SENSORS, SENSOR NETWORKS, SENSOR INFORMATION PROCESSING

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Mathematical Methods for Sensor Information Processing Department

MMSIP Department Staff:
9 persons: mathematicians, engineers, students

3 Associate Professors, PhD,

1 Post PhD

1 Assistant Professor,

2 Programmers,

1 PhD regular student

1 Technical Assistant.

Head: Assoc. Prof. Kiril Alexiev

Staff:


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Violeta Bogdanova


Margarita Dikova


Snejana Shtereva


Volodymyr Kudriashov


Georgi Shishkov


Nevena Popova

Staff:

Stoyan Markov

Donka Angelova ret.

Ludmil Bojilov ret.

Boriana Vassileva ret.

Pavlina Konstantinova ret.

Vera Behar ret.

Emil Semerdjiev

A little history

The Department is established about 30 years ago for R&D in Bulgarian industry and military electronics. Almost all Bulgarian serial manufactured radars for meteorological, air-defence and marine surface surveillance were developed with participation of the members from our team. We participated also in R&D of new military communication systems.

A little history – cont.

Since 1987 the team was moved in Bulgarian Academy of Sciences in a newly established department named "Mathematical methods for sensor information processing". The main idea was by employing complex mathematical approaches on high performance computers to solve basic problems of sensor systems like:

- Multiple target tracking;
- Multiple sensor data fusion;
- Change detection, behaviour estimation;
- Data association problems;
- Estimation of non-linear and non-Gaussian dynamic systems, etc.

A little history – cont.

By all these 20 and more years, we have also made a concerted effort to transition our defense-developed technologies to the civilian applications (health, robotics, automation), to make a transition from isolated closed form of research to international collaboration.

Main research achievements

- Annually we publish about 20 peer-reviewed papers, many of them in journals with IF;
- We have several successfully graduated PhD students, and several PhD students, which were going to finish their theses … somewhere in Europe and Canada. This year we have two PhD students, which are preparing their PhD defence and one regular PhD student (first year);
- This year we have 1 Postdoc from Kharkov, Ukraine and we are waiting one more to arrive till the end of the year;
- Two of us are participating actively in educational process at the universities having regular courses;
- This year 15 students conducted their practice in the department;

Main research achievements – cont.

- We have regular thematic interdisciplinary seminar;
- In the last 5 years we have organized regularly annual symposiums in the framework of bigger international conferences and one IEEE conference on intelligent applications;
- All scientists are members of different Bulgarian and international scientific professional organisation like IEEE, ISIF, UAI, UMB, etc.,
- We organized one NATO ASI and participated in several others NATO ASI on the hot topics of research;
- We participated in two COST actions;
- We have well-established scientific collaboration with colleagues from ONERA – France, from the University of Bradford, Lancaster University in England, University of Sheffield, "Lucian Blaga"- University of Sibiu, and etc.

Currently running projects

- Mathematical methods for sensor information processing – budget;
- AComIn: Advanced Computing for Innovation, FP7 Capacity Programme, Research Potential of Convergence Regions, 2012-2015 ;
- Preprocessing Algorithms of Remote Sensing Spectral Data and Images, contract No DFNI – I01/8 with Bulgarian Science Fund, 2012-2015;
- Industrial scientific research for image's quality and stabilization enhancement based on inertial sensors", contract BG161PO003-1.1.06-0037-C0001 with Bulgarian Innovation Fund, 2013-2015;
- ETN-FETCH: Future Education and Training in Computing: how to support learning at any time anywhere, Erasmus Thematic Network No. 539461-LLP-1-2013-1-BG-ERASMUS-ENW (2013-2016).

Our experience includes:

- 3D scene reconstruction;
- Innovative approaches for fusion of uncertain, imprecise, highly conflicting sensor data at various levels of abstraction based on Dezert-Smarandache theory for plausible and paradoxical reasoning;
- Algorithms for adaptive non-linear filtration, segmentation and interpretation of gray-scale images;
- Algorithms for space-time adaptive processing;
- Monte Carlo methods for system identification;
- Neural networks;
- Intelligent control and optimization.

Sensors

In God we trust. All others must supply data!

PTZ IP Camera
Infrared Camera
Hyperspectral Camera
Superfast Camera
Eye Tracker
Acoustic Camera
Radar
Inertial sensors
Laser Sensor
3D Scanner

Radar

RAdio Detection And Ranging

Once, upon a time…

It pays to heed history, because it repeats itself.

The date – 29.12.1887! Heinrich Hertz showed that radio waves were reflected by metallic objects.

In those 10 days Hertz did many successful experiments on interference, phase in wire, velocity of propagation and on the shadowing effects of metal sheet.

Some history

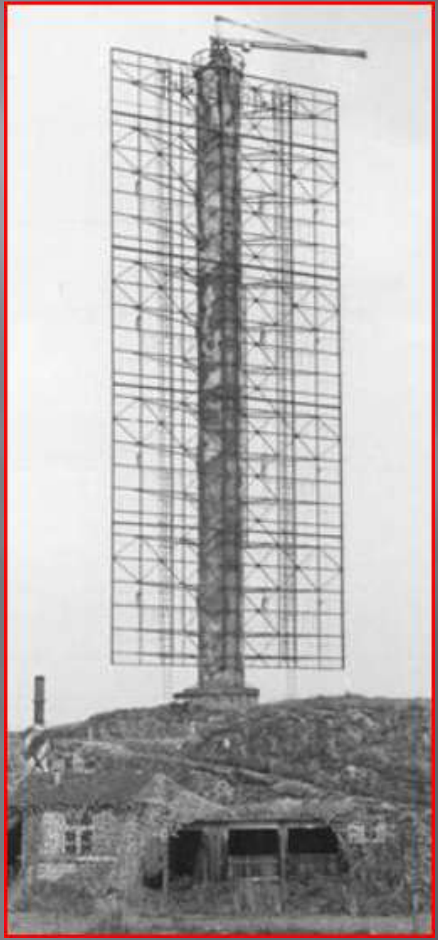
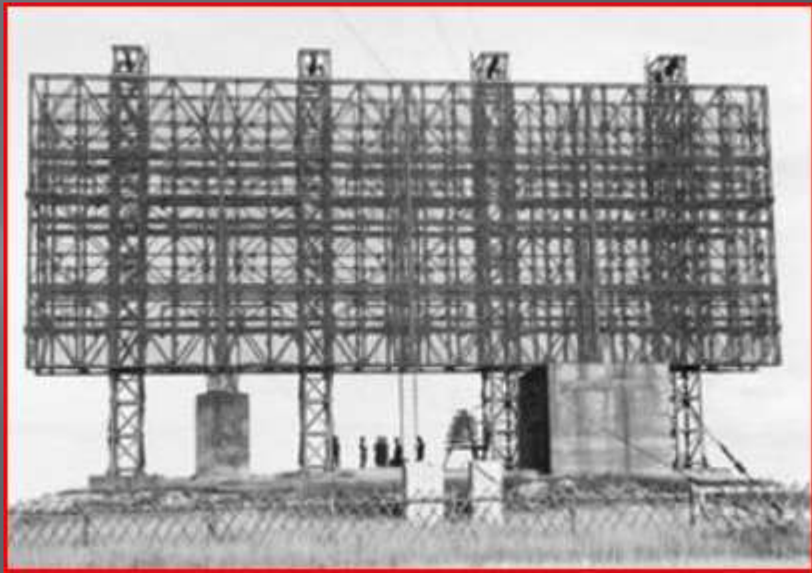
Christian Hulsmeyer was the first who used radio waves to detect the presence of distant metallic objects, in April 1904. He received Patent for his pre-radar device (called telemobiloscope). He demonstrated the feasibility of detecting the presence of a ship in dense fog from the Hohenzollern bridge in Cologne, and later patent a related amendment for ranging.

Some history

A little before and during the Second World War, developments by the British, German, French, Soviets, American, Italy and Japan researchers led to the modern version of radar.

Robert Watson-Watt demonstrated the capabilities of a working prototype to the British Air Ministry in January 1935. It served as the basis for the Chain Home air defence radar, the first bistatic radar (separated transmit and receive antennas, located on a few hundred meters).

Some history

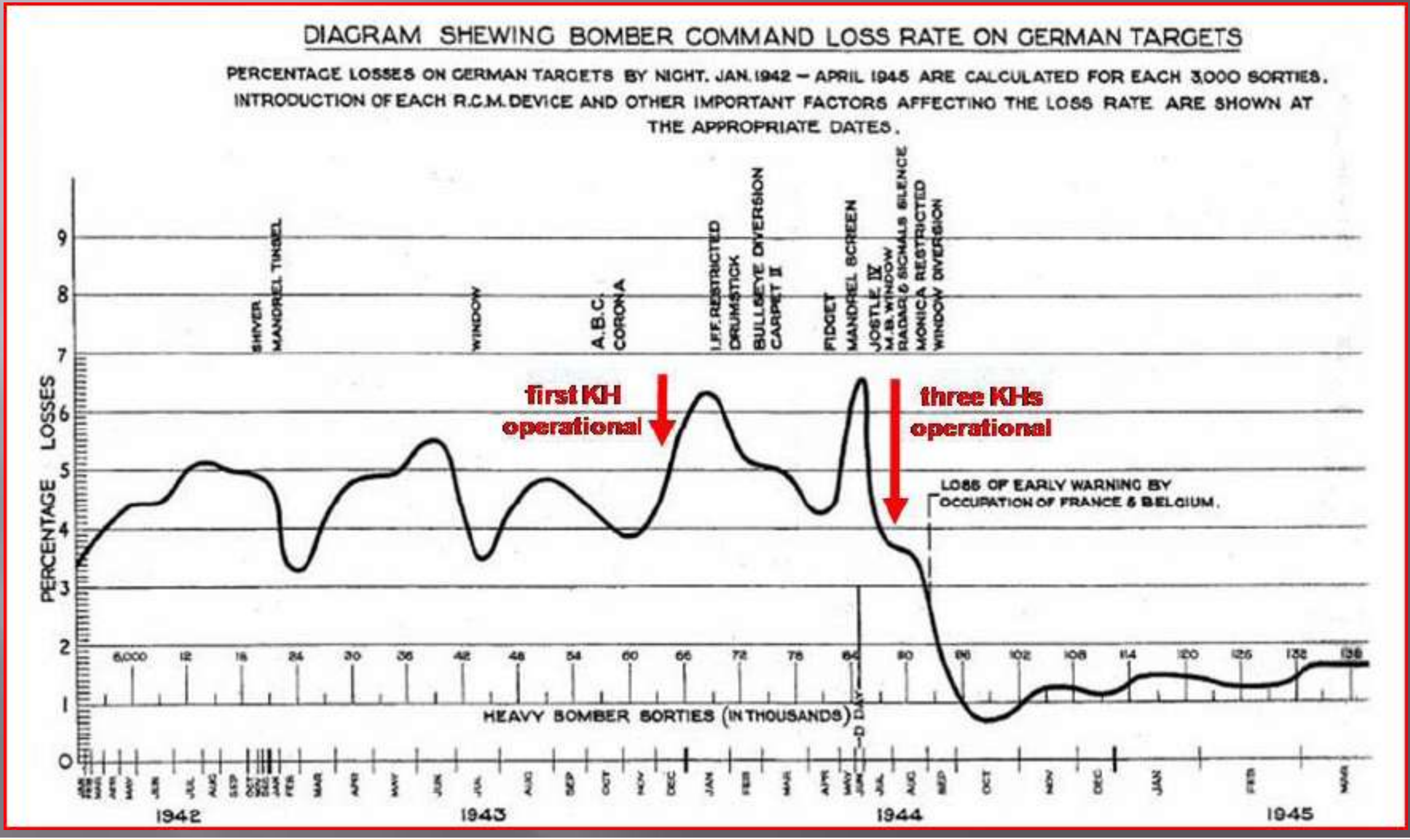




Freya Wassermann Mammut

Some history

The British scientists learned about the German air defense system mostly by interception of the radar signals and they developed one of the first jammers - MANDREL, a low-power (~2W) noise barrage jammer employed against FREYA and its derivatives. Introducing MANDREL, Bomber Command losses fell significantly.

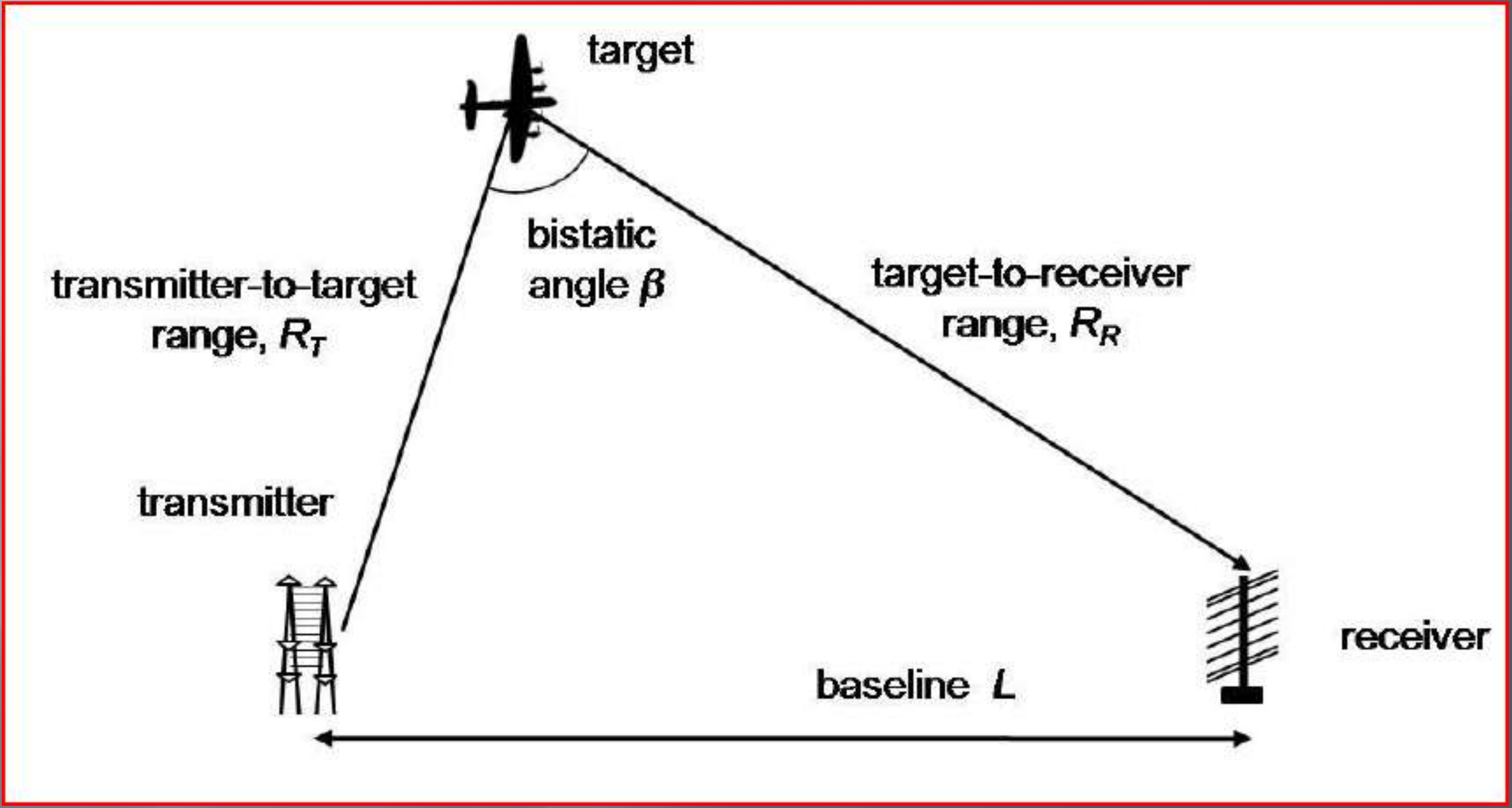
Some facts from WW2



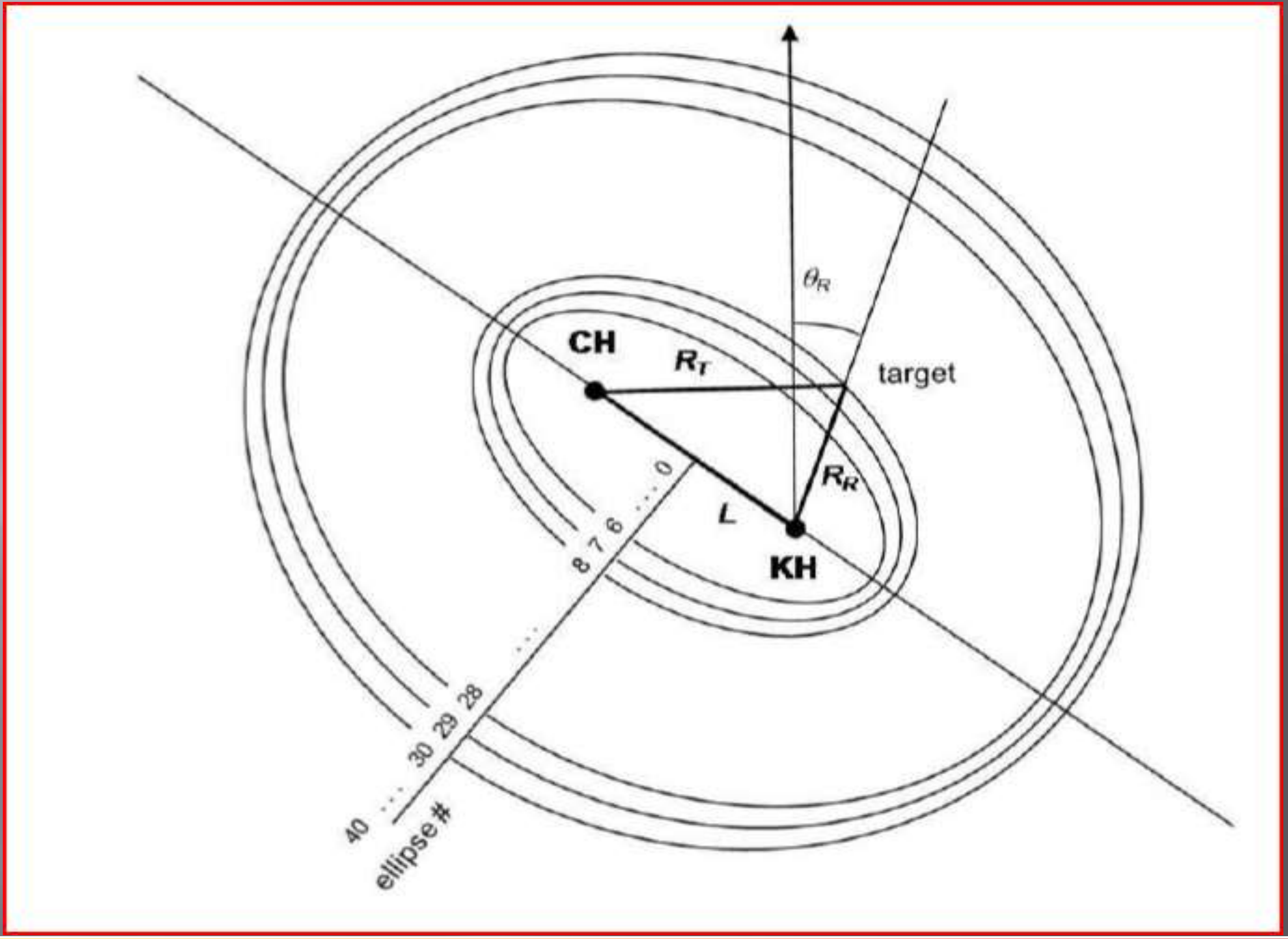
Some history

In response the Germans widened the band first to 120 – 140 MHz then to 120 – 160 MHz, and ultimately even wider. Thus the frequency coverage of MANDREL had to be increased accordingly. The Germans developed devices for Identification Friend or Foe (IFF), as well as devices to distinguish aircraft from static clutter on the basis of Doppler and on the basis of the modulation of echoes by aircraft propellers.

Klein-Heidelberg multisite radar



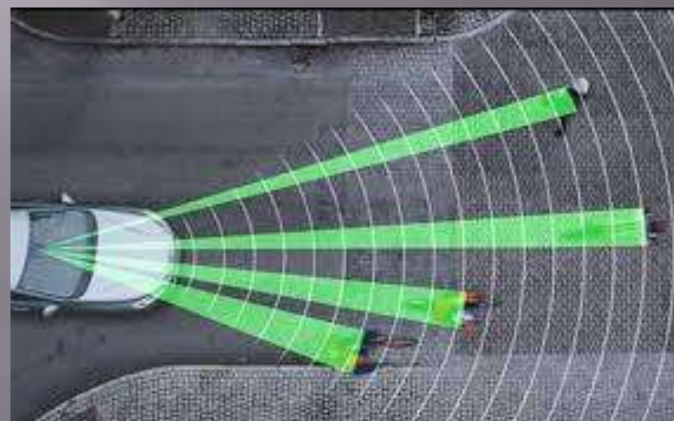
K-H target detection



Now

ARTHUR can detect guns at 31 km, mortars at 55 km and rockets at 50 - 60 km and locate targets at a rate of 100 per minute with CEP 0.2% of range for guns and rockets and 0.1% for mortars.

