and video-signals it is well-known that only about 2.5% of the biggest coefficients may be used for signal recovery and the discrimination between the restored signal and the original one can not be easily found.

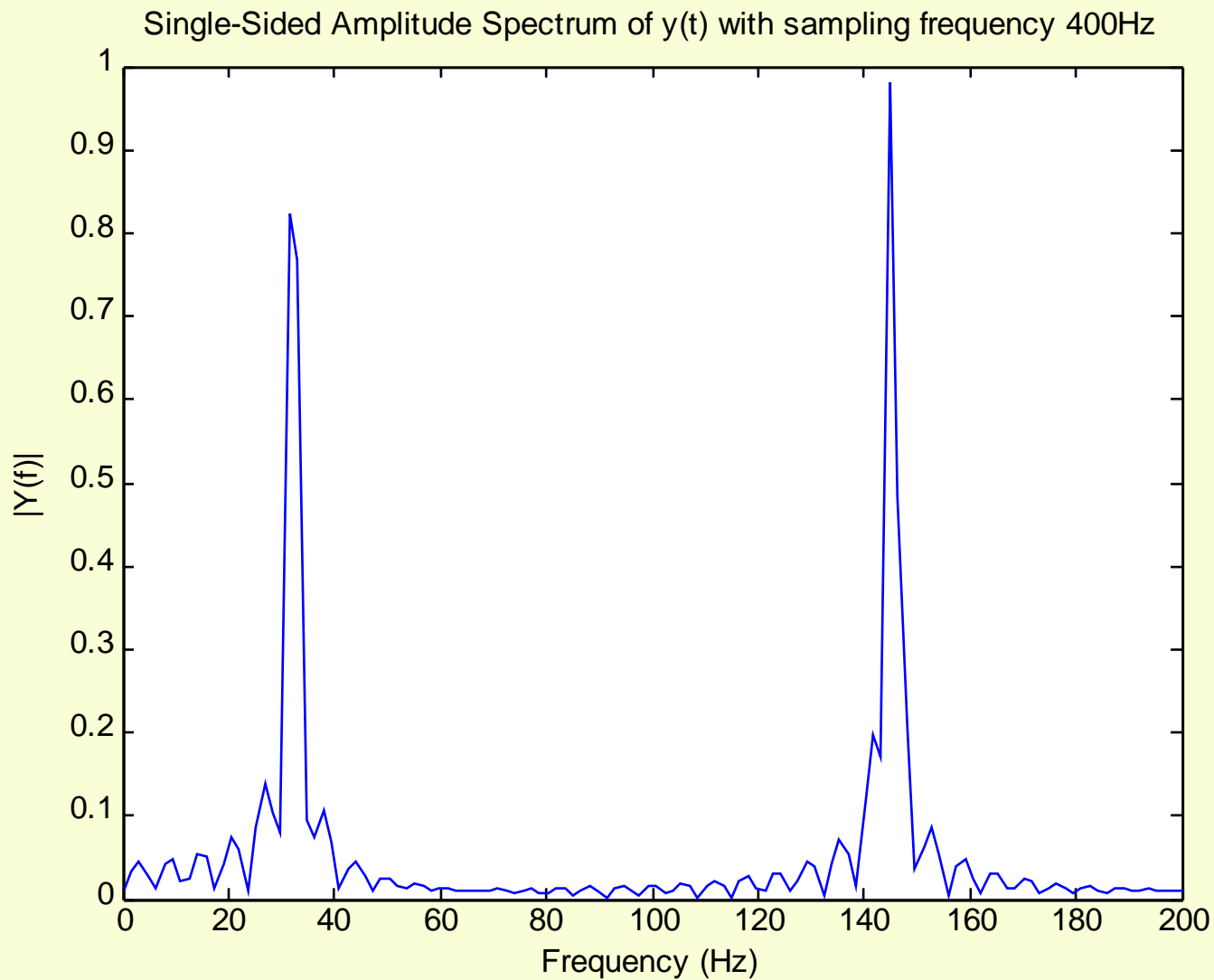


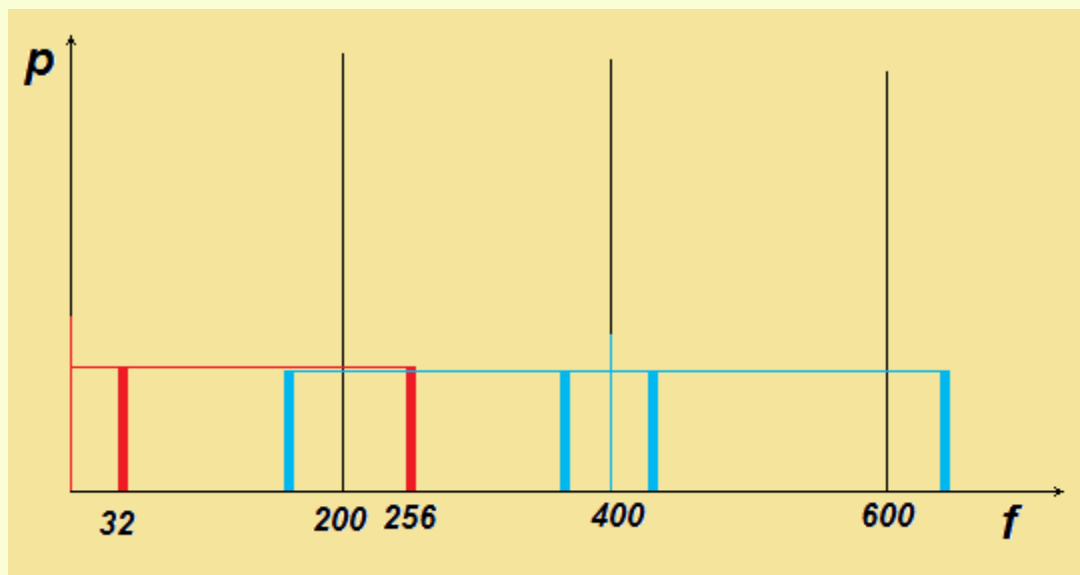


$$\sum_{i=-\infty}^{\infty} \delta(t - iT) = u(t)$$

Single-Sided Amplitude Spectrum of  $y(t)$  with sampling frequency 60012Hz









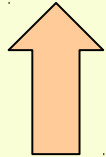