Continuous waves car radars



New tendencies

The radar system detects and tracks objects around the car, warning the driver of a potential collision or initiating electronic stability control intervention.

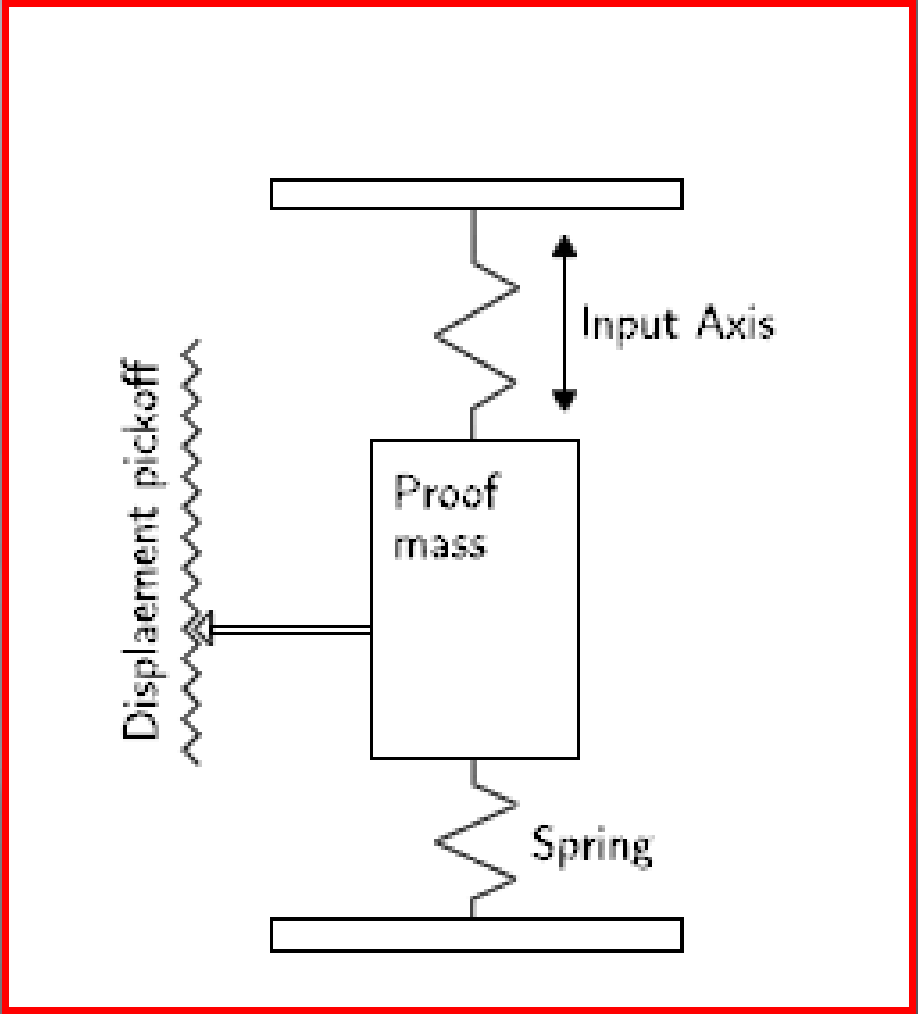
Inertial Measurement Unit

Little History

- Lighthouse/Pharos of Alexandria built between 280 and 247 BC
- Compass - invented as a device about 206 BC
- Spinning top effect – invented ???, theoretically Euler, 1765, Теория движения твердых тел)
- Gyroscope – invented in 1852 by French scientist and physicist Leon Foucault
- 1909 first gyro-compass (Germany)
- V2 – first inertial navigational system (1942 two gyros and one accelerometer)
- 1958 entire standalone INS mounted on submarine – position error 10 miles for 97 hours (1830 miles distance)

Now…

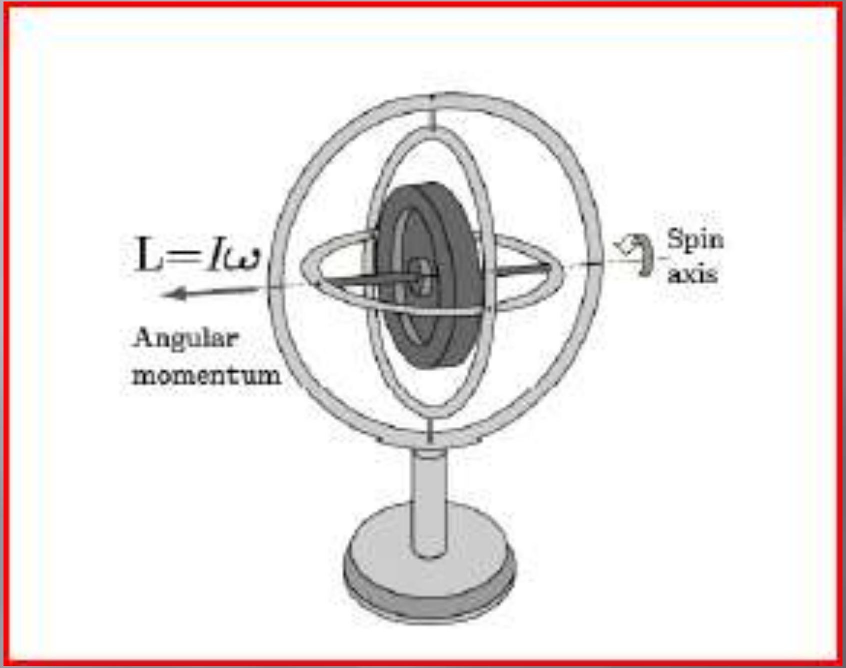
Principle of operation of IMU sensor



Accelerometers

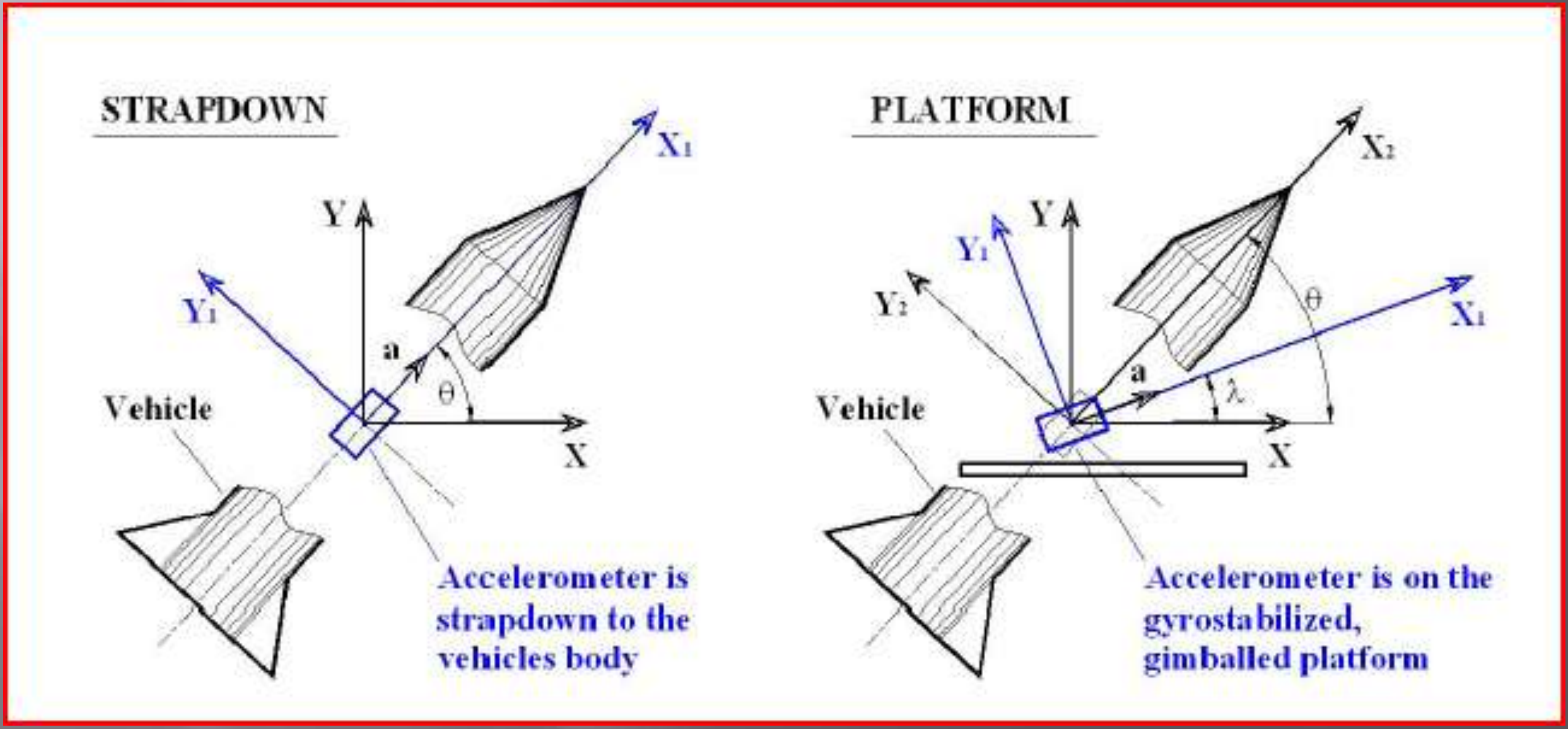
The accelerometers detect the combined magnitude and direction of linear and gravitational accelerations

Gyros



The gyroscopes measure the angular rate of rotation about one or more axes. They are not dependent on gravity.

Types of IMU


STRAPDOWN
X1
Y
Y1
a
θ
Vehicle
X
Accelerometer is strapdown to the vehicles body
PLATFORM
X2
Y
Y1
Y2
θ
X1
a
λ
Vehicle
X
Accelerometer is on the gyrostabilized, gimballed platform

Strapdown ←→Gimbailed

The inertial sensors of a strapdown system fully follow the vehicle's angular motion. Hence, the measurement of specific force must be transformed from the body frame into that reference coordinate frame in which the integrations of acceleration are to take place.

In gimbailed navigation systems, the inertial sensors are mounted on gimbals whose orientations are nominally stationary relative to either the intermediate or the reference coordinate frame.

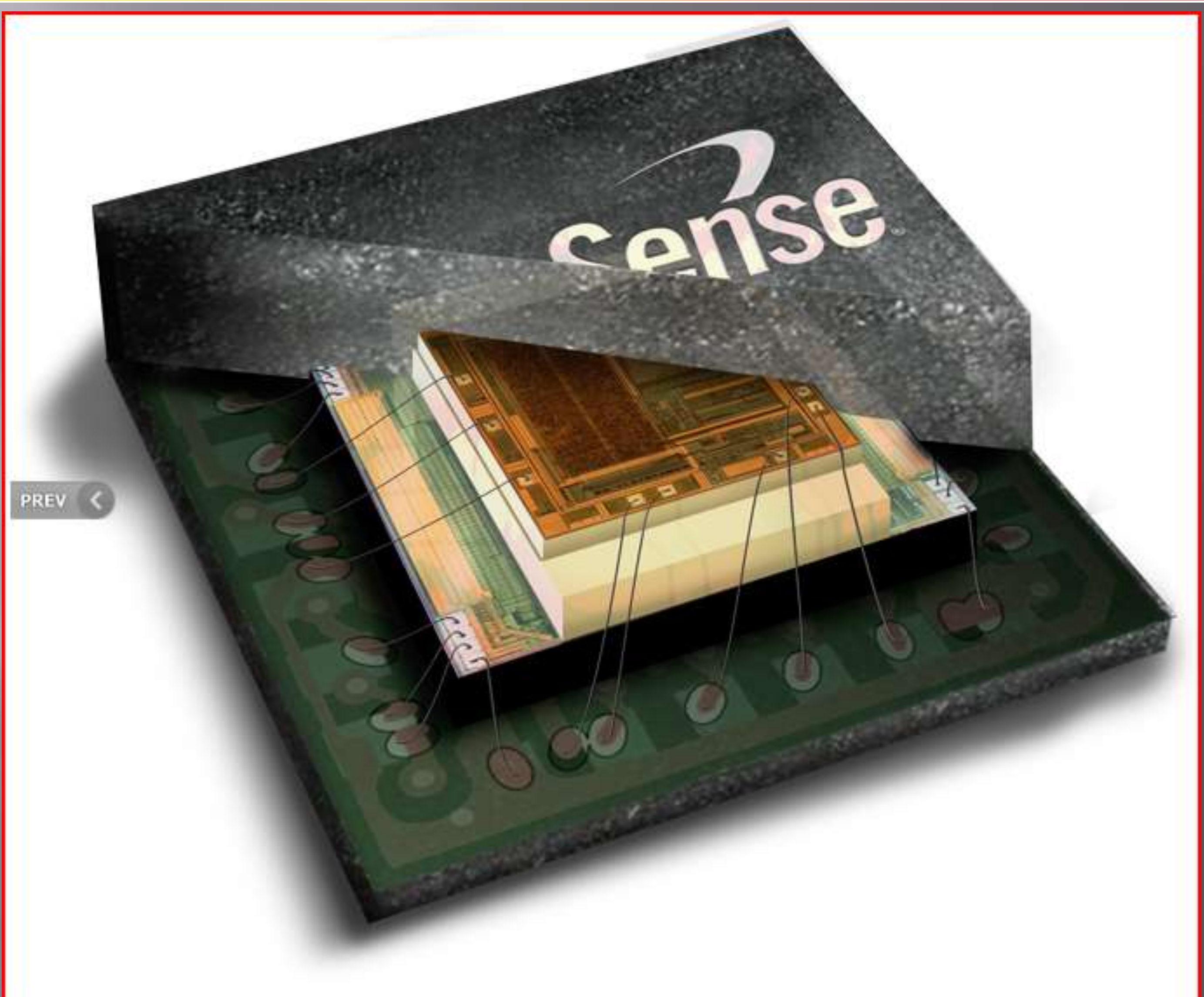
Why MEMS?

- These sensors are inexpensive: most MEMS sensors in mass production quantities cost a few dollars.
- These sensors are truly miniature - usually less than (10x10x5 mm) in size, and they consume little power (< *50 mA).*

Why not MEMS?

The biases of MEMS gyros can be brought down to a level of less than 300 degrees per hour after appropriate temperature compensation. Such a large drift, even assuming an accurate initialization of attitude, will lead to very large position errors after almost 10 seconds of INS-only navigation.


sense
MPU-6050
CLOSE



MPU-9150 Motion Tracking device

Figure 1. Top side of the MPU-60X0 9-Axis EV Board

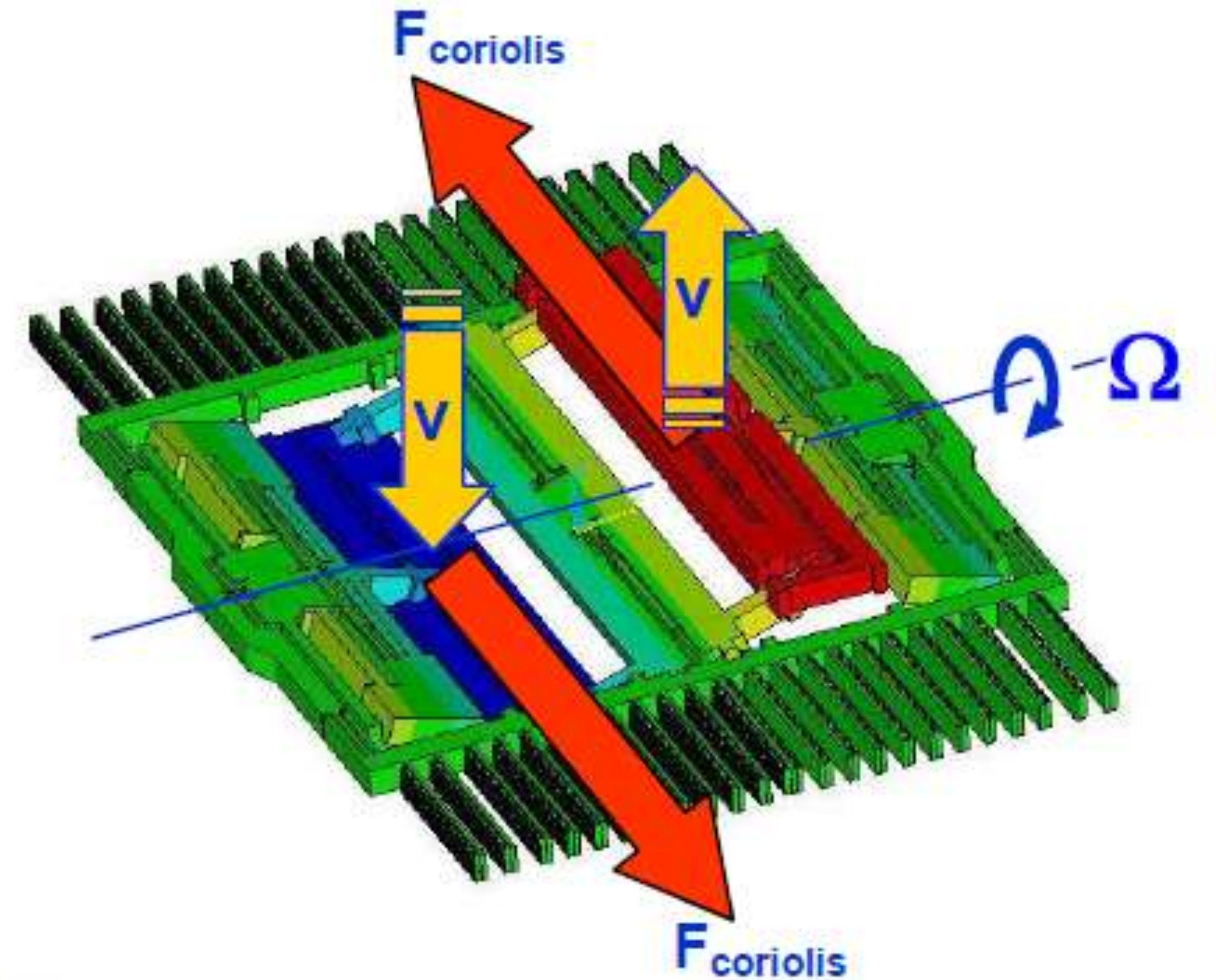


Figure 3: X-axis gyroscope driven mode

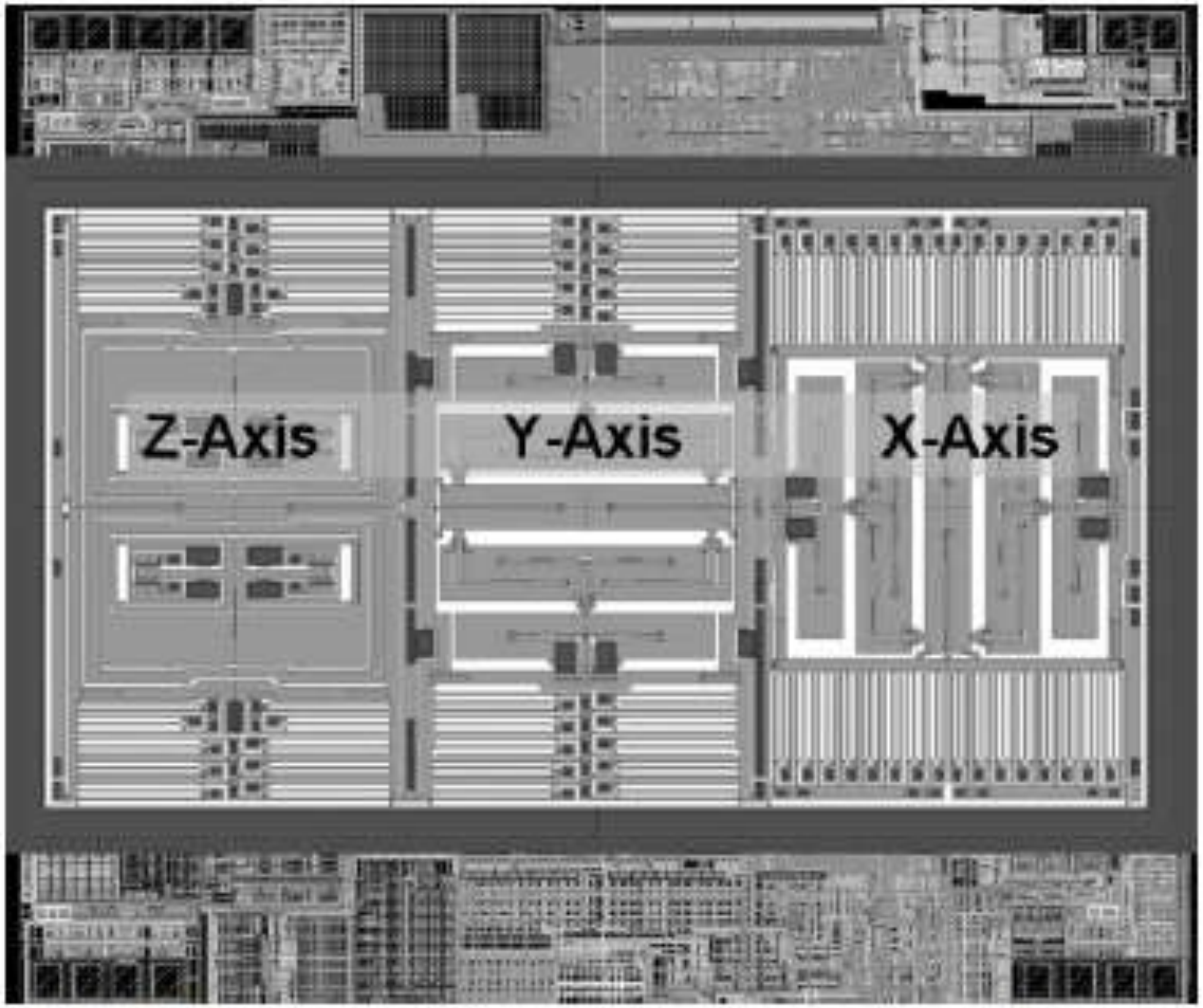
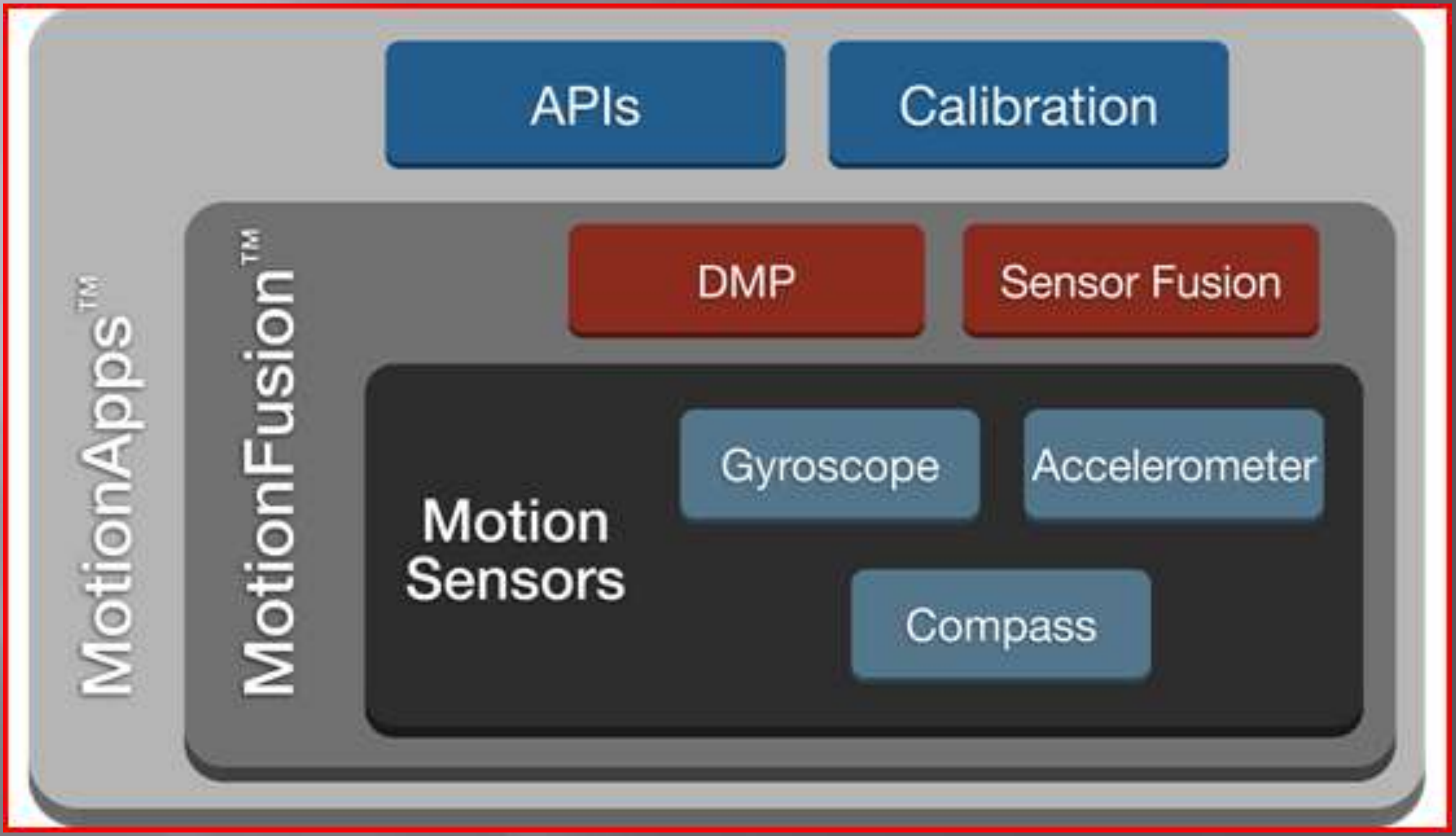


Figure 7: MPU-3000, 3-Axis gyroscope in 2.8mm x 2.4mm

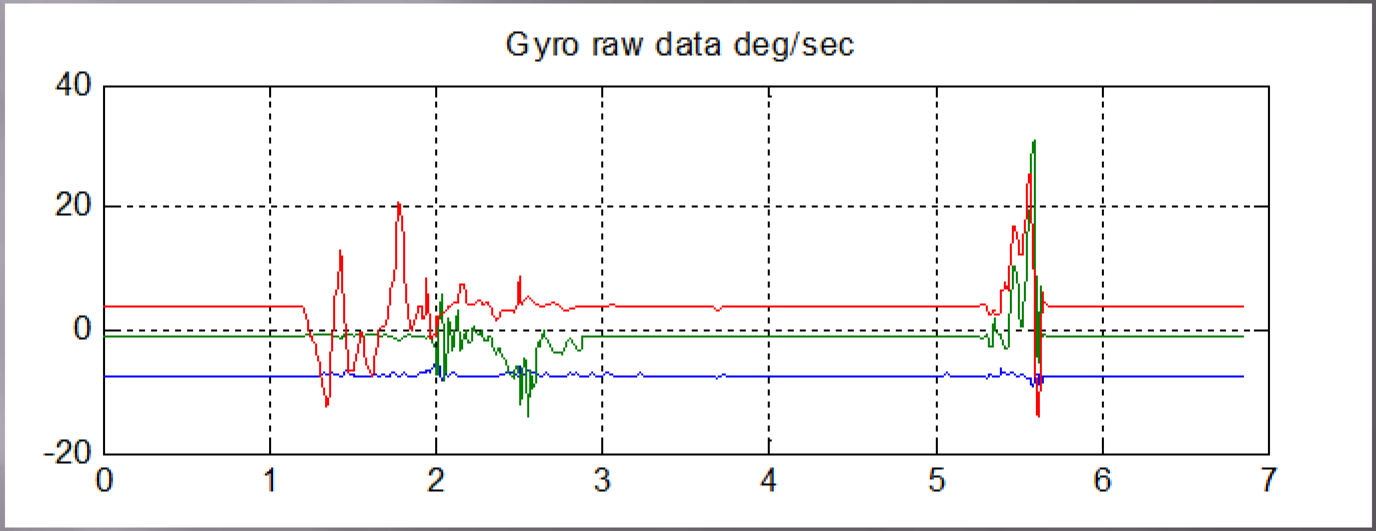

APIs
Calibration
MotionApps™
MotionFusion™
DMP
Sensor Fusion
Motion Sensors
Gyroscope
Accelerometer
Compass

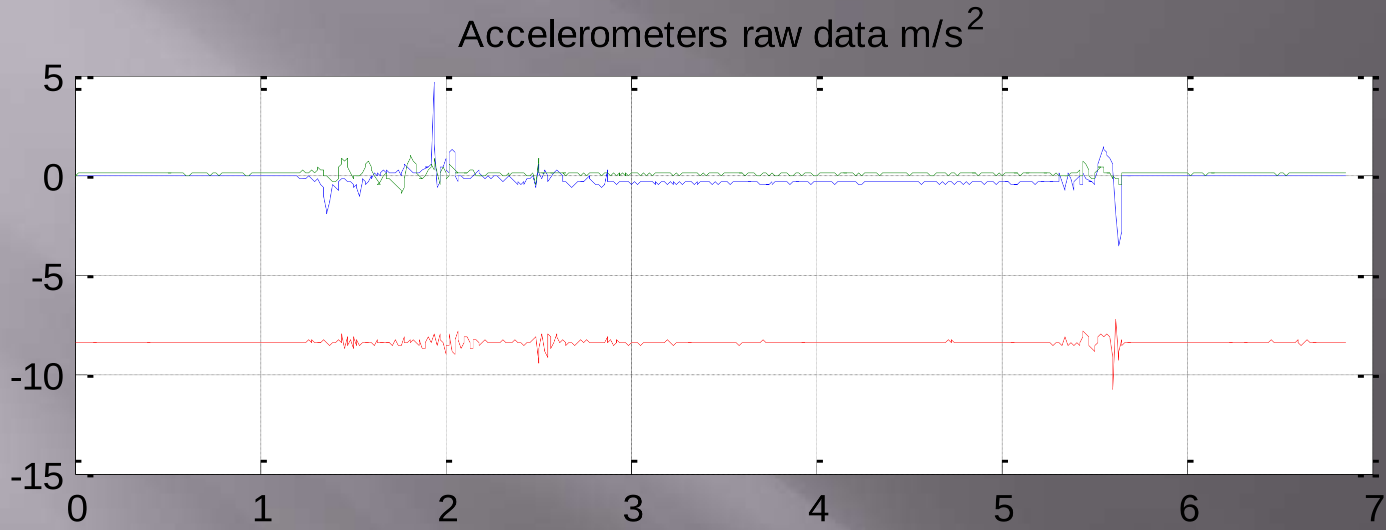
Part #	Gyro Full Scale Range	Gyro Sensitivity	Gyro Rate Noise	Accel Full Scale Range	Accel Sensitivity	Digital Output	Logic Supply Voltage	Operating Voltage Supply	Package Size
UNITS:	(°/sec)	(LSB/°/sec)	(dps/√Hz)	(g)	(LSB/g)		(V)	(V +/-5%)	(mm)
 MPU-6000	±250 ±500 ±1000 ±2000	131 65.5 32.8 16.4	0.005	±2 ±4 ±8 ±16	16384 8192 4096 2048	I²C or SPI	VDD	2.375V–3.46V	4x4x0.9
 MPU-6050	±250 ±500 ±1000 ±2000	131 65.5 32.8 16.4	0.005	±2 ±4 ±8 ±16	16384 8192 4096 2048	I²C	1.8V±5% or VDD	2.375V–3.46V	4x4x0.9

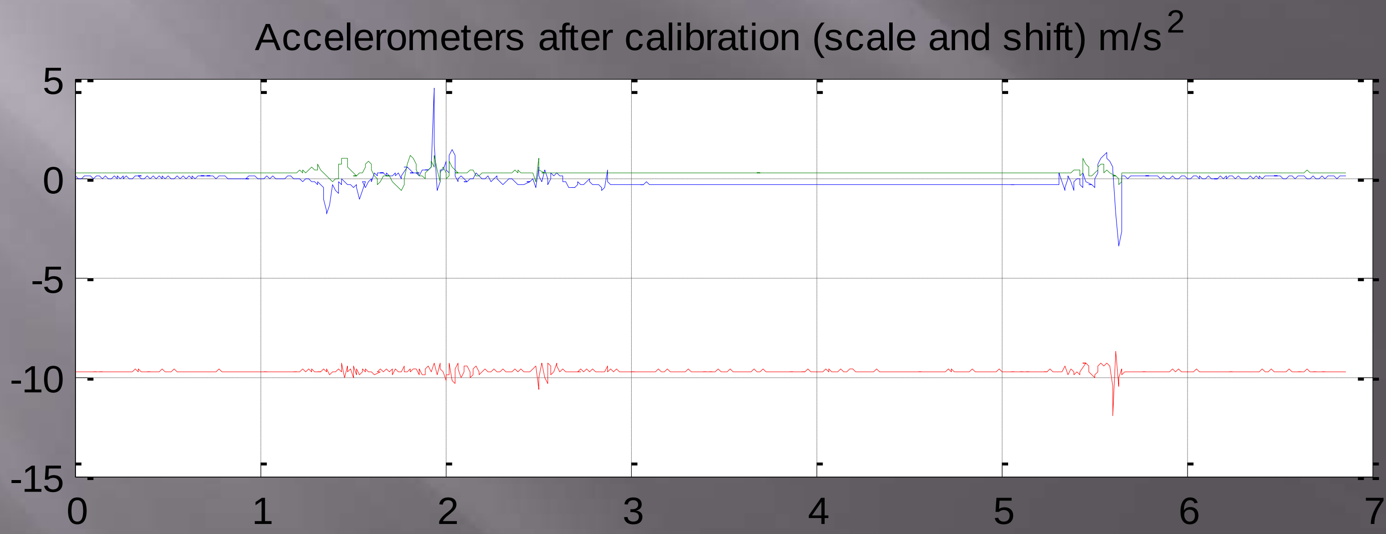
dps – degree per second
LSB – Least significant bit
http://www.vectornav.com/index.php?option=com_content&view=article&id=21&Itemid=11

TABLE I. ACCUMULATED ERROR DUE TO ACCELEROMETER BIAS ERROR

Grade	Accel. Bias Error [mg]	Horizontal Position Error [m]			
		1 s	10 s	60 s	1 hr
Navigation	0.025	0.00013	0.012	0.44	1600
Tactical	0.3	0.0015	0.15	5.3	19000
Industrial	3	0.015	1.5	53	190000
Automotive	125	0.62	60	2200	7900000


Gyro raw data deg/sec
40
20
0
-20
0
1
2
3
4
5
6
7


Accelerometers raw data m/s2
5
0
-5
-10
-15
0
1
2
3
4
5
6
7


Accelerometers after calibration (scale and shift) m/s2
5
0
-5
-10
-15
0
1
2
3
4
5
6
7

II. PROBLEM DESCRIPTION

The body motion in an inertial coordinate system can be described by following equation:

$$\vec{r}_i = \vec{r}_0 + \int_0^t \int_0^t \left(\vec{g} + \vec{a}_i(t)\right) dt\,dt \qquad (1)$$

The body space orientation can be described accordingly:

$$\vec{v} = \vec{v}_0 + \int_0^t \vec{\omega}_i\,dt \qquad (2)$$

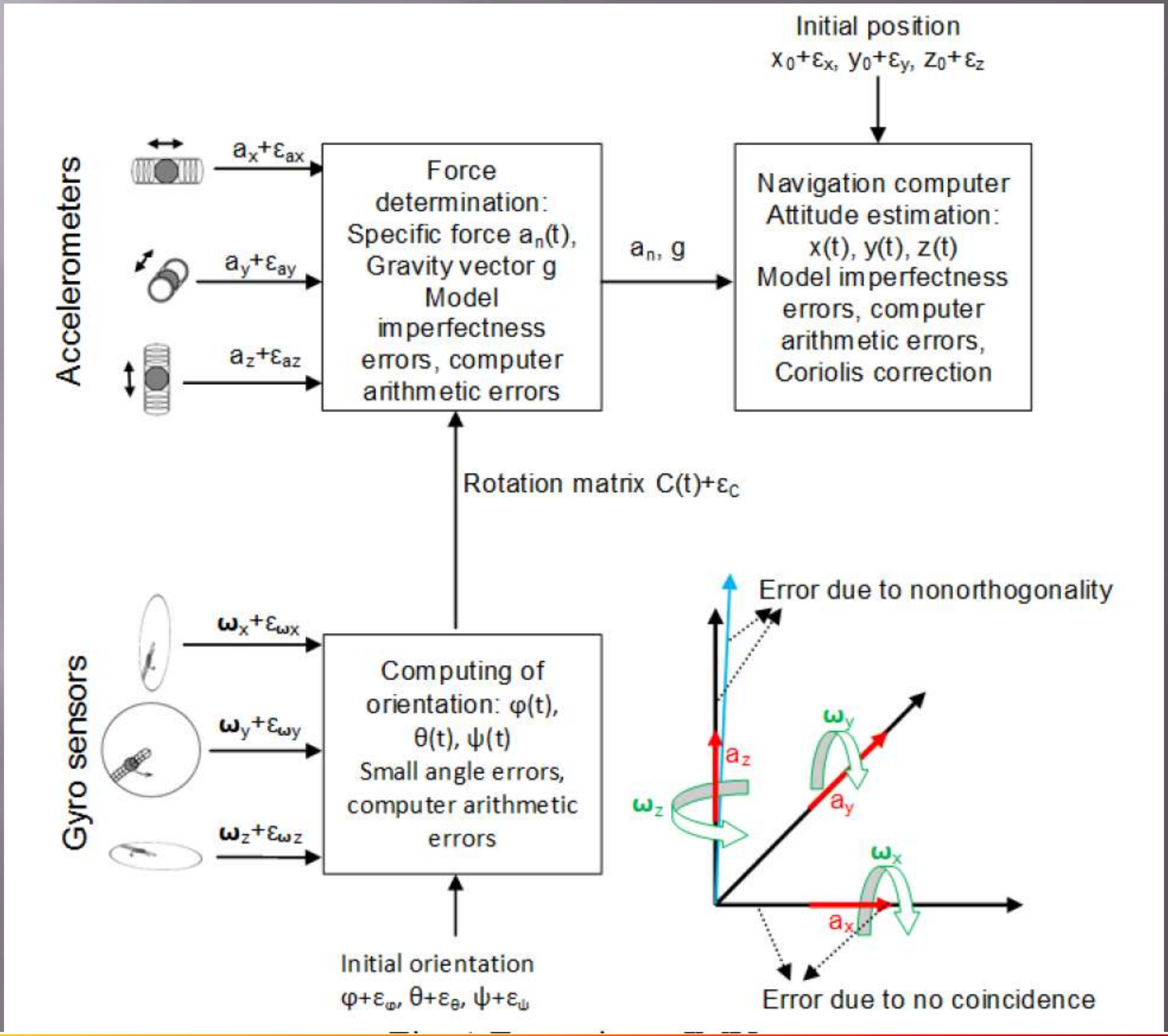
Calibration

a_x = (data_arr(6,:)-s1)/a1;

a_y = (data_arr(7,:)-s2)/a2;

a_z = (data_arr(8,:)-s3)/a3;

The shifts s1, s2, s3 and scaling coefficients a1,a2,a3 are estimated by optimization procedure with averaged data from several positions of the sensors


Initial position
x0+εx, y0+εy, z0+εz
Accelerometers
ax+εax
ay+εay
az+εaz
Force determination: Specific force an(t), Gravity vector g Model imperfectness errors, computer arithmetic errors
an, g
Navigation computer Attitude estimation: x(t), y(t), z(t) Model imperfectness errors, computer arithmetic errors, Coriolis correction
Rotation matrix C(t)+εC
Gyro sensors
ωx+εωx
ωy+εωy
ωz+εωz
Computing of orientation: φ(t), θ(t), ψ(t) Small angle errors, computer arithmetic errors
Initial orientation
φ+εφ, θ+εθ, ψ+εψ
Error due to nonorthogonality
ωy
az
ωz
ay
ωx
ax
Error due to no coincidence