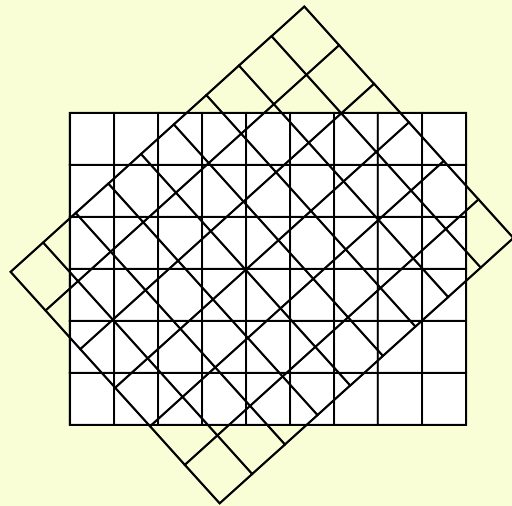
# How to use alias information?

**1. Generate „in plane” camera rotation on random angle**

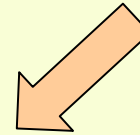
**(angle  $\neq k \frac{\pi}{2}$ ,  $k = 1, 2, \dots$  ). When such images are**

**registered, the sampling rate is changed.**

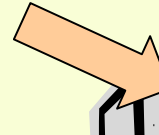
**2. Using camera “zoom”. The change of zoom rescale the scene in the same sampling rate, hence the sampling rate of one and same scene element is changed.**