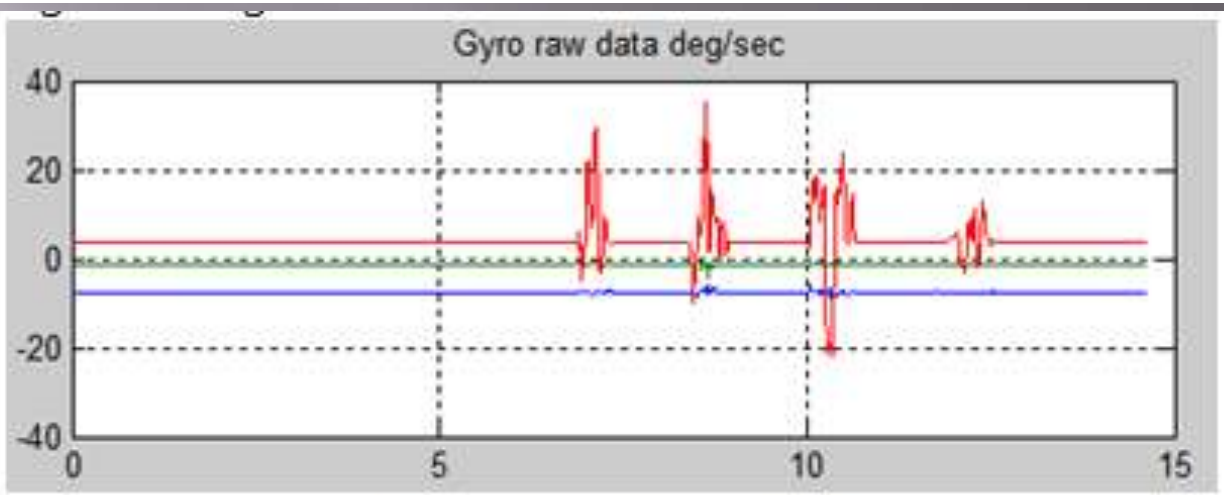


Figure 3. Gyro raw signals

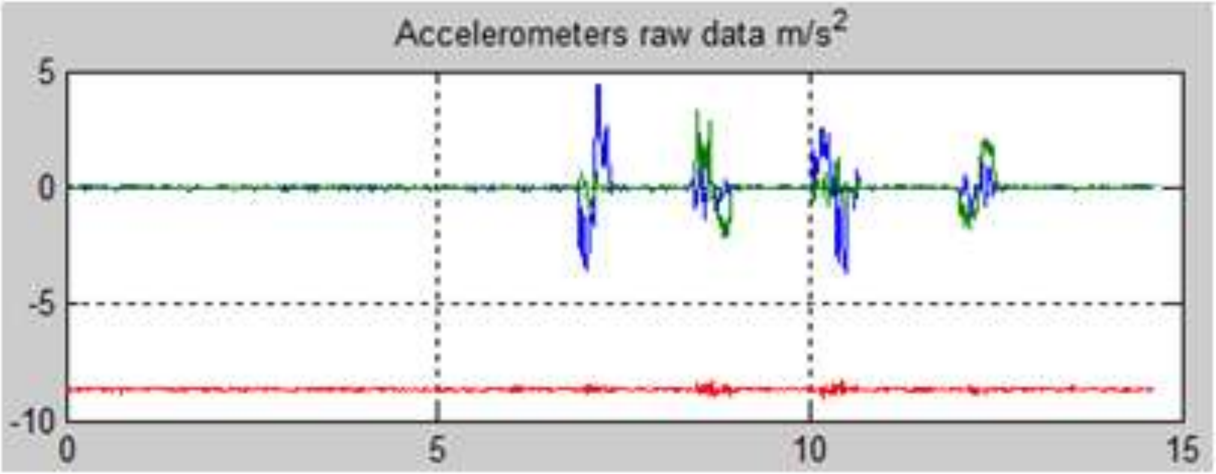
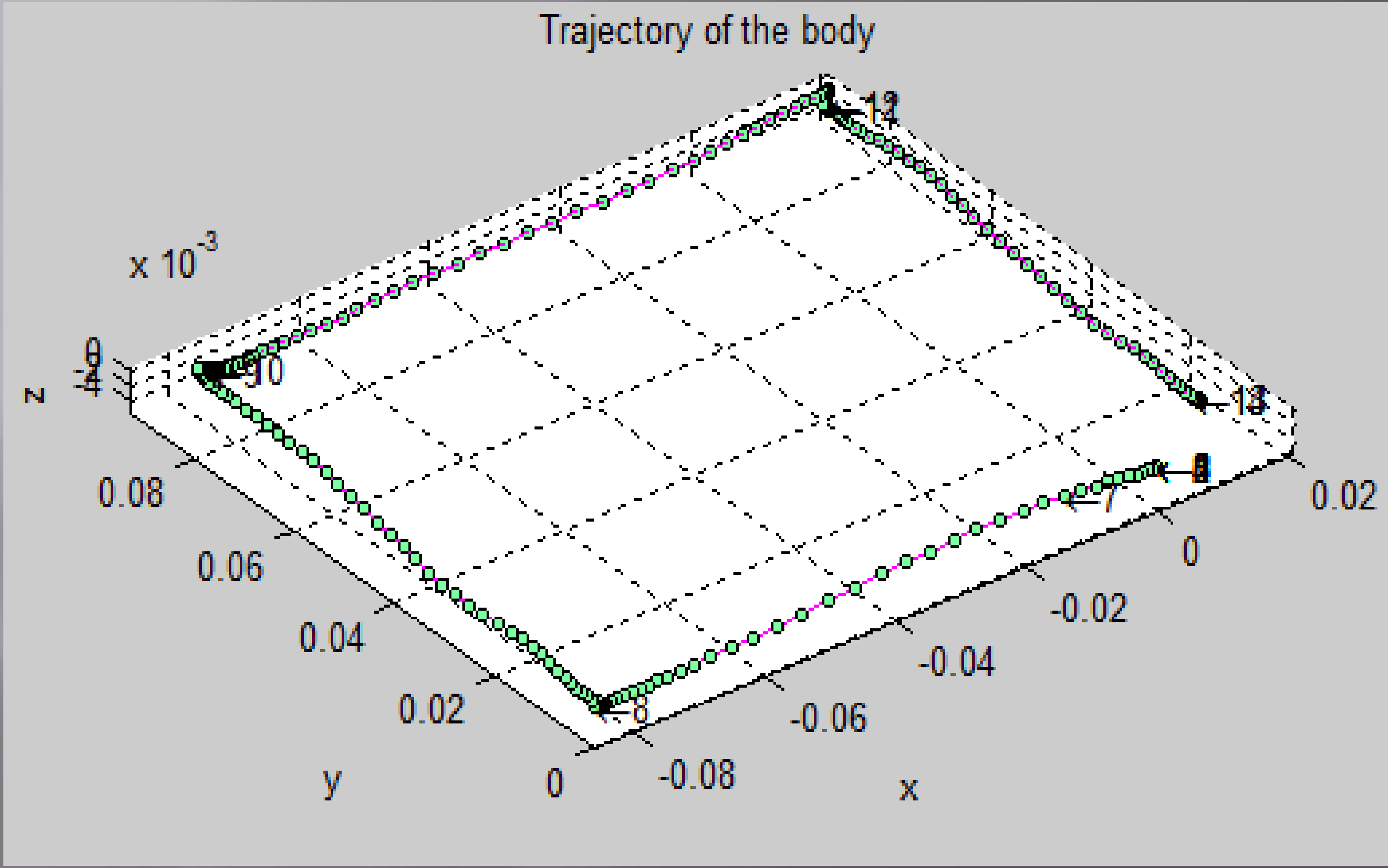
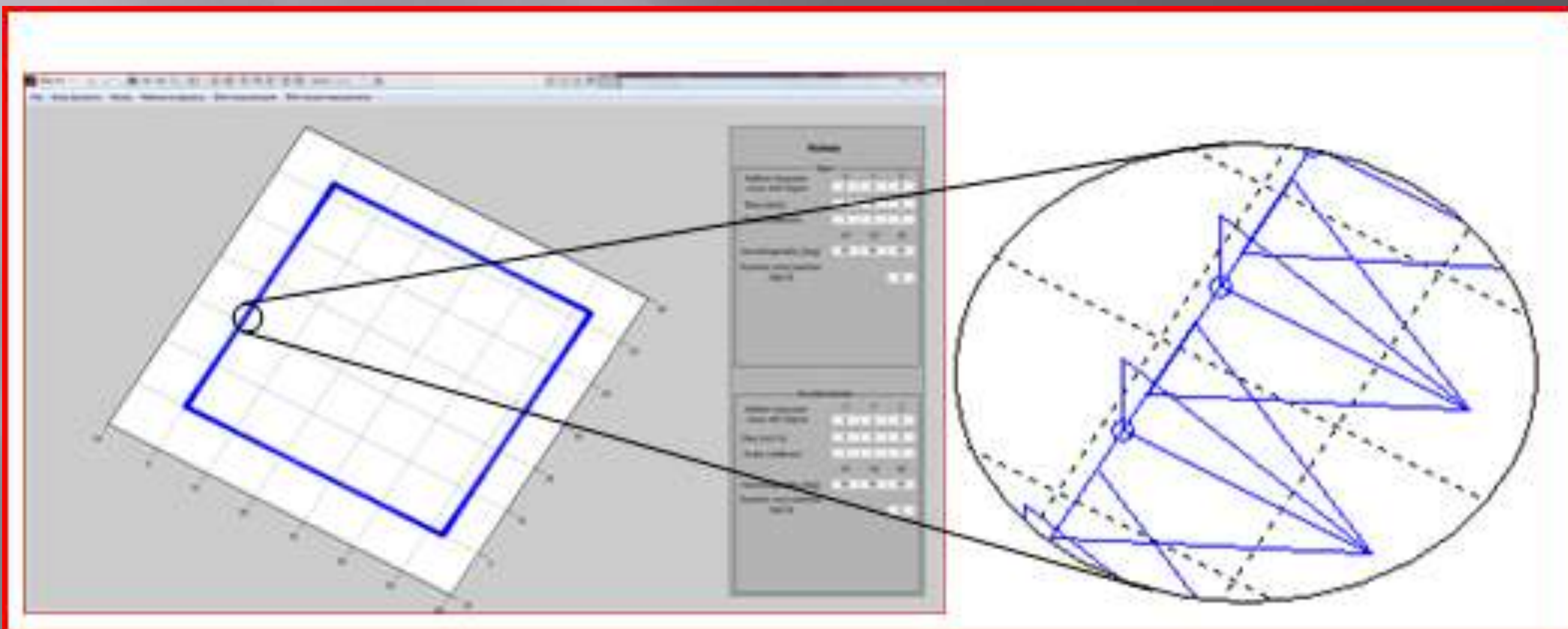


Figure 4. Accelerometer raw signals


Trajectory of the body
x 10^-3
z
0
-2
-4
0.08
0.06
0.04
0.02
0
y
-0.08
-0.06
-0.04
-0.02
0
0.02
x
7
8
10
13
12

IMU interface



Sensor Networks

Generalized description of SN

- Sensor networks have emerged as a fundamentally new tool for monitoring spatially distributed phenomena.
- The sensor network consists of homogeneous or heterogeneous sensors spread in a global surveillance volume, which act jointly for solving optimally the required tasks.

Sensors

- Competitive sensors provide independent measurements of the one and the same physical phenomenon;
- Complementary sensors provide different modality information for one and the same observed object. It can be combined to give a more complete image of the phenomena being studied.

Advantages of sensor networks

- Increased confidence: more than one sensor can confirm the same target
- Reduced ambiguity: joint information from multiple sensors reduces the set of hypotheses about the target
- Improved detection: integration of multiple measurements of the same target improves signal-to-noise ratio, which increases the assurance of detection.

Advantages of sensor networks

- Increased robustness: one sensor can contribute information where others are unavailable, inoperative, or ineffective;
- Enhanced spatial and temporal coverage: one sensor can work when or where another sensor cannot;
- Decreased costs: a suite of "average" sensors can achieve the same level of performance as a single, highly-reliable sensor and at a significantly lower cost.

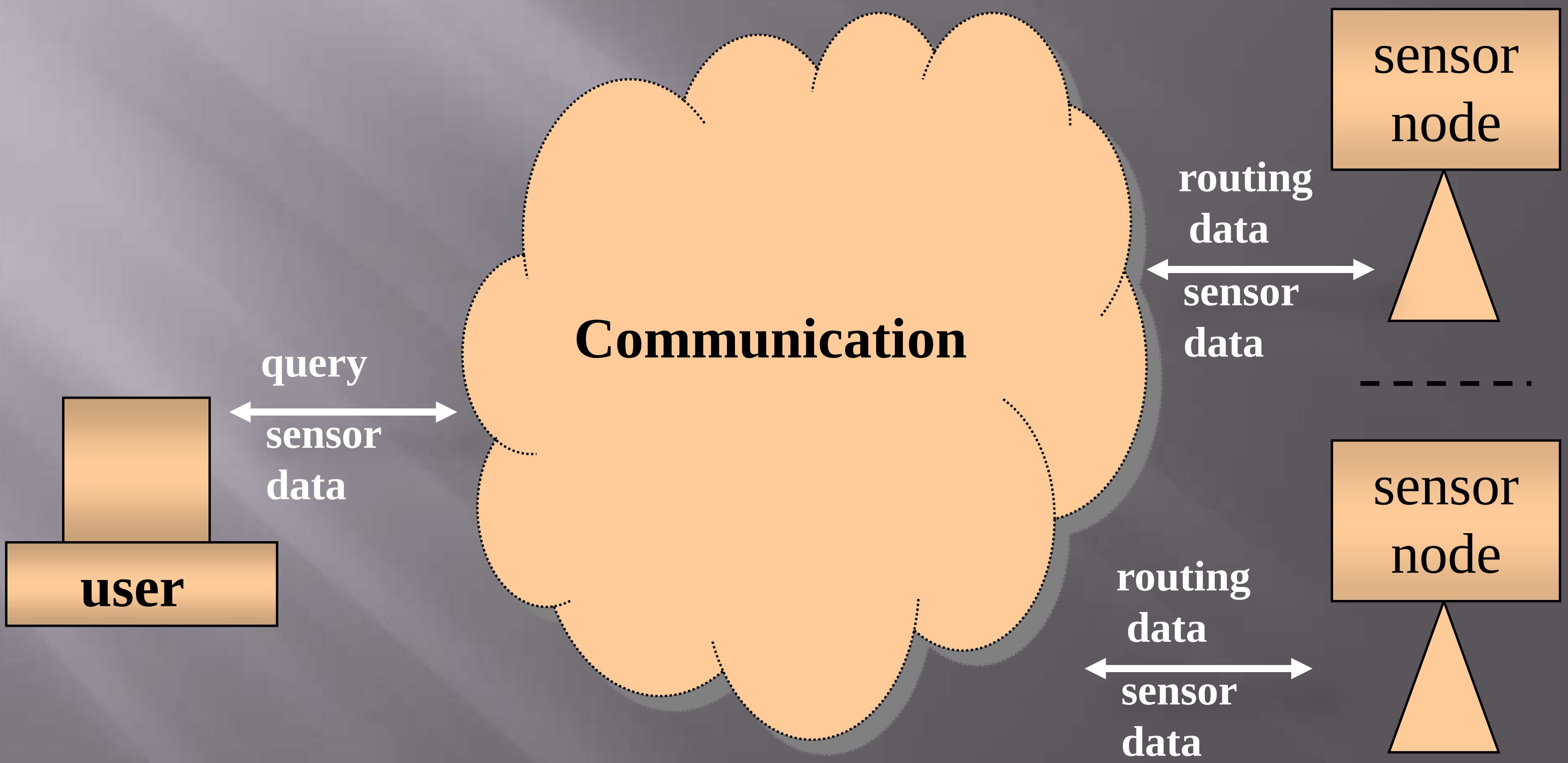
Application fields

- Armed forces;
- Coast (terrestrial) Guard;
- Police;
- Fire Departments;
- Environmental Protection;
- “Smart” home;
- Health care.

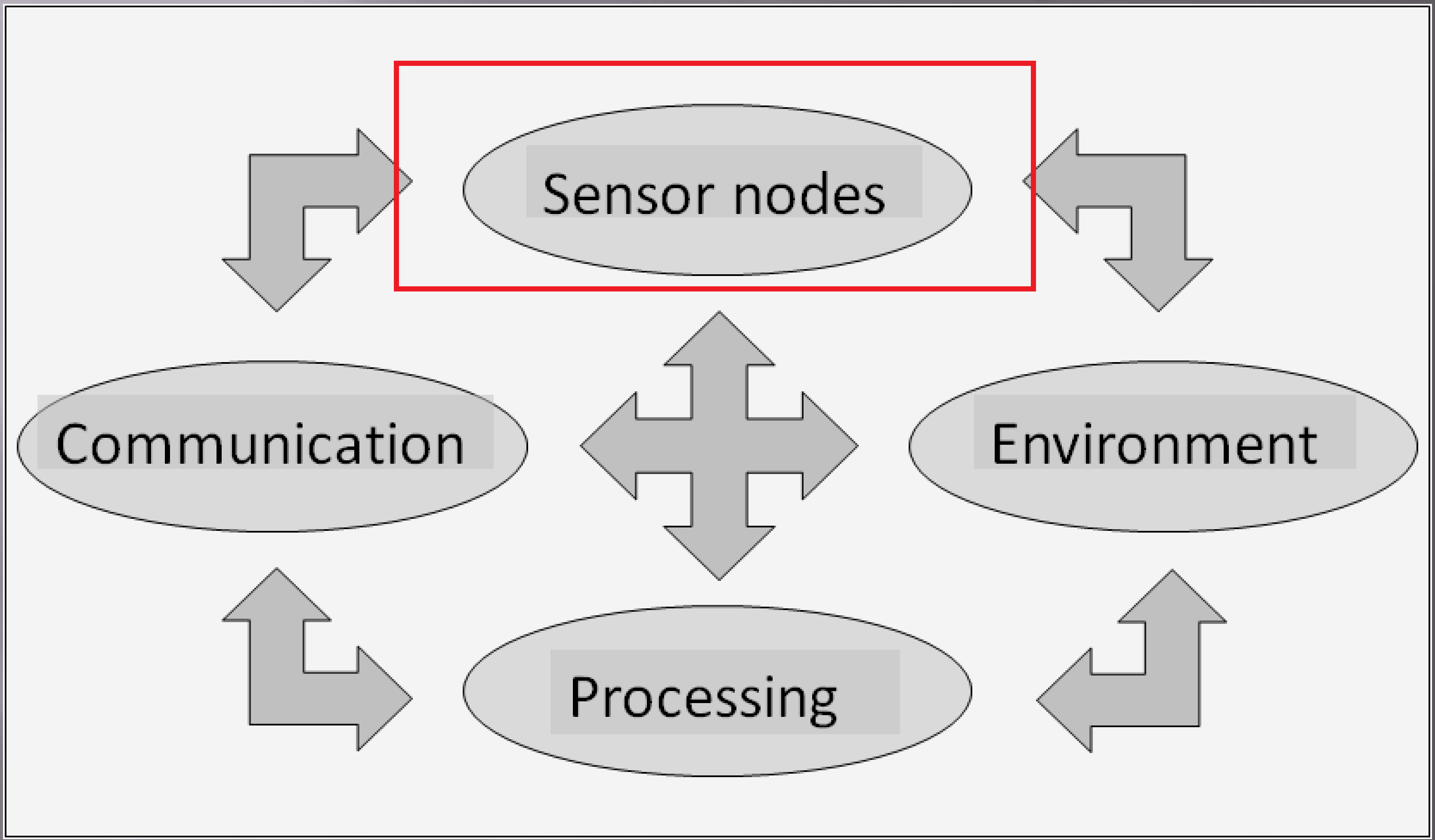
Fundamentals of the sensor networks

- Computer networks
- Wireless communications
- New protocols
- Agent system
- Grid technology
- Network Operating systems