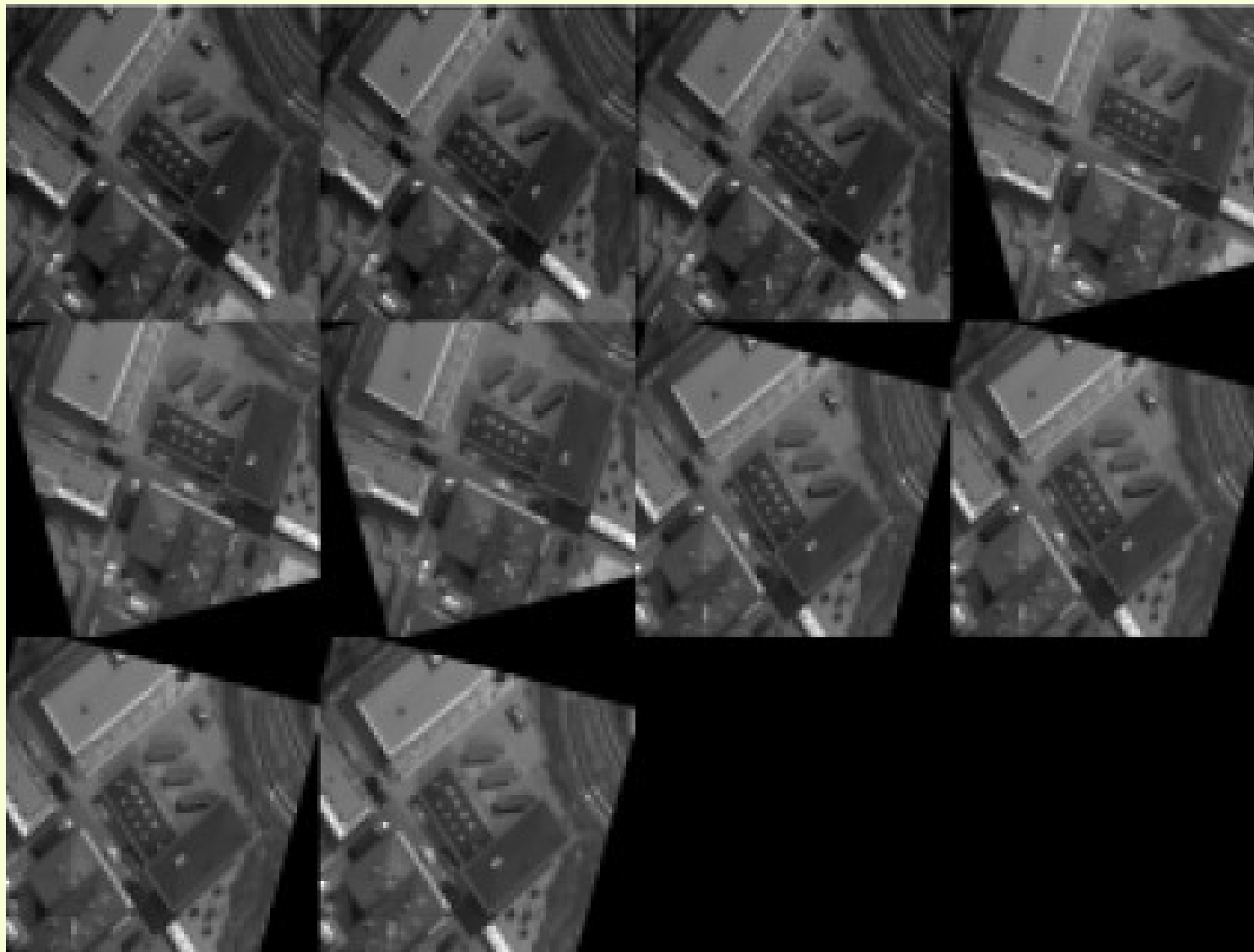
**In plane  
rotation**



**zoom**



# Low-resolution images



# Enhanced image





Figure 5: An 80x40 simulated LR resolution test target image

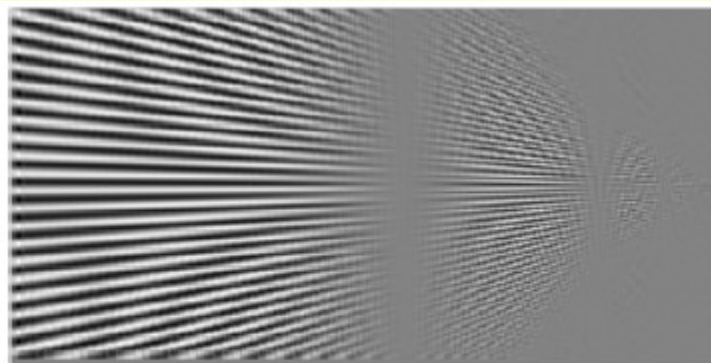


Figure 7: Restored 400x200 HR resolution test target image, no camera rotation

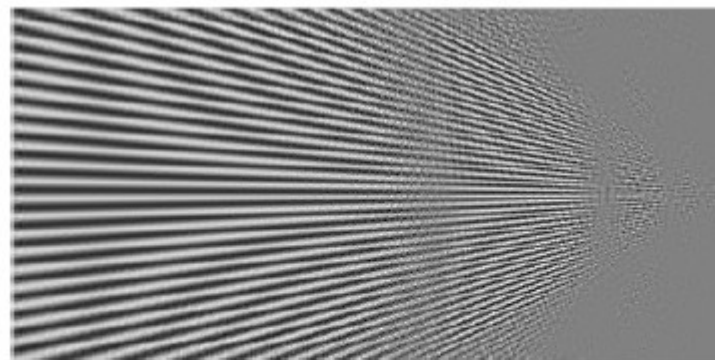
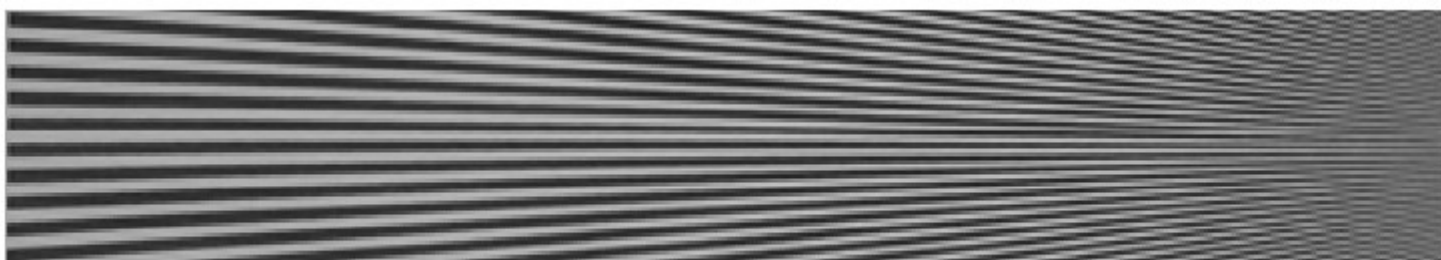


Figure 8: Restored 400x200 HR resolution test target image with camera rotation



**FIGURE 4.** Very high resolution photo of a resolution test target (detail)



**FIGURE 5.** Same detail of one of the 357 by 263 pixel low-resolution photos of the resolution test target



**FIGURE 6.** Same detail of the 892 by 657 super-resolved image, using 10 images taken using the same zoom



**FIGURE 7.** Same detail of the 892 by 657 super-resolved image, using 10 images taken under two different zooms

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### Technology News

## Compressed sensing ups data acquisition resolution, cuts cost

August 19, 2010 | R. Colin Johnson | 222903295



Compressed sensing has been a laboratory curiosity for several years, but now the technology has been cast in an inexpensive hardware prototype that could enable ultrasound, radar and other data-acquisition applications to increase resolution while reducing costs.

Compressed sensing can let lower-speed hardware acquire data just as accurately as existing systems or can be used to make systems more accurate at the same sampling speed. Defense contractors are working with Technion to increase the resolution of existing radar systems; medical contractors are seeking to downsize their hardware at the same resolution.

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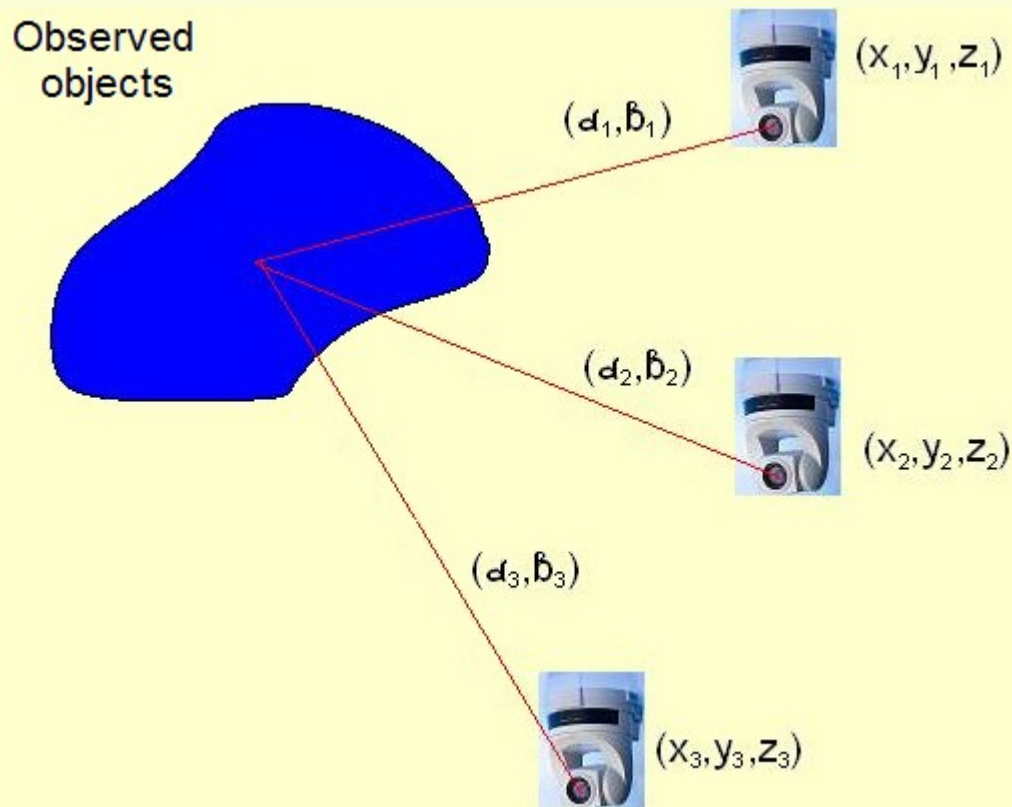


"We are creating aliasing—just what we teach EEs not to do," said Eldar. "We are folding the high-frequency signal into the lower-frequency domain, all aliased, but modulated by a known high-frequency signal. The key to the post-processing step is to recognize that all the information is still there, just aliased into a low-frequency domain, [and that] by using all four channels together, the original [signal] can be reconstructed."

# 3D scene reconstruction is important for:

- Object localization;
- Object tracking;
- Discovering space-time relations between participants in the scene;
- Object behavior estimation;
- Future events prediction.