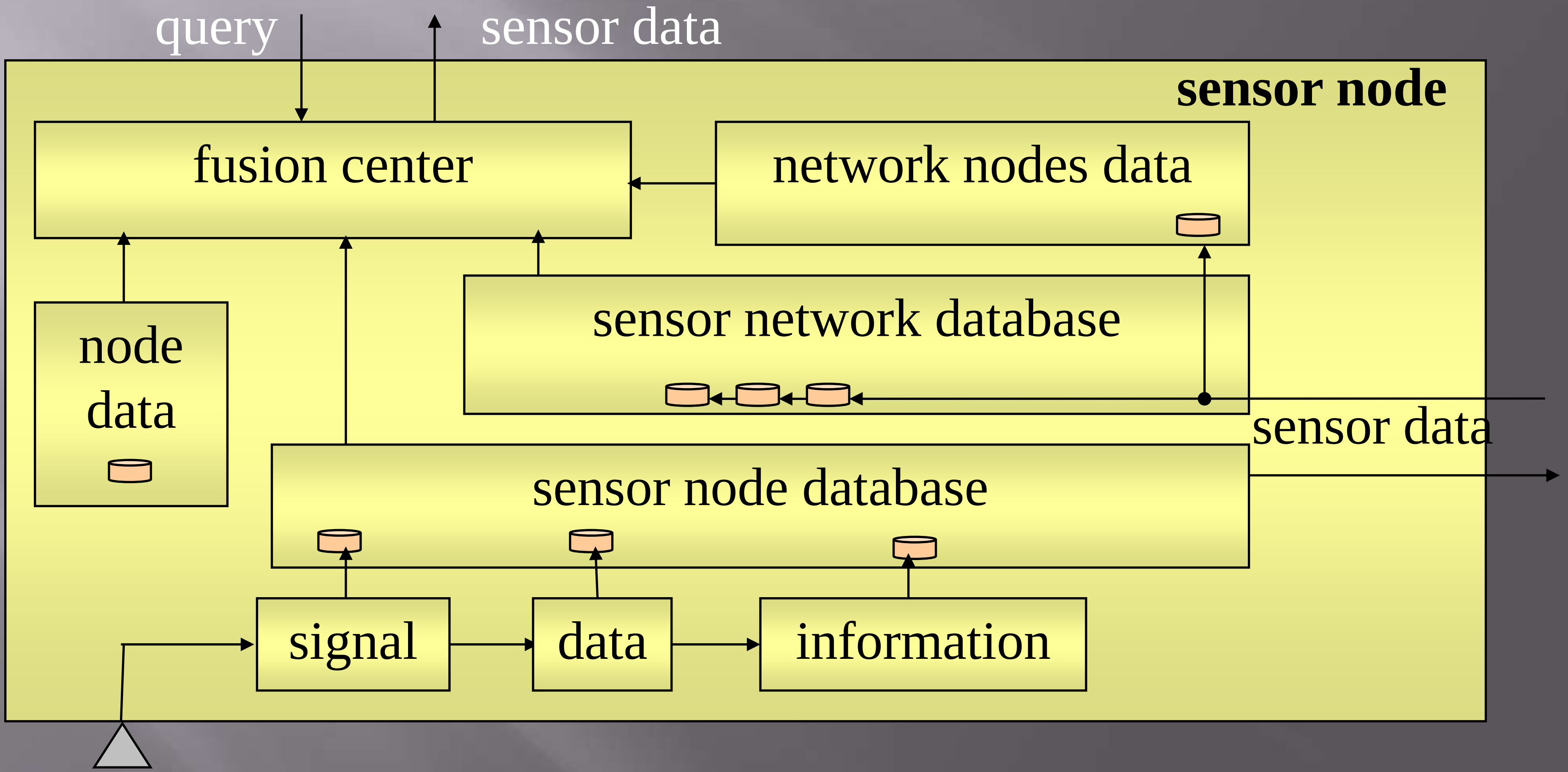
Architecture of sensor network



Sensor network components



Generalized architecture of sensor node



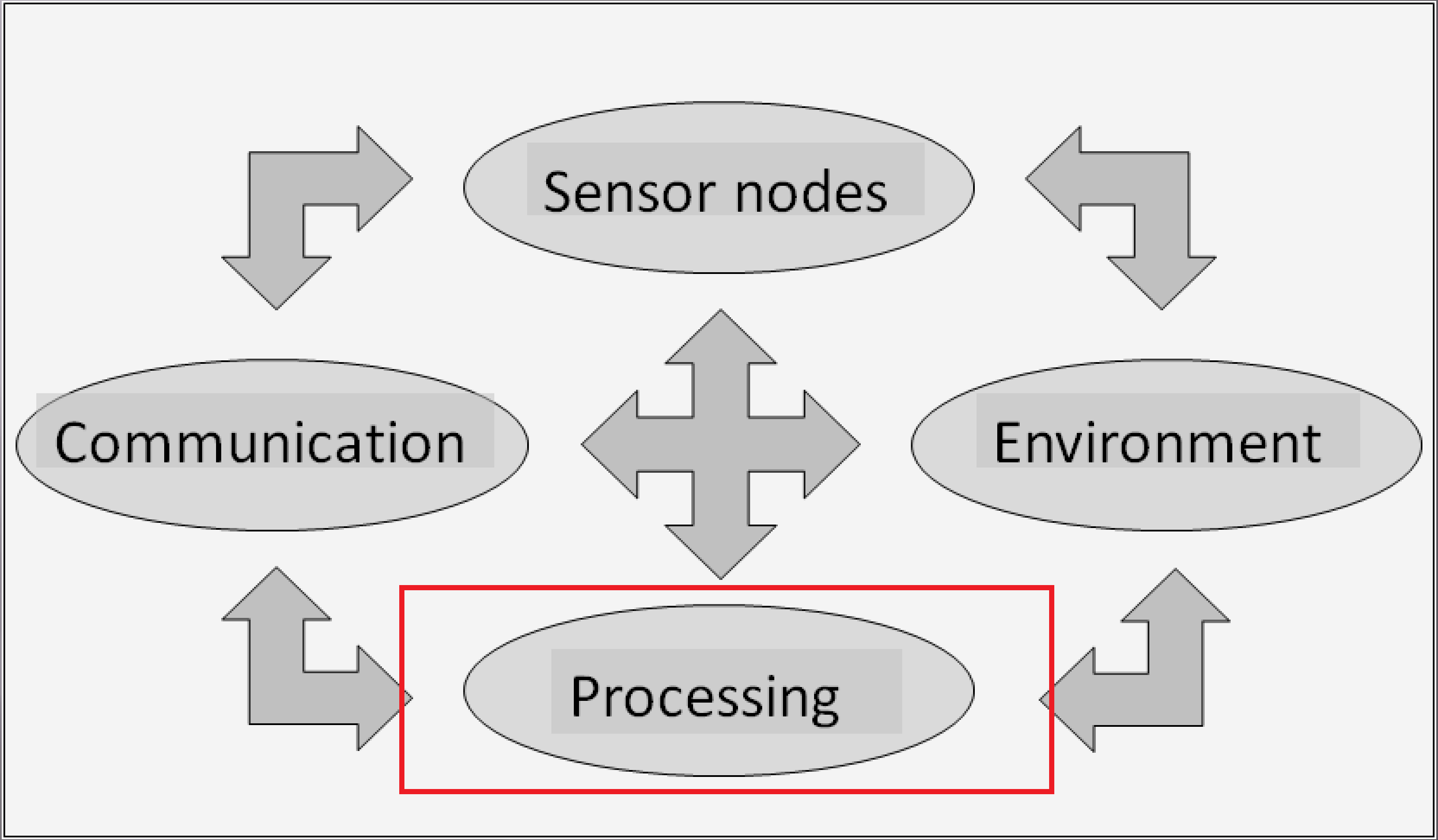
Important characteristics

- Geo-synchronization - A source must know the geographical positions of any destination to which it wishes to send, and must label packets for that destination with its position. Example - Grid's location service (GLS) for ad hoc networks with dynamic nodes
- Time synchronization
  - Local
  - Global
  - Example - Network Time Protocol (NTP)

Sensor characteristics

- Field of view – FOV;
- Maximal and minimal detection range;
- Probability of correct/incorrect detection;
- Measurement rate;
- Measurement noise characteristics;
- Moving platform parameters.

Sensor network components



Data processing algorithms

The most popular algorithms are Kalman and extended Kalman filters, AR and ARMA estimators, different transformations, correlation algorithms, template matching algorithms, Sobel, Prewitt, Canny, Roberts, Laplacian, Hough, Radon edge detection, nearest-neighbor association algorithm, different kind of probabilistic association rules, hybrid estimation procedures as interactive multiple modeling, etc.

Definition of Data and Information Fusion

Wikipedia:
Sensor fusion is the combining of sensory data such that the resulting information is in some sense better than would be possible when these sources were used individually.
Better = more accurate, more complete, or more dependable.

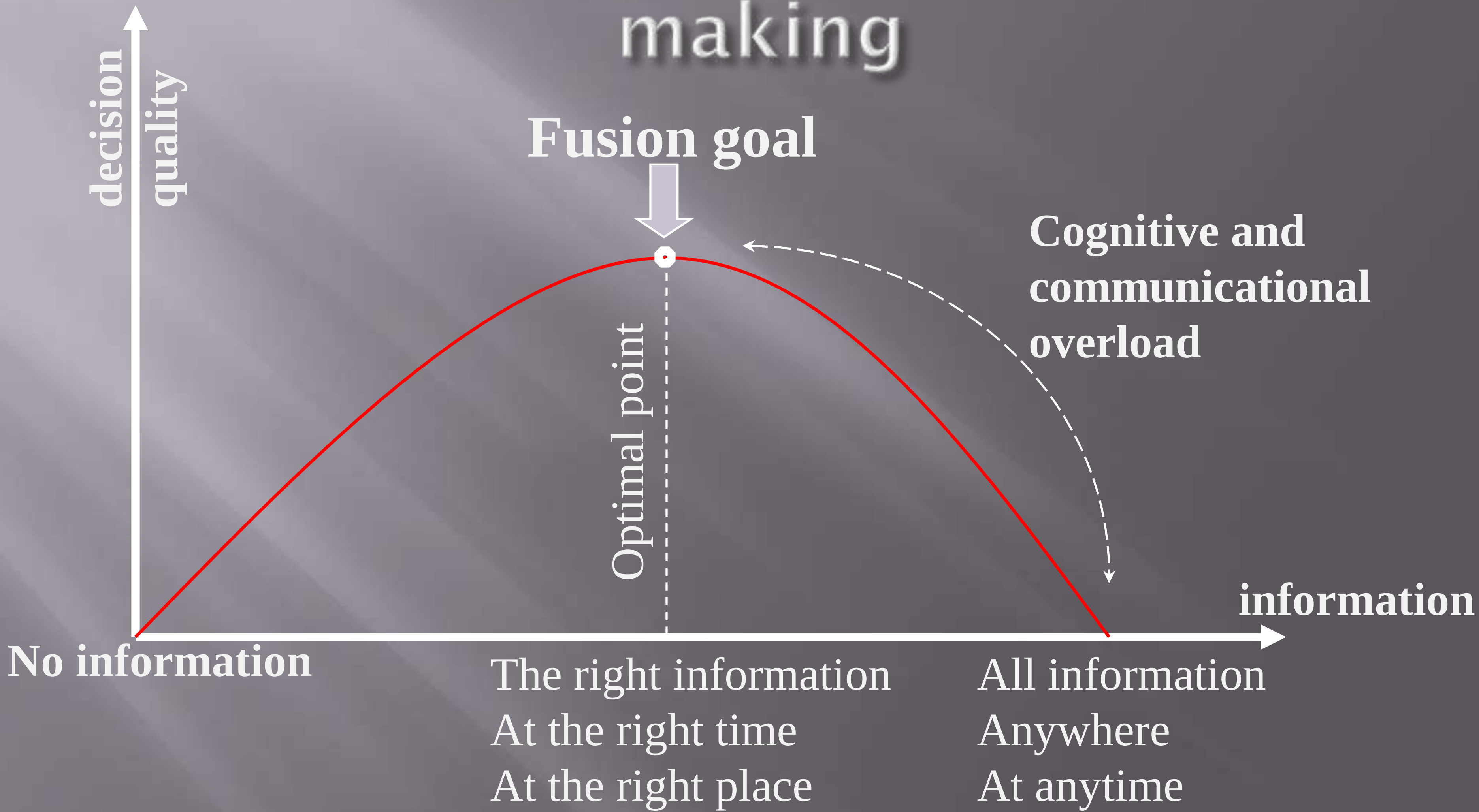
Definition of Data and Information Fusion

Remark:
In definition above "combination of data" is not very suitable phrase. We have to find better one, for example "simultaneously processed data"

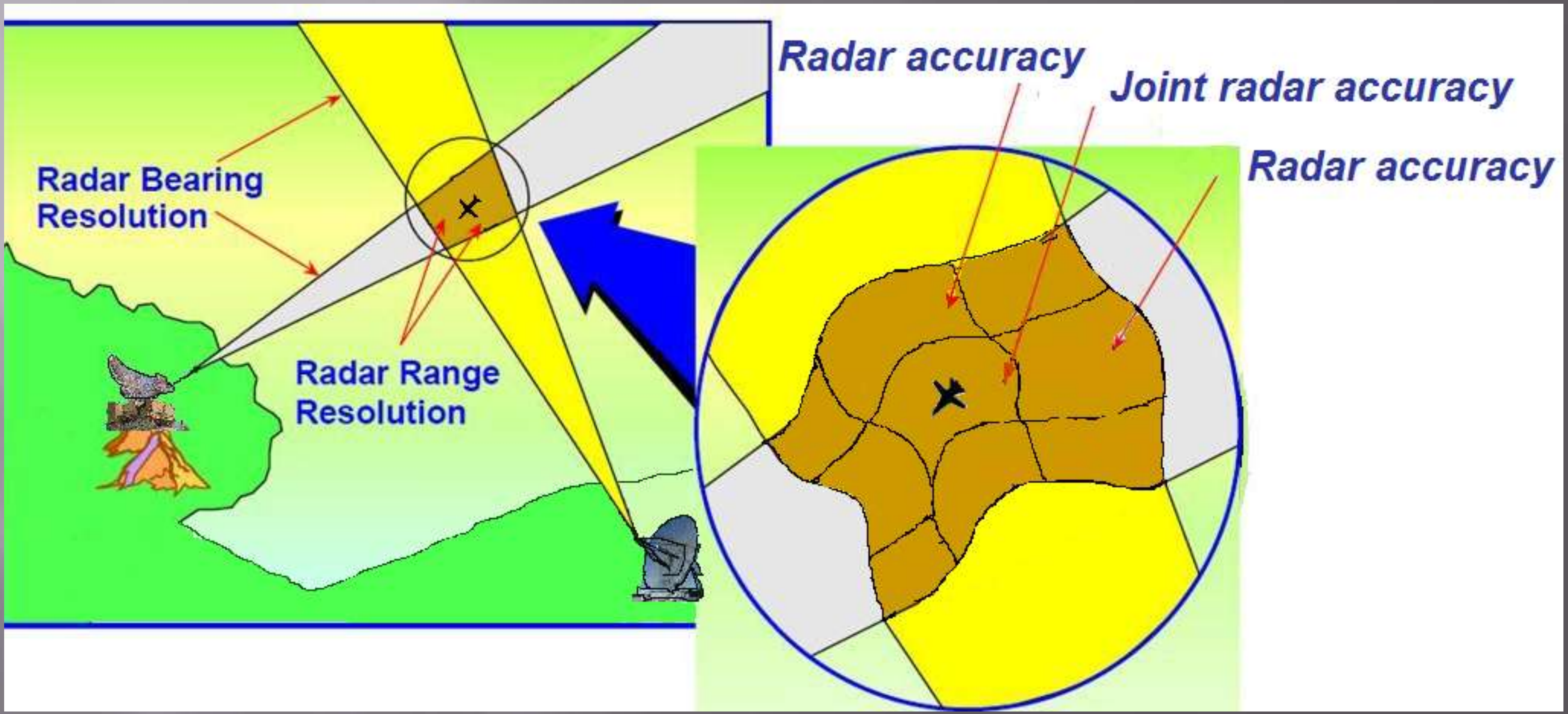
Benefits from Fusion Process

- **The first and the most important remark is that fusion process is necessary most of all to reduce (to filter) input information through its integration (merging) and generalization.**
- **Fusion process is necessary to improve accuracy.**
- **Fusion process is necessary to reduce uncertainty.**

Fusion and quality of decision making



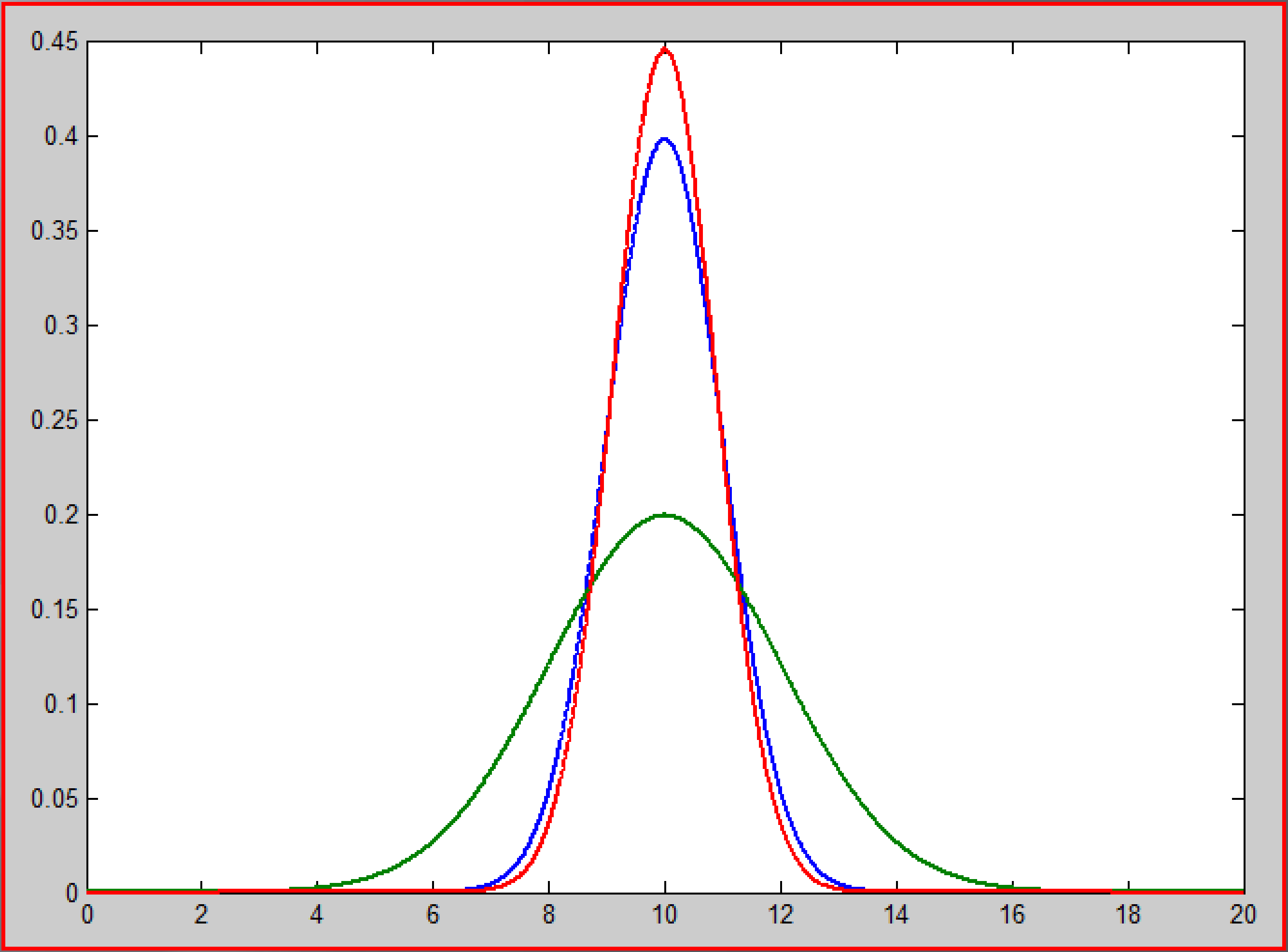
Accuracy Enhancement



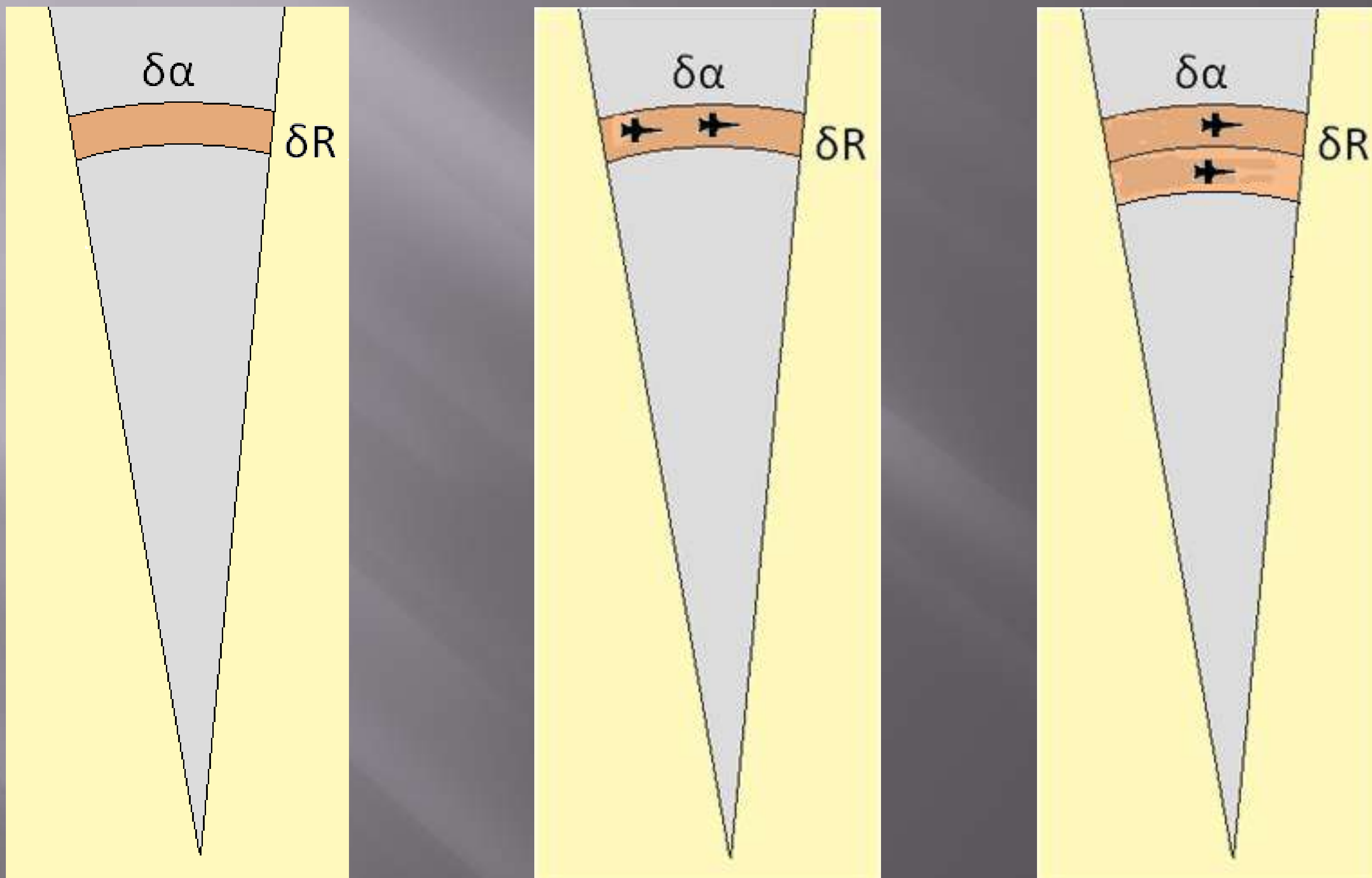
Uncertainty reduction

$$\frac{1}{\sigma^2_{Fusion}} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}$$

$$\sigma_1 = 1; \quad \sigma_2 = 2$$
$$\mu_1 = \mu_2 = 10$$

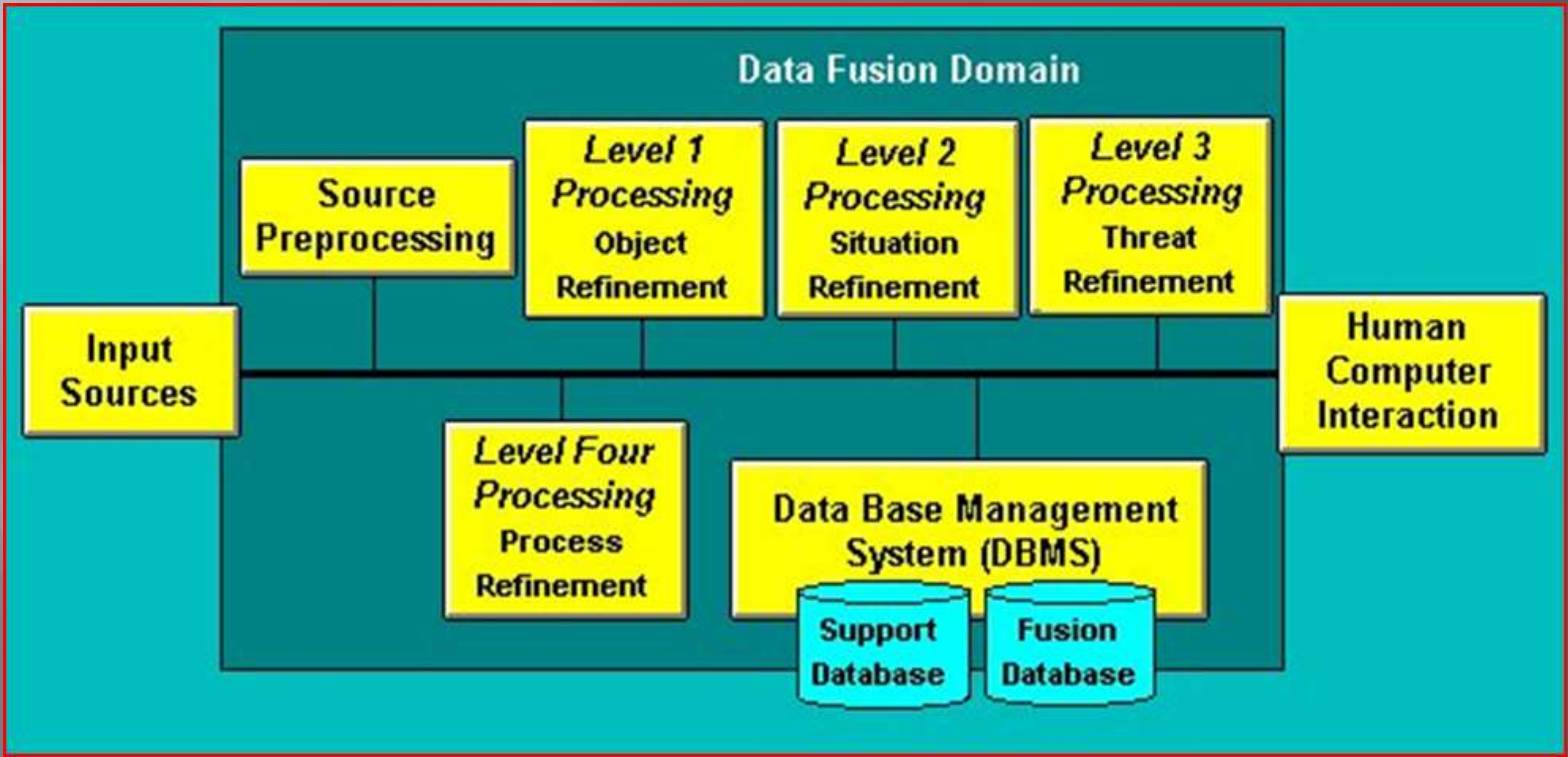


Resolution enhancement



Structure of Data and Information Fusion

(JDL - Joint Directors of Laboratories Data Fusion Group)



Level 1

Temporal data fusion

Sensor data fusion

Temporal data fusion

- The simplest tracking filter is alpha-beta filter. It is suitable for tracking of moving with constant velocity targets without steady-state error. The alpha-beta-gamma filter has ability to track even accelerating targets without steady-state error.

- Kalman filter is a classical optimal estimating algorithm for dynamical linear system with Gaussian measurement and system noise. The modification of Kalman filter - Extended Kalman filter is developed for non-linear systems. The EKF gives particularly poor performance on highly non-linear functions because only the mean is propagated through the non-linearity. The unscented Kalman filter (UKF) uses a deterministic sampling technique to pick a minimal set of sample points (called sigma points) around the mean.

Mathematical description

Linear dynamic system (Markovian presentation):

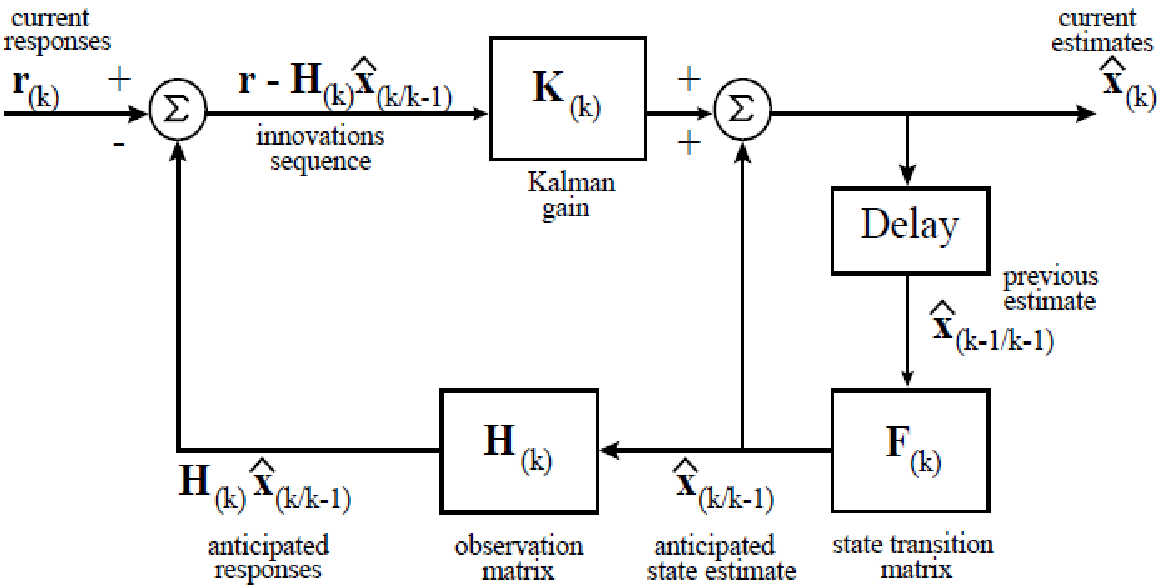
$$x(k+1) = F(k)x(k) + G(k)u(k) + v(k)$$

$$z(k) = H(k)x(k) + w(k)$$

The Kalman filter gives optimal solution for additive Gaussian noises

Classical Kalman Filtering

Kalman Filter Operation



State Estimate Update:

$$\hat{x}_{(k/k)} = \hat{x}_{(k/k-1)} + K * (r_{(k)} - H_{(k)}\hat{x}_{(k/k-1)})$$

current estimate = anticipated estimate + Kalman gain * current response minus anticipated response

Description

Markovian - semi Markovian $x(k+1) = F(x(k), x(k-1), \ldots, x(0))$

Linear - non-linear dynamic system $x(k+1) = F(x(k))$

Additive - non additive system noise $x(k+1) = F(x(k), v(k))$

Gaussian - non Gaussian system noise $v \neq N(v, m_v, \sigma_v)$

Additive - non additive measurement noise $z(k) = H(x(k), w(k))$

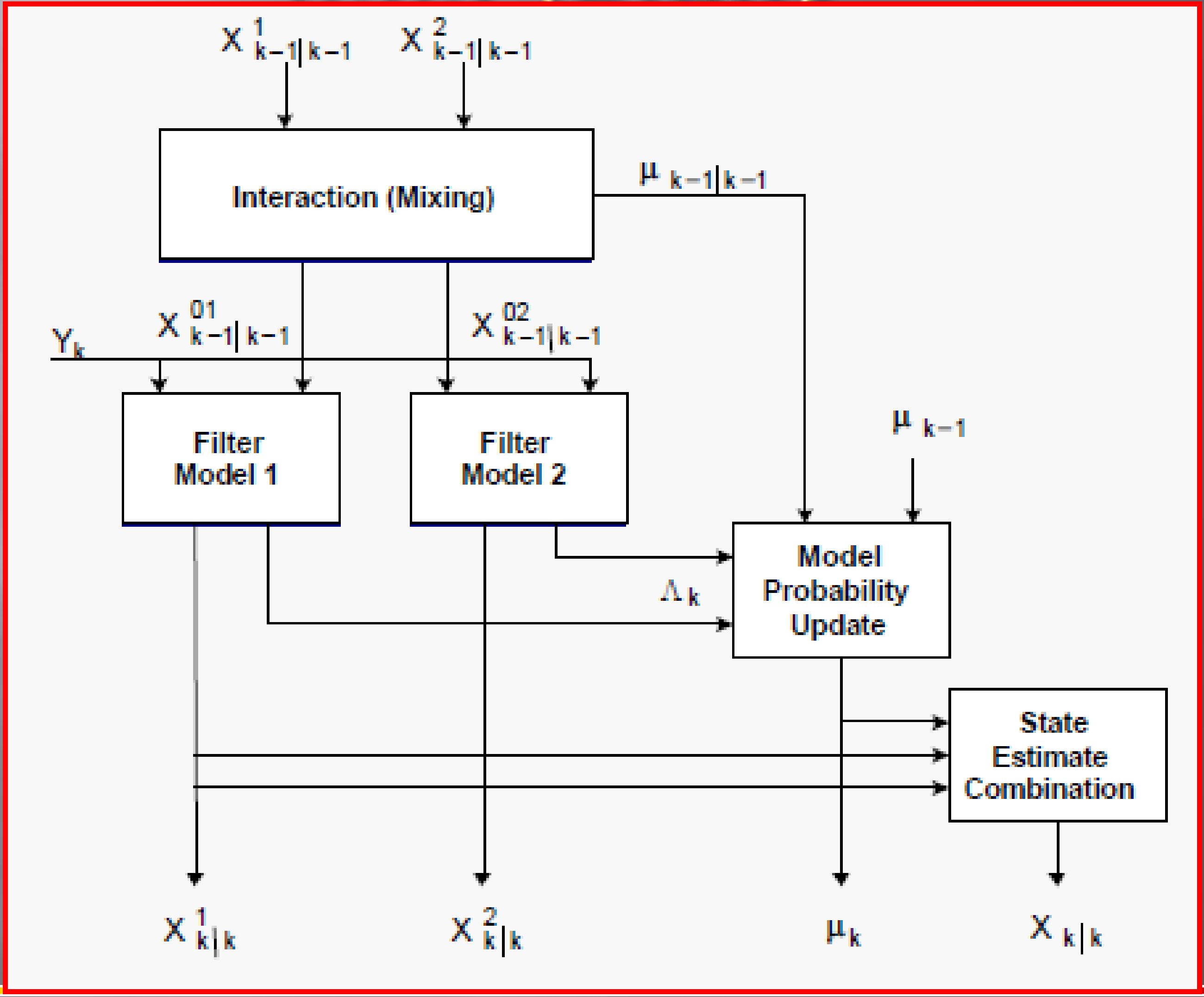
Gaussian - non Gaussian measurement noise $w \neq N(w, m_w, \sigma_w)$

More complicated algorithms

- The theoretically most powerful approach for manoeuvring targets tracking is known to be Interacting Multiple Models estimator. Generalized Pseudo-Bayesian (GPB) estimators different orders, Fixed structure IMM, Variable Structure IMM, Probabilistic Data Association IMM are variants. The most important feature is that all these estimators use in parallel several models for modelling of the estimated system.

- Particle filters, also known as Sequential Monte Carlo methods (SMC), are sophisticated model estimation techniques based on simulation. Particle filters generate a set of samples that approximate the filtering distribution to some degree of accuracy. Sampling Importance Resampling (SIR) filters with transition prior as importance function are commonly known as bootstrap filter and condensation algorithm.

IMM (Blair)


$X^1_{k-1|k-1}$
$X^2_{k-1|k-1}$
Interaction (Mixing)
$\mu_{k-1|k-1}$
Y_k
$X^{01}_{k-1|k-1}$
$X^{02}_{k-1|k-1}$
Filter Model 1
Filter Model 2
μ_{k-1}
Λ_k
Model Probability Update
State Estimate Combination
$X^1_{k|k}$
$X^2_{k|k}$
μ_k
$X_{k|k}$

Single target Bayes nonlinear filter

Prediction step

$$f_{k+1/k}(x_{k+1} \mid z^k) = \int f_{k+1/k}(x_{k+1} \mid x^k)\, f_{k/k}(x_k \mid z^k)\, dx_k$$

Update step

$$f_{k+1/k+1}(x_{k+1} \mid z^{k+1}) \propto f(z_{k+1} \mid x_{k+1})\, f_{k+1/k}(x_{k+1} \mid z^k)$$

Measurement equation (nonlinear)

$$z^{k+1} = h(x_k, w_k)$$

Transition state equation (nonlinear)

$$x_{k+1} = g(x_k, v_k)$$

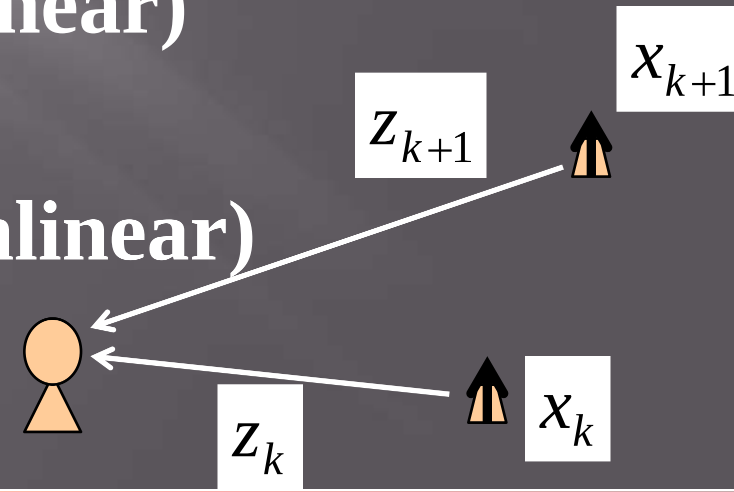


Image Fusion

Image fusion algorithms can be categorized into next three levels:

- low (pixel);
- mid (feature);
- high (semantic).

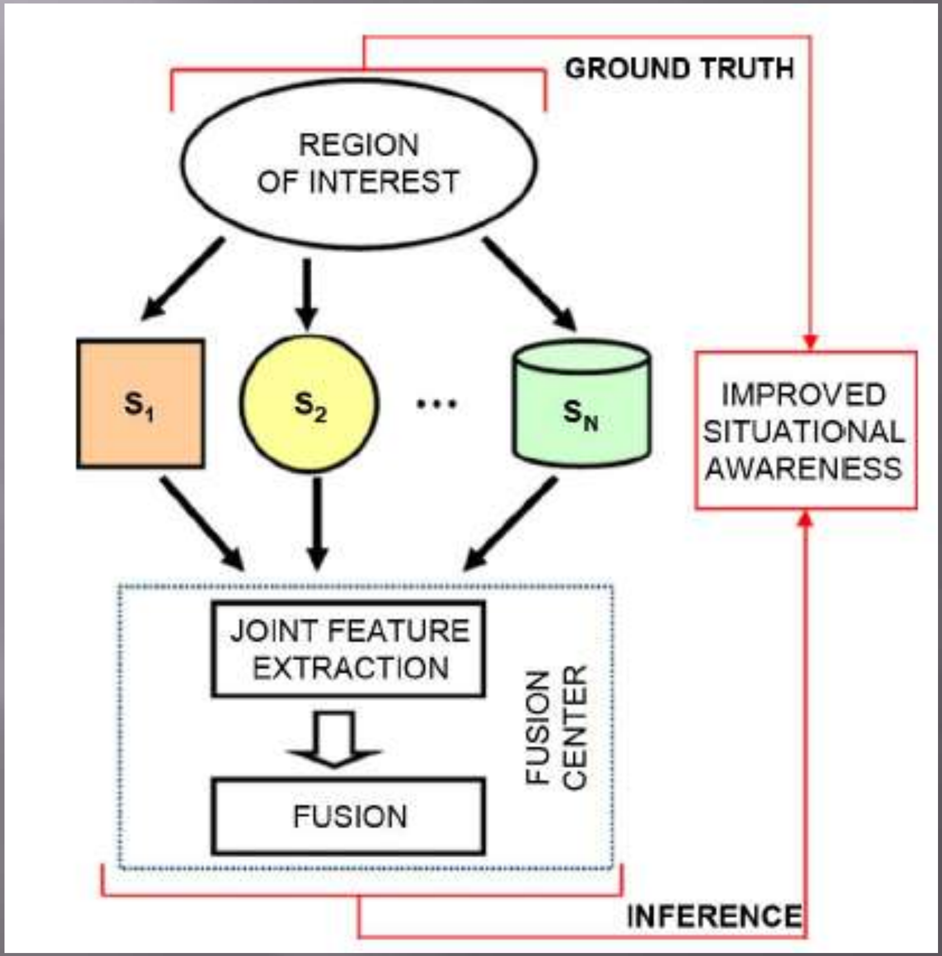
Low level Image Fusion

Pixel-level algorithms work either in the spatial domain or in the transform domain. Although pixel-level fusion is a local operation, transform domain algorithms create the fused image globally. By changing a single coefficient in the transformed fused image, all (or a whole neighborhood of) image values in the spatial domain will change. As a result, in the process of enhancing properties in some image areas, undesirable artifacts may be created in other image areas.

Feature level Image Fusion

Feature-based algorithms typically segment the images into regions and fuse the regions using their various properties. Feature-based algorithms are usually less sensitive to signal-level noise. Toet first decomposed each input image into a set of perceptually relevant patterns. The patterns were then combined to create a composite image containing all relevant patterns. Nikolov et al. developed a technique that fuses images based on their multi-scale edge representations, using the wavelet transform proposed by Mallat and Zhong. Another mid-level fusion algorithm was developed by Piella, where the images are first segmented and the obtained regions are then used to guide the multiresolution analysis.

Feature level Image Fusion



Semantic level Image Fusion

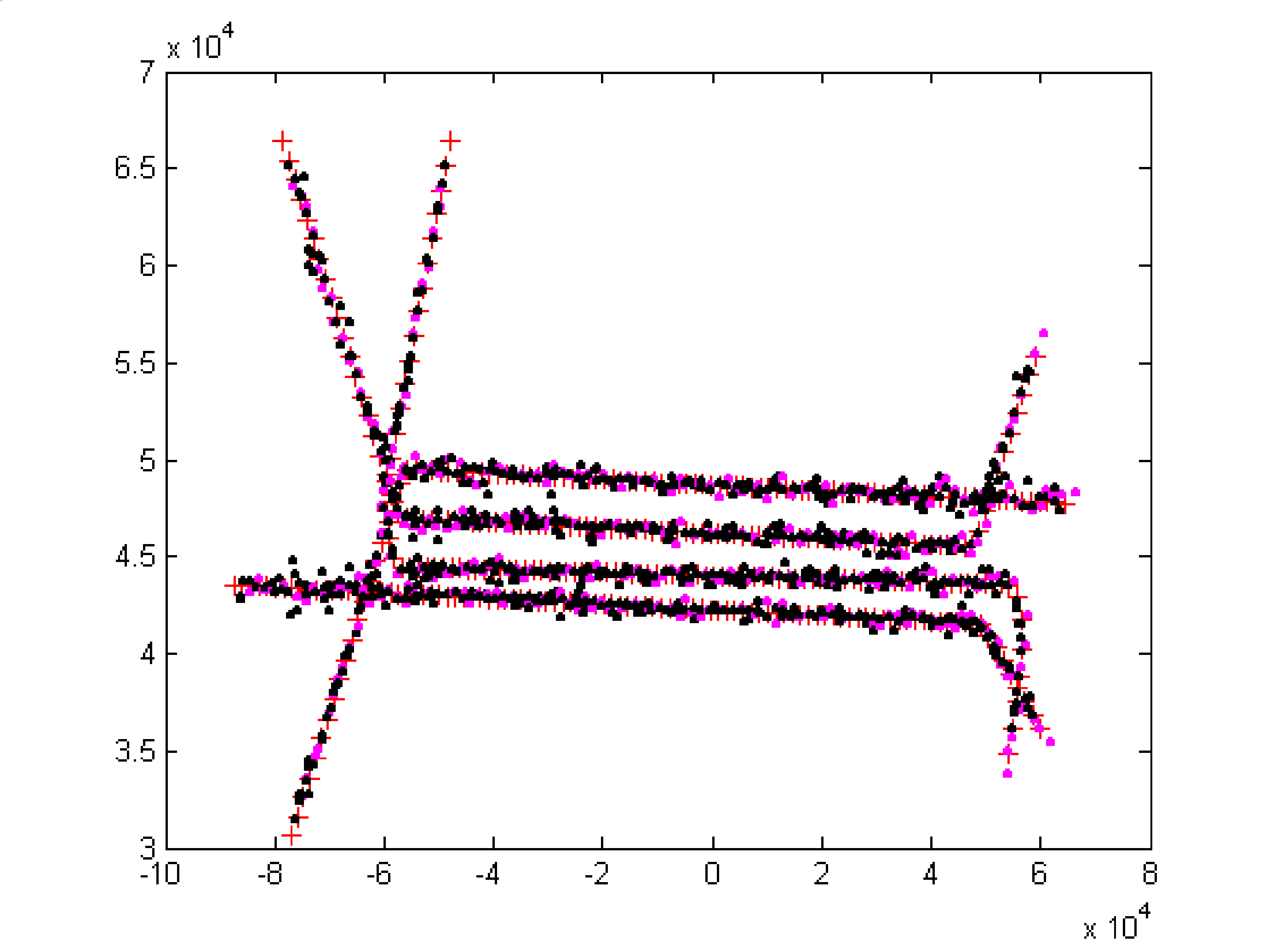
High-level fusion algorithms combine image descriptions, for instance, in the form of relational graphs. High-level fusion algorithms require correspondence between image descriptions for comparison and fusion. Finding this correspondence can be considered a part of the fusion algorithm.