# Miltisensor (stereo) approach stereopsis/depth perception



# Depth recovering by focusing

**Today, all cameras use different auto-focusing systems and algorithms. The auto-focus system, established in most PTZ IP cameras is based on one of the approaches of the passive focus.**

**Usually they use the fact that the accurately focused image has the highest contrast among all images in the same scene.**

# Depth from defocus

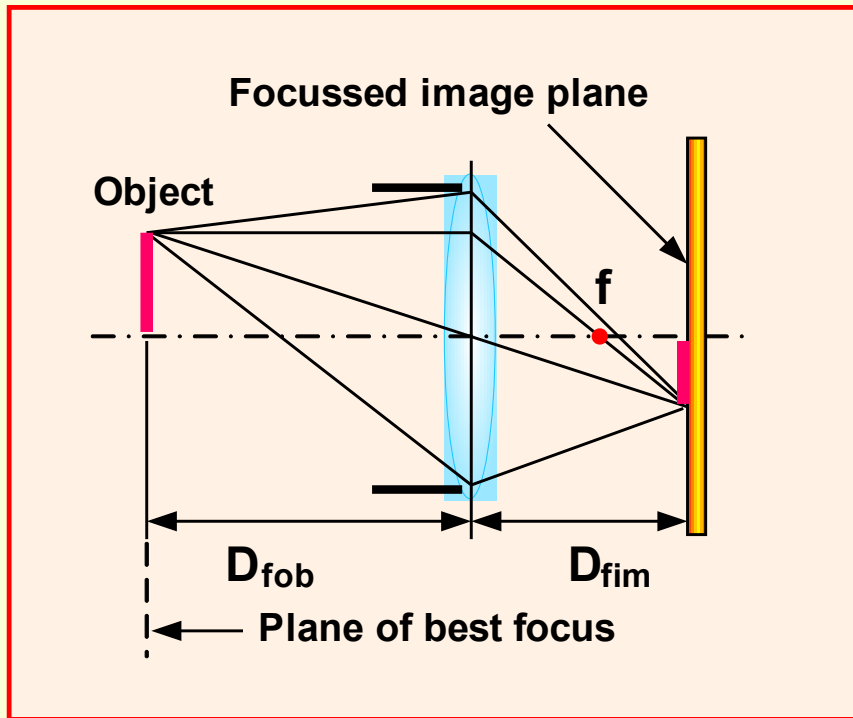
**The algorithm steps:**

- Several frames (2-8) are required from camera on one and same scene. In every frame a different camera focus is set;**
- Edge detection algorithm is applied (Canny);**
- The blur spot diameter is estimated for every line of interest in the processed frames;**
- The estimates for blur diameter for a particular line from all processed frames are input parameters for an optimization procedure for line fitting (Levenberg–Marquardt).**

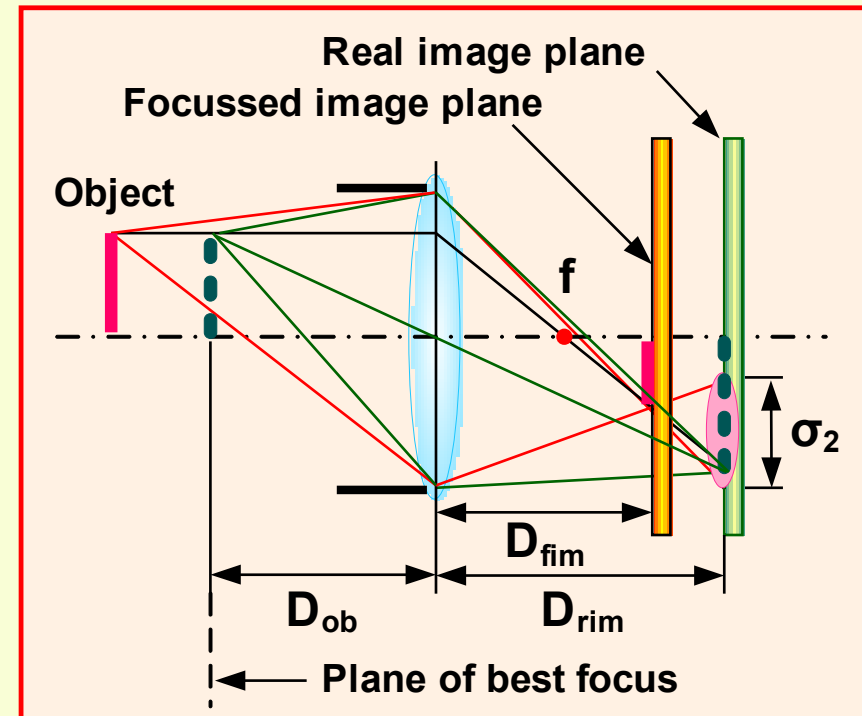
# Blur spot diameter estimation

Blur spot estimation is carried out onto detected edges. This reduces the number of analyzed image fields. The brightness profile on the processed edge is built and blur width is estimated. The integration of results for many points is applied to reduce the influence of Gaussian additive noise. Also, it is considered the gradient of intensity, not the intensity itself to diminish the role of intensity.