Data association methods

- The Nearest Neighbor method associates the nearest measurement to the track prediction. The more complicated Global Nearest Neighbor minimizes cluster cost function in measurement distribution.

- The probabilistic data association filter (PDAF) and its extension to multiple targets – joint PDAF (JPDAF), solve the same task of measurement identification in a simpler way. In the JPDAF hypotheses are built for the measurements and targets only for the current scan. In this way the number of hypotheses is additionally reduced but the chance of combinatorial explosion in dense target and clutter scenarios still remains.

Example: IMM JPDAF

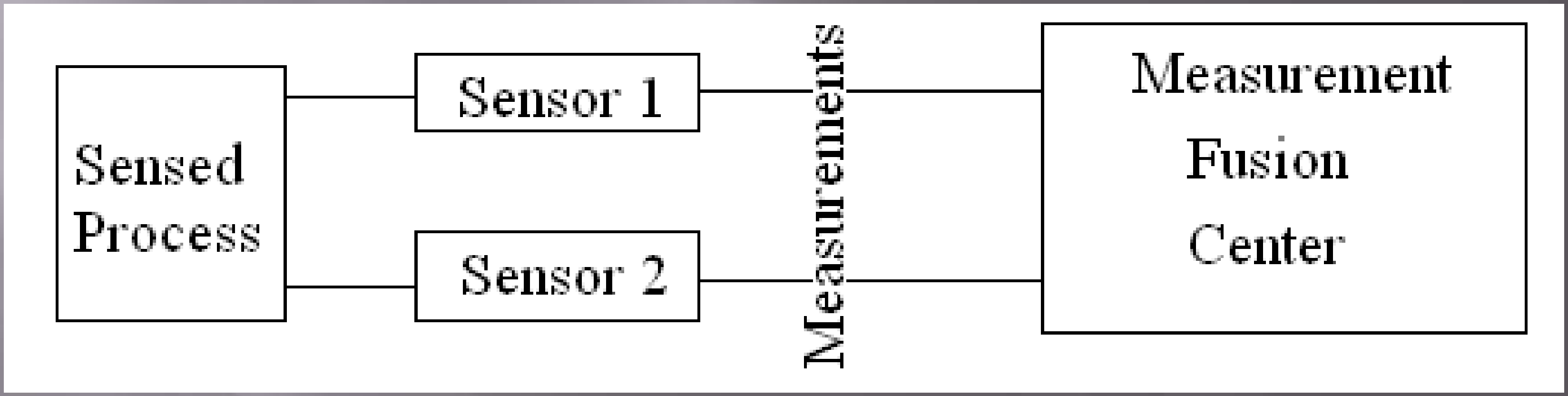


Data association methods

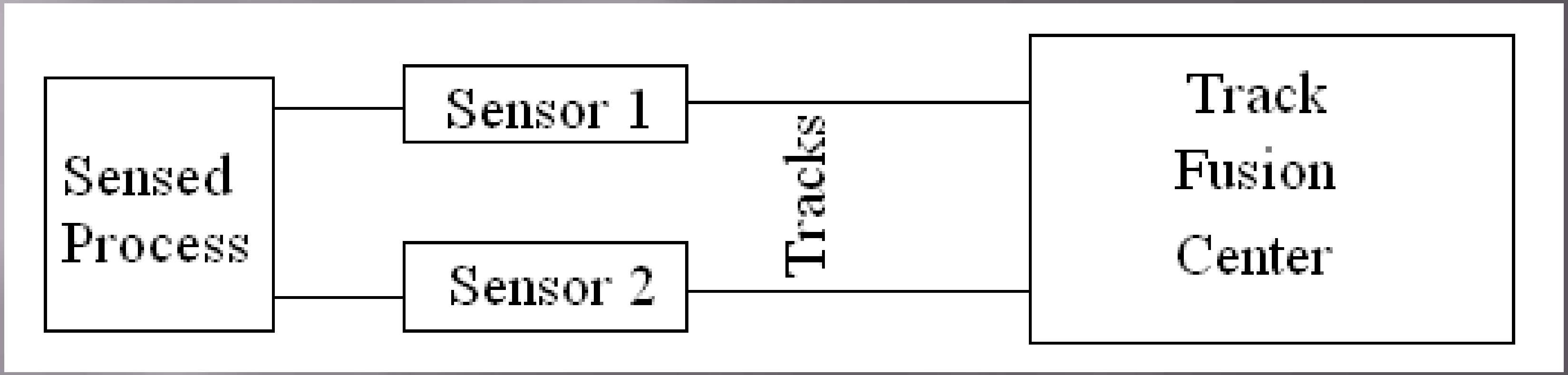
- In Multiple Hypothesis Tracking approach all measurements received at a scan are assigned to initialized targets, new targets or false alarms. A number of hypotheses are generated. Every one supposes a possible assignment scheme between measurements, received in all scans, and the targets - confirmed, new ones or false. Pruning and gating techniques are used to retain the most likely hypotheses and in this way to reduce their number

- Finite Set Statistics considers all measurements as measurements from a generalized sensor and all targets as a generalized target of interest. Fusion of information from one and the same sensor but from different moments of time

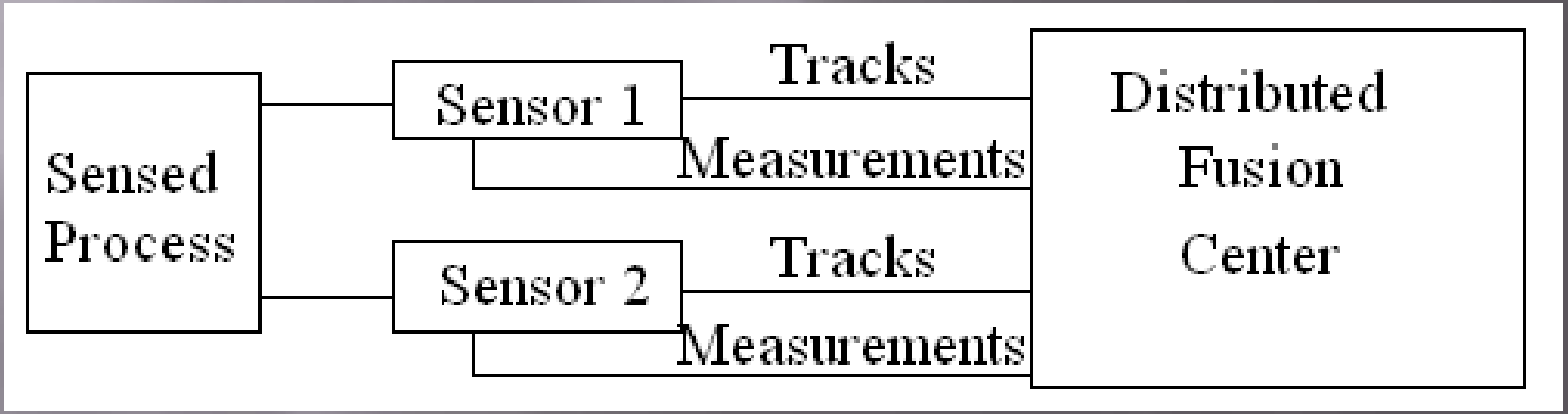
Fully Centralized Measurement Fusion Architecture



Fully Centralized Trajectory Fusion Architecture



Distributed Decision Fusion Architecture



Homogeneous sensor fusion

- *AND Operator.* This method transforms the output of the sensors in a binary yes/no consensus operating with logical AND. After that thresholds are applied to find the result. The procedure is very simple, intuitive and fast, if the values of thresholds are determined in advance. The method does not take into account the degree of confidence of each sensor.

- *Weighted Average*. This method takes a weighted average of available sensor data and uses it as the fused value. Usually the weights are proportional to accuracy of sensors or to credibility of sensor information.

- *Voting*. The voting schemes main advantage is computation efficiency. Voting involves the derivation of an output data object from a collection of n input data objects, as prescribed by the requirements and constraints of a voting algorithm. The voting algorithms can be quite complex in terms of content and structure of the input data objects and how they handle the votes (weights) at input and output.

Simple Example

When both sources are reliable, there is a consensus and it is reasonable to find solution in the cross-section of D_1 and D_2 - sets of corresponding sources: $x \in D_1 \cap D_2$.

If the two sources do not agree, we have disjunction $x \in D_1 \cup D_2$ The hypothesis for reliability of the sources is no longer credible and three other hypotheses appear: 1) First source is correct, the second is incorrect; 2) First source is incorrect, but second is incorrect; 3) Both sources are incorrect. How to find the correct hypothesis? As a precaution, all available information is kept and we hold up .

Sensor Fusion

- Information Theory;
- Dempster-Shafer Belief Theory;
- Dezert Smarandache Theory(DSmT);
- *Fuzzy Reasoning.*
- *Geometric Methods*

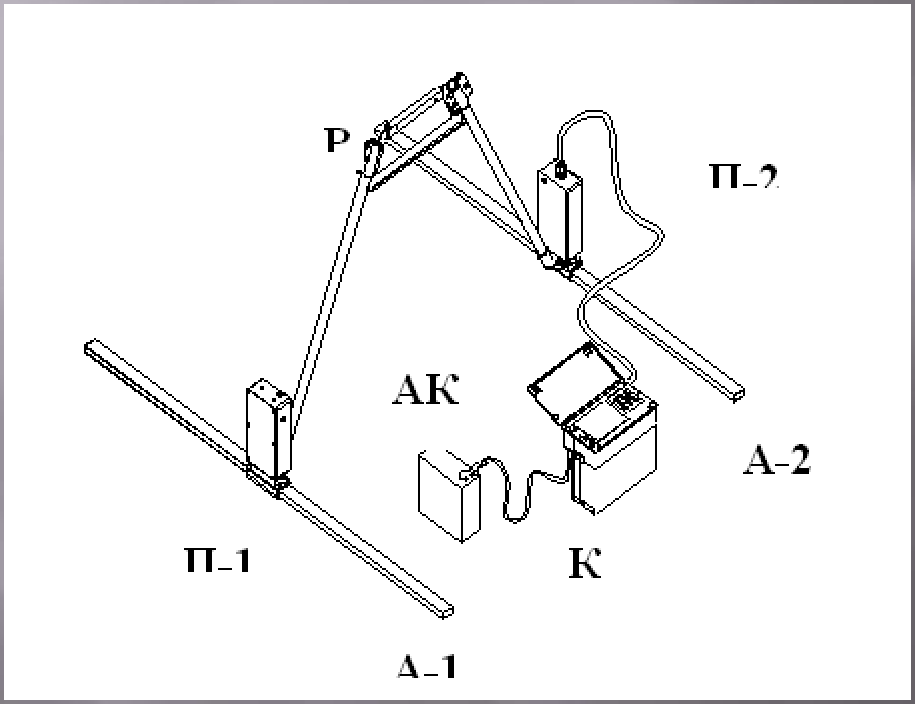
Level 2,3,4 fusion

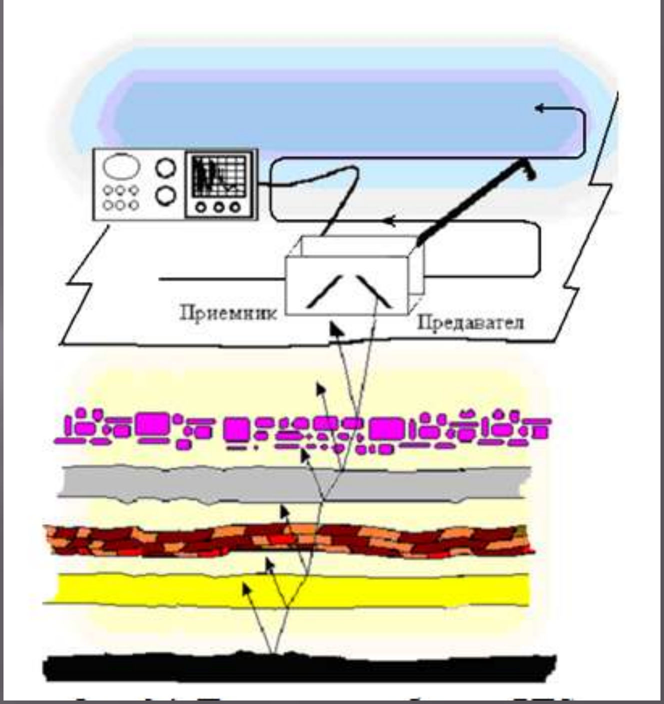
- Belief Propagation Nets
- Markov Random Fields
- Factor Graphs
- Game theory
- Expert systems

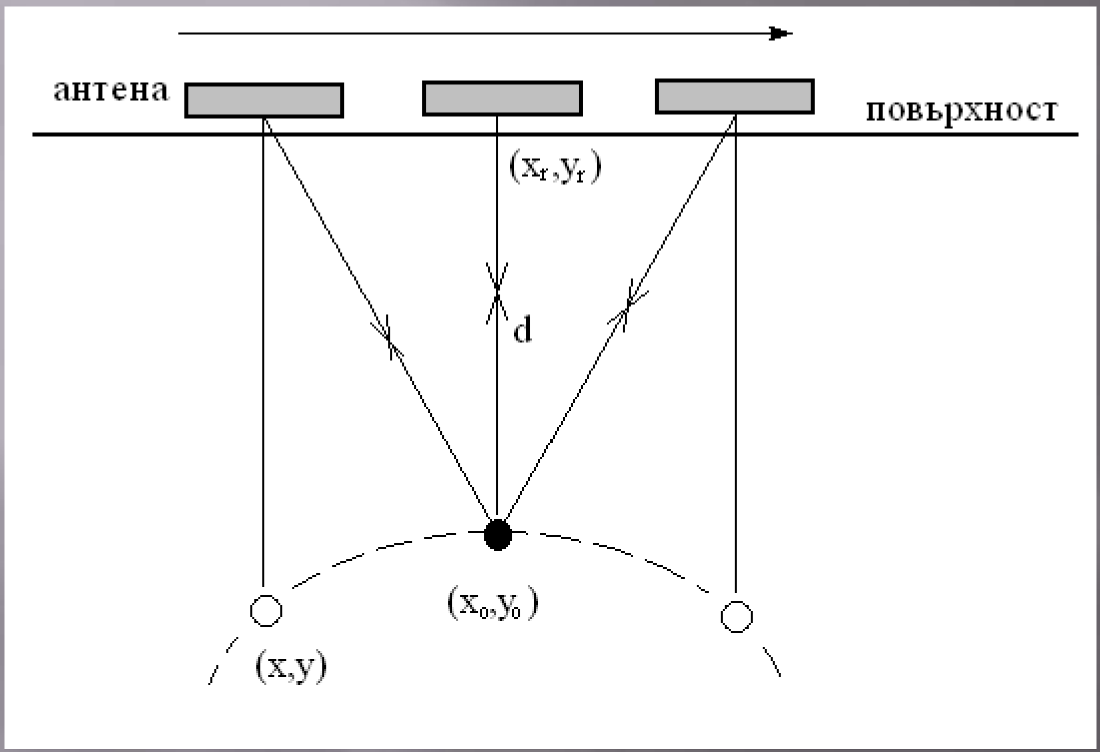
Examples

- Ground Penetrating Radar
- Bearing sensor fusion
- Prostate cancer detection;
- Superresolution
- 3D scene restoration
- Face detection and recognition