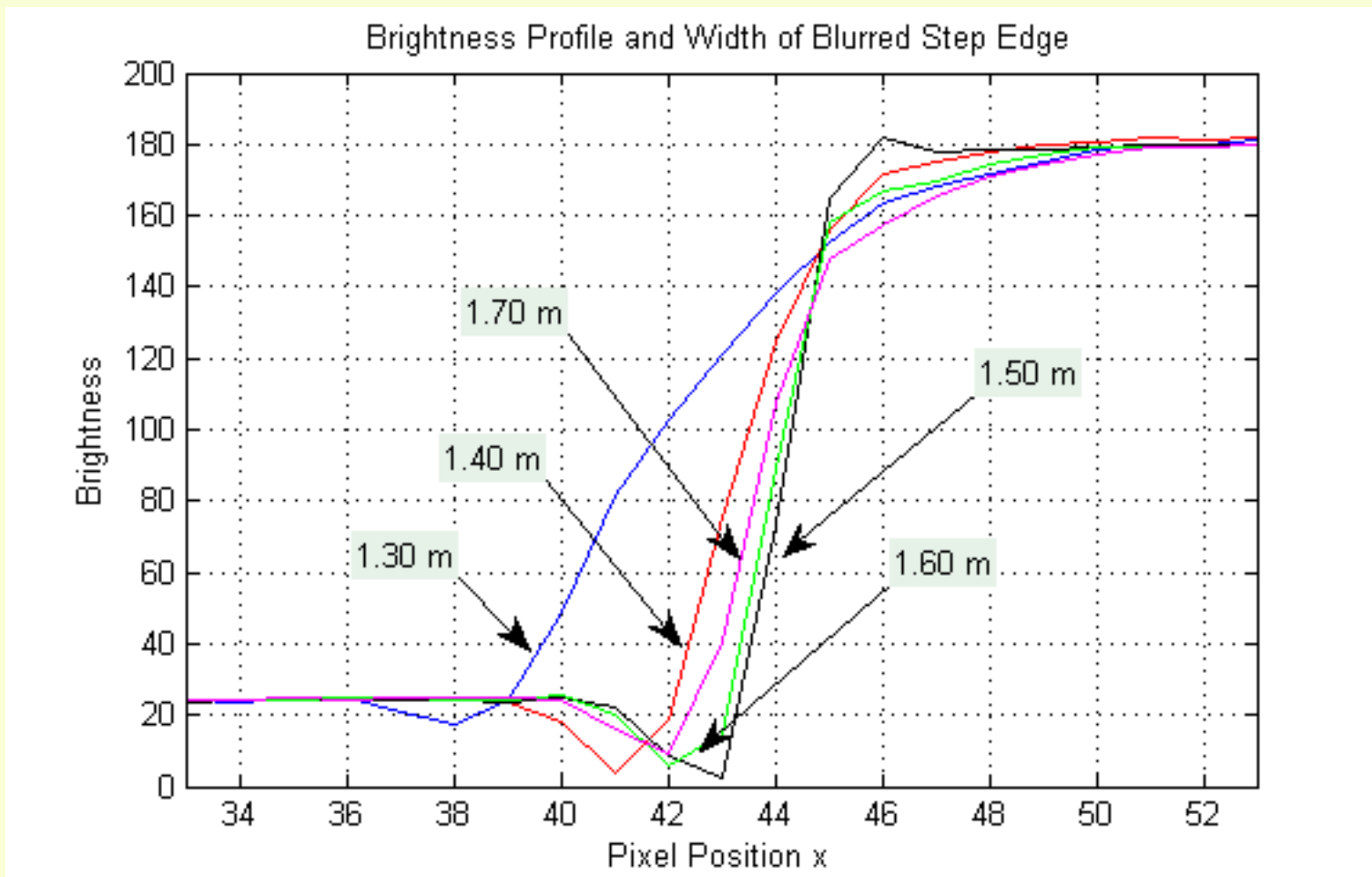
## Focused object



## Object out of focus



# Blur spot diameter estimation – cont.





# Mathematical model of defocus blur

The main equation describing dependencies in this model is based on the Gaussian lens law:

$$\frac{1}{f} = \frac{1}{D_{fob}} + \frac{1}{D_{fim}}$$

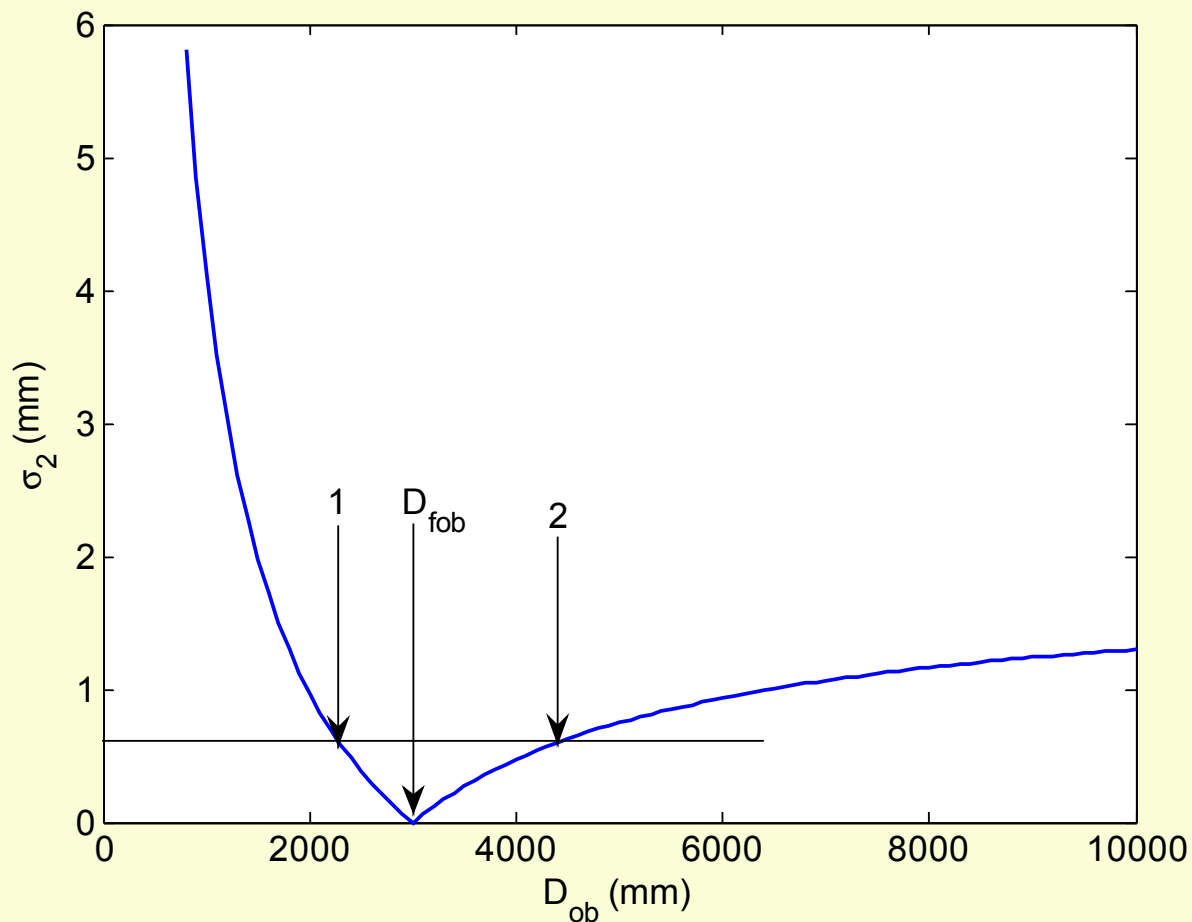
$$D_{fim} = \frac{fD_{fob}}{D_{fob} - f}$$

$$\sigma_2 = \frac{B_2}{D_{fim}} \text{abs}(D_{rim} - D_{fim})$$

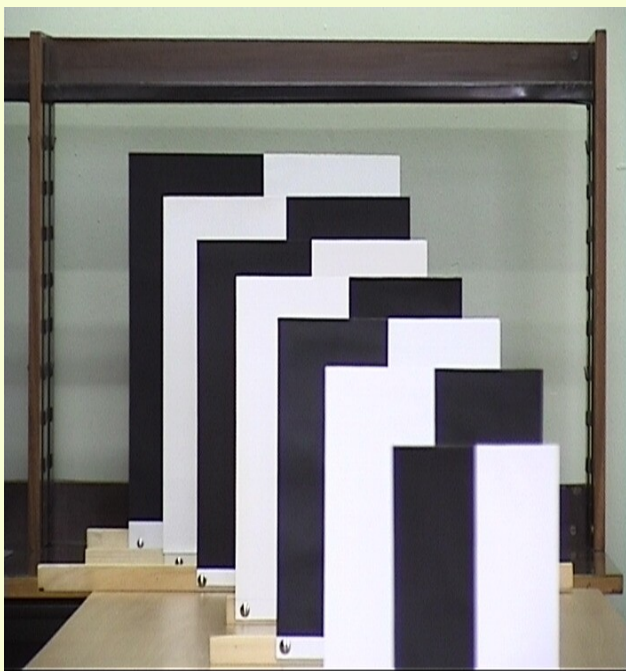
$$D_{rim} = \frac{fD_{ob}}{D_{ob} - f}$$

$$\sigma_2 = \frac{B_2}{D_{fim}} \text{abs} \left( \frac{fD_{fob}}{D_{fob} - f} - \frac{fD_{ob}}{D_{ob} - f} \right)$$

# Mathematical model of defocus blur



# Experimental results



**Scene 1 – templates**



**Scene 2 – real scene**



**Scene 3 – real scene**

# Experimental results

Test templates – scene 1 Zoom 9x			Real Scene 2 Zoom 6x		Real Scene 3 Zoom 6x	
	Inside Edges	Outside Edges				
Real distance [m]	Estimated distance [m]	Estimated distance [m]	Real distance [m]	Estimated distance [m]	Real distance [m]	Estimated distance [m]
3.0	3.16	2.67	1.37	1.30	3.78	1.64
3.5	3.20	3.27	1.77	1.68	3.22	1.20
4.0	3.65	3.72	2.43	1.49	2.81	2.50
4.5	3.91	4.02	2.04	1.99	2.47	1.75
5.0	4.54	4.68	2.04	1.62	1.69	1.65
5.5	4.83	5.04	1.91	1.92	1.65	1.49
6.0	5.27	4.91	2.06	1.86		

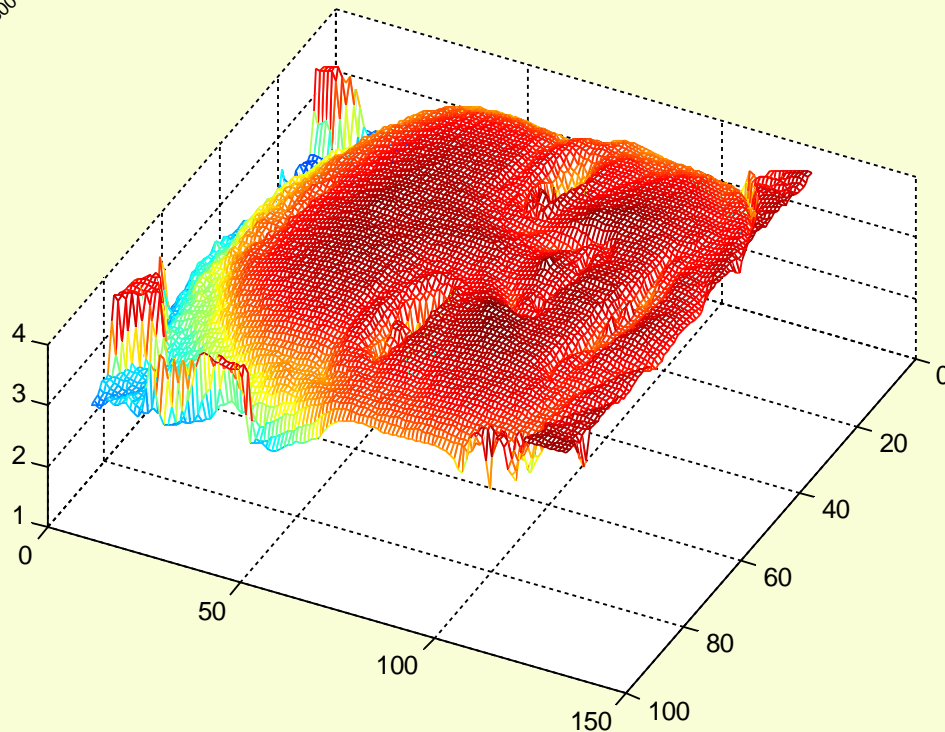
## Plane depth recovery

$$P \approx I = K \frac{1}{D_l^2} \frac{1}{D_c^2} \approx K \frac{1}{(\text{Depth})^4}$$

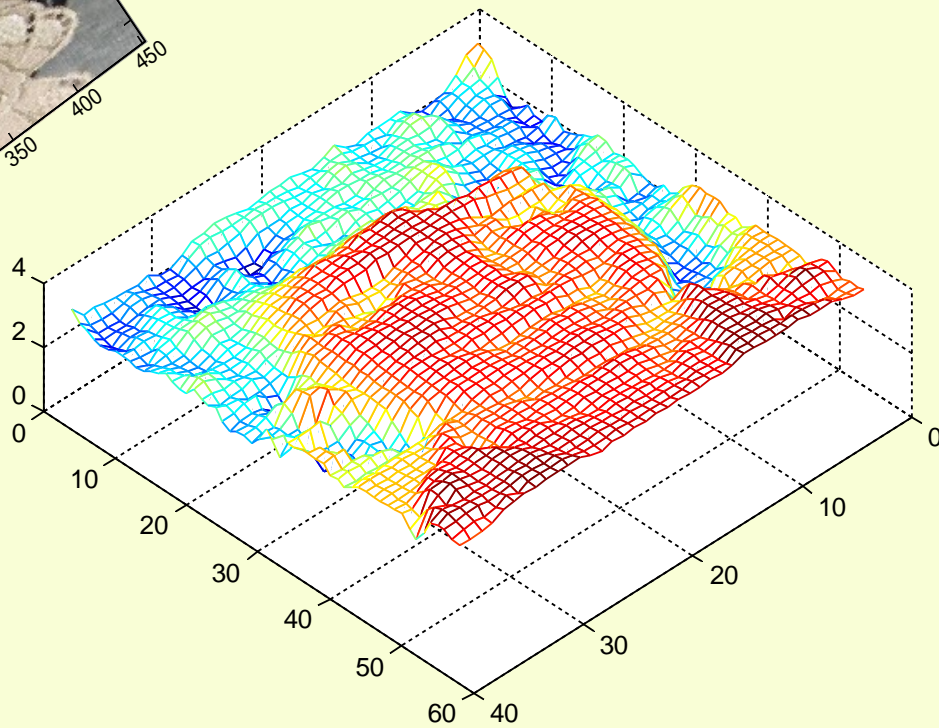
where

$D_l$  -Distance between object and light source

$D_c$  - Distance between object and camera







# Acknowledgments

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