Ground Penetrating Radar

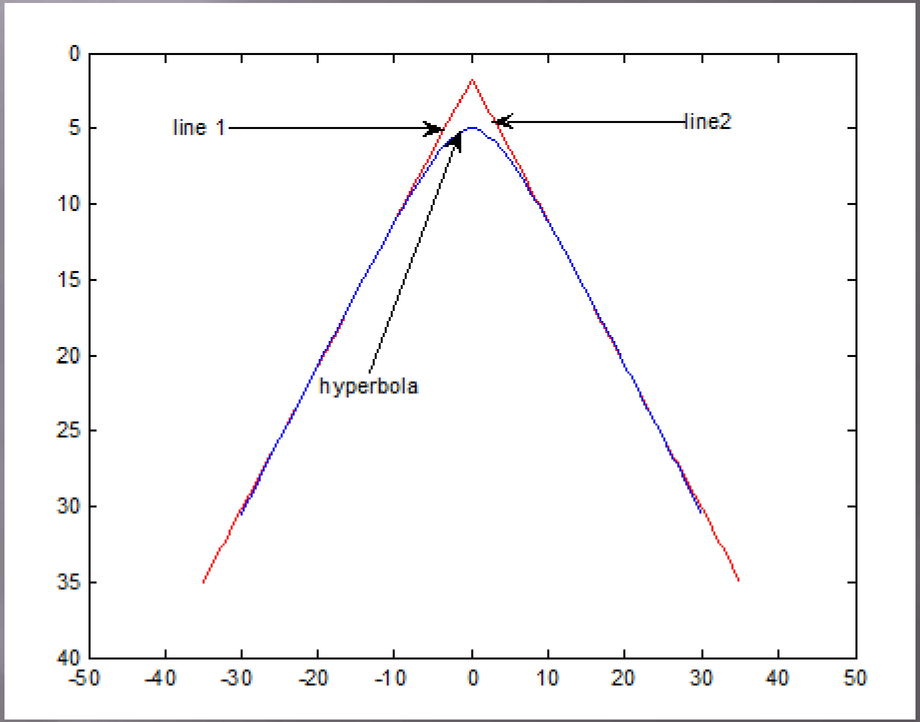


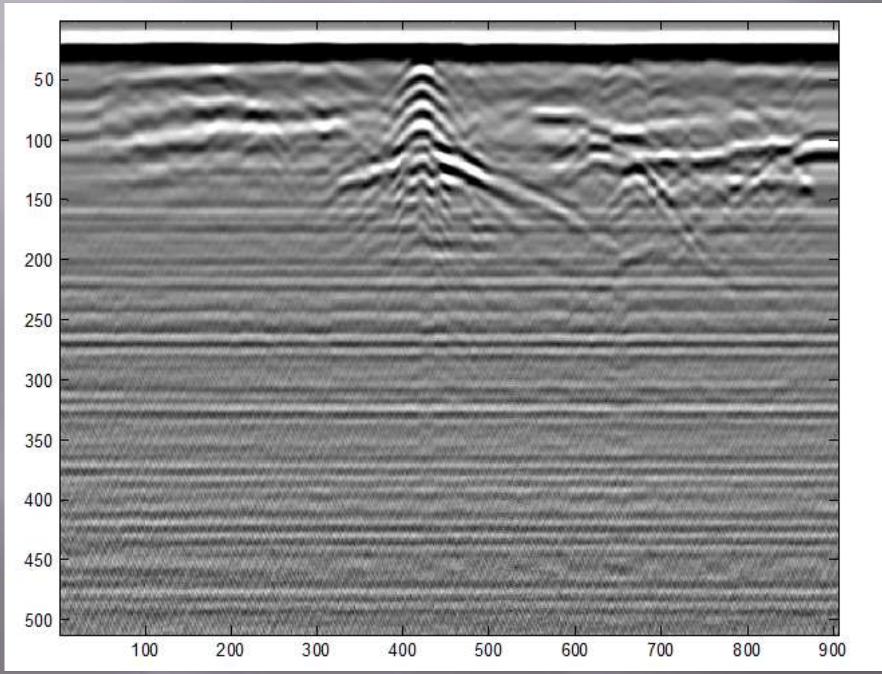


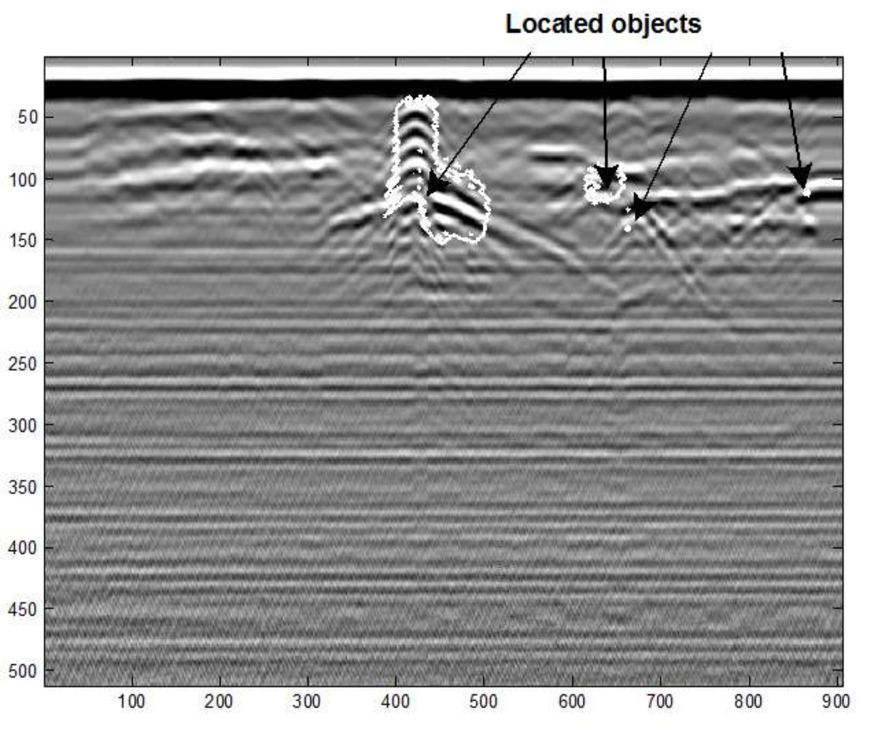


$$y(t_i) = \sqrt{\left(x_0 - x(t_i)\right)^2 + d_{\min}^2}$$

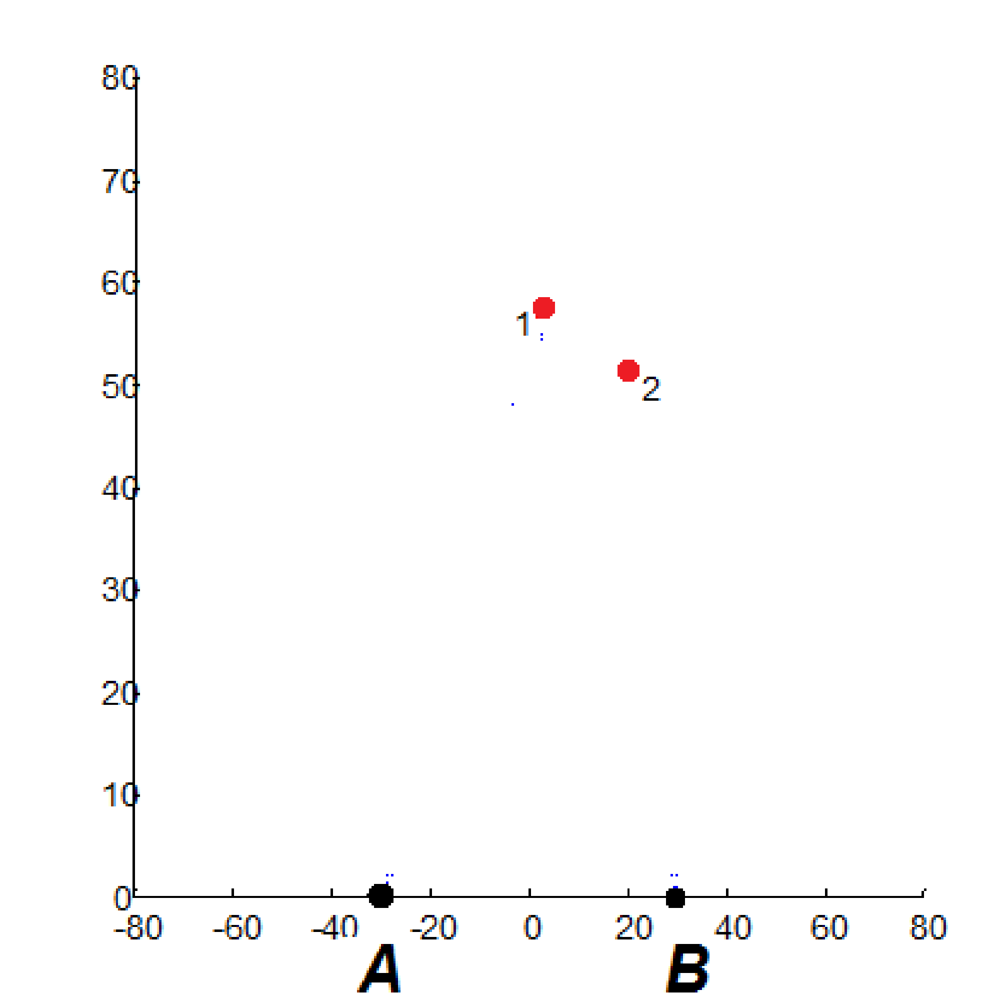
Object detection



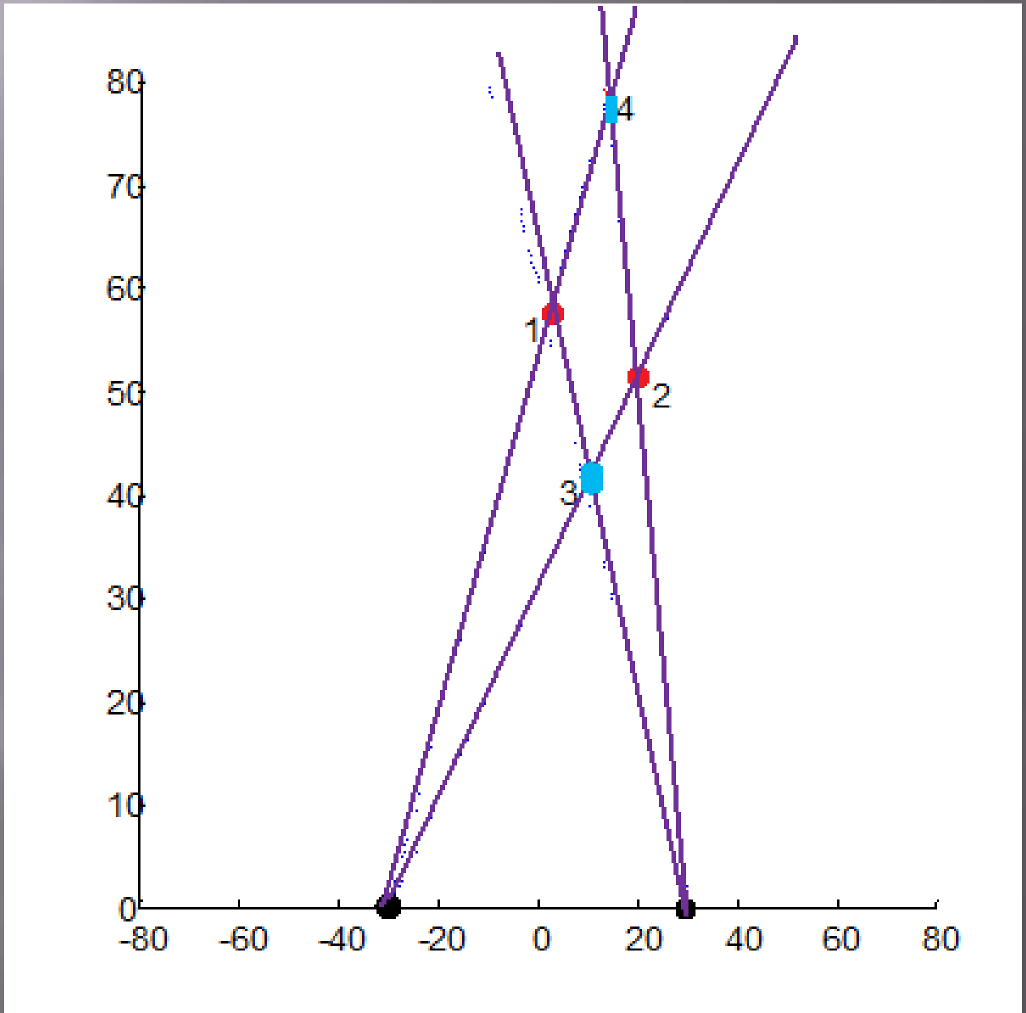

50
100
150
200
250
300
350
400
450
500
100
200
300
400
500
600
700
800
900


Located objects
50
100
150
200
250
300
350
400
450
500
100
200
300
400
500
600
700
800
900

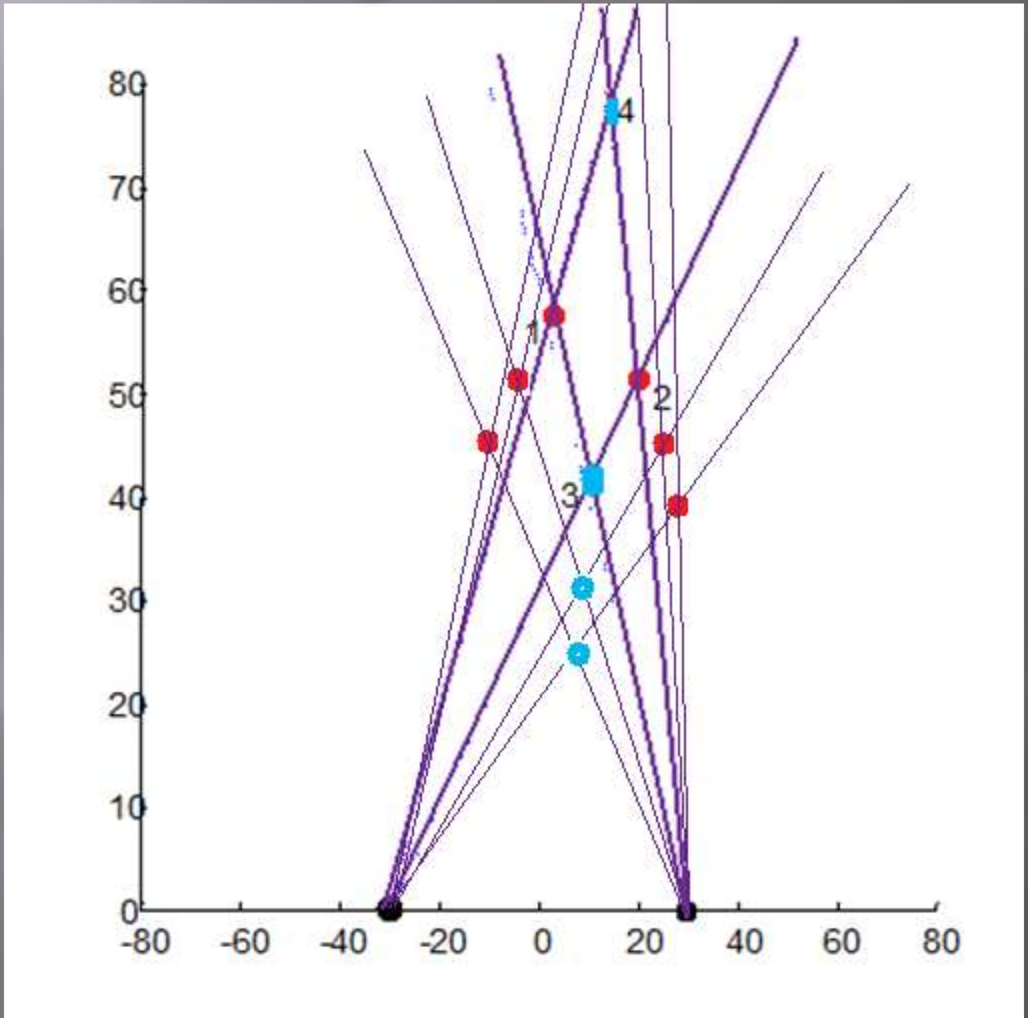
Bearing sensor fusion



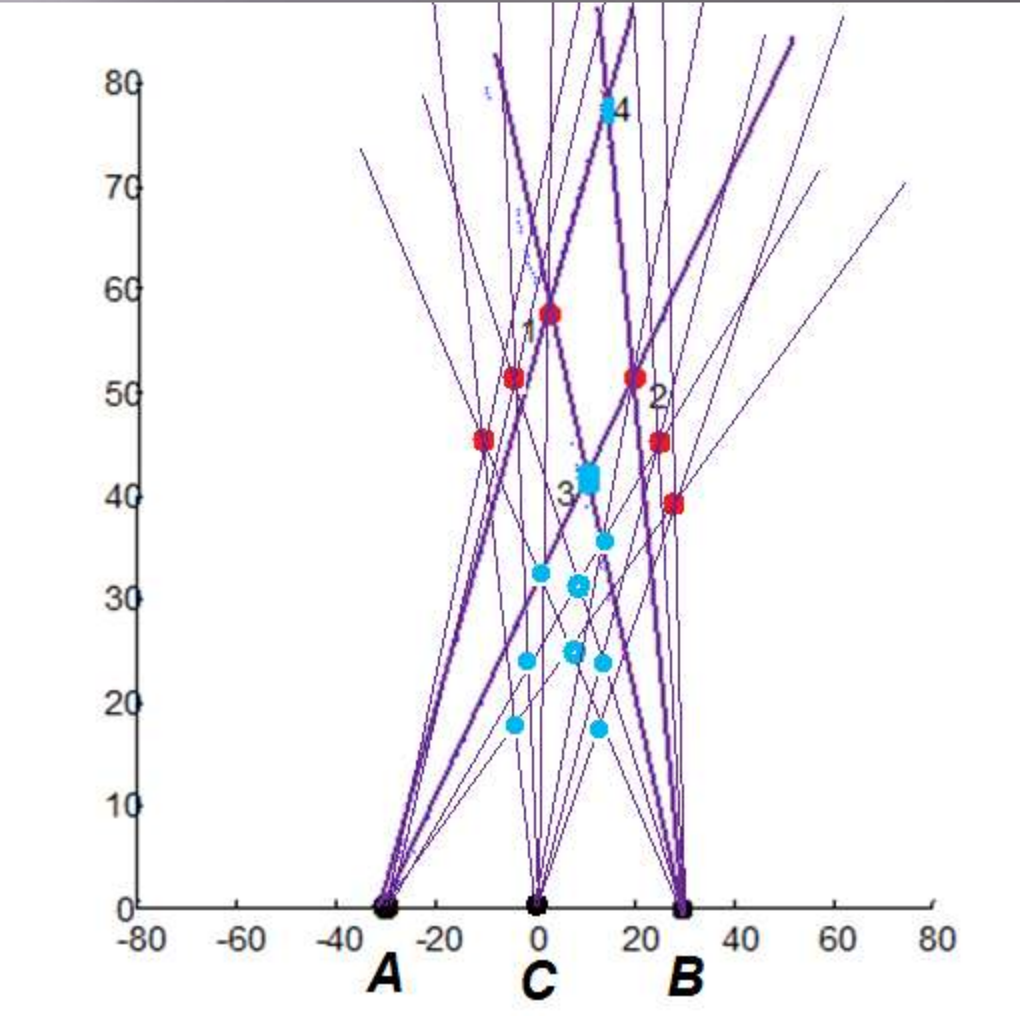
Bearing sensor fusion



Bearing sensor fusion



Bearing sensor fusion



Prostate image

How to process images

Usually, the normal prostate gland has a homogenous, uniform echo (**isoechoic**) pattern. A PCa may take on unique ultrasound findings. Most ultrasound-detected lesions found to be carcinoma are described as **hypoechoic regions with irregular borders**. However, this is **not a rule**.

It was reported by Lee et al, that 70%-80% of prostate cancers arise from the **peripheral zone** of the prostate, on the contrary of transition zone, which is the site of the location of benign prostatic hyperplasia.

The transition zone becomes moderately **hypoechoic** in comparison with the central and peripheral zones. The highest predictive values for prostate cancer are seen in **hypoechoic lesions** that are well defined and are **larger than 1 cm**.

However, **not all hypoechoic regions in the peripheral zone are prostate cancer**. Potential hypoechoic lesions also include **prostatitis, prostatic infarction, dilated glands, smooth muscle bundles, scarring, and prostatic intraepithelial neoplasia**.

The analysis shows, that effective image processing algorithms have **to reduce** the specific for ultrasound images **noise**, **discover hypoechoic regions in the peripherial zone, segment any irregularity, asymmetries and extensions and detect fields with higher blood flow**.

The methods for image quality improvement can be divided into four groups:

- ❑ Filtering
- ❑ Multi-level segmentation
- ❑ Texture analysis
- ❑ Doppler image segmentation

→ **Fusion**

Filtering procedures:

The most appropriate algorithms for noise reduction are smoothing filters. The linear filters suppress pixel noise but have poor edge-blurring effect. The nonlinear filters are especially chosen to preserve sharp edges simultaneously smoothing the surfaces.

Some of the available filters are: adaptive nonlinear Gaussian, anisotropic diffusion, combined stick filter, Kuwahara(1,2,3) and others. The most promising results were received for the images, processed by nonlinear Gaussian and dual tree complex wavelet filters.

Multi-level segmentation

Intends to differentiate the areas with different intensities.

Two algorithms were developed:

- Fast Otsu algorithm;
- LMQ (Lloyd-Max Quantizer) algorithm.

Two problems were solved :

- Suitable choice of the number of thresholds;
- Threshold’ values determination.

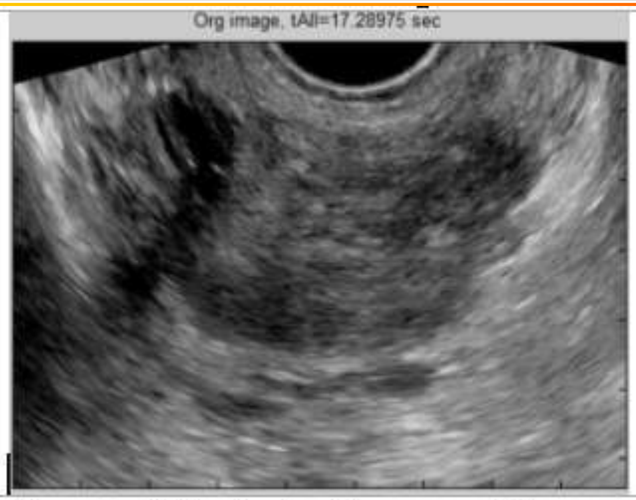
Texture analysis

Detects irregularities and anomalies in the prostate image on the base of automatic description of particular region.

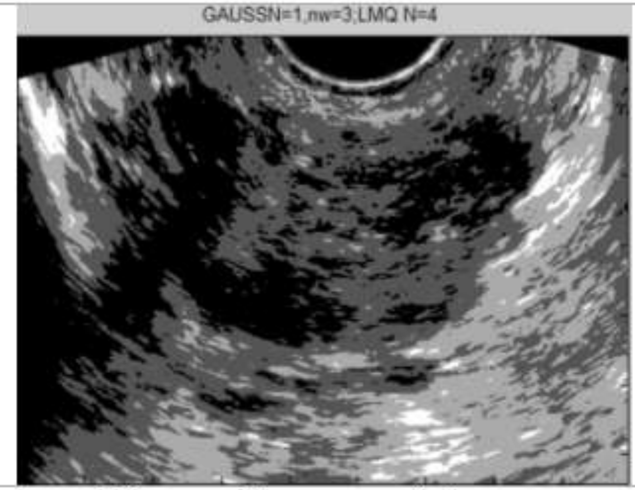
The so-called co-occurrence matrices are used. The analysis allows us to evaluate a number of coefficients, which characterize the texture of the analyzed image. The received values are deterministic, image dependent only and are not influenced by personal assessment. The image is segmented in the space of these parameters, using clusterization technique.

Doppler image segmentation

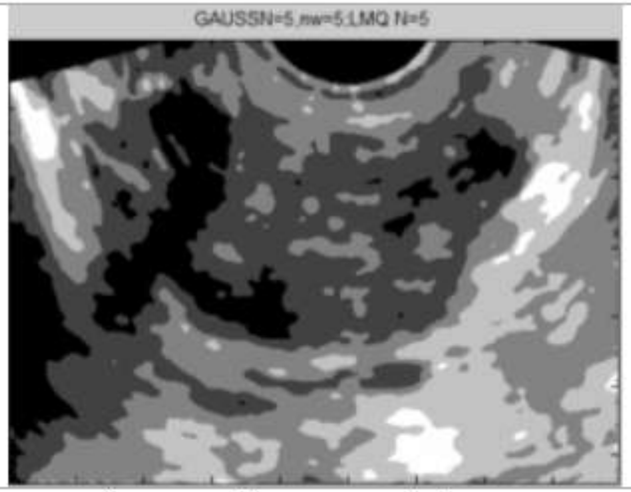
The proposed algorithm separates the areas of increased blood flow in the Doppler or Power Doppler images.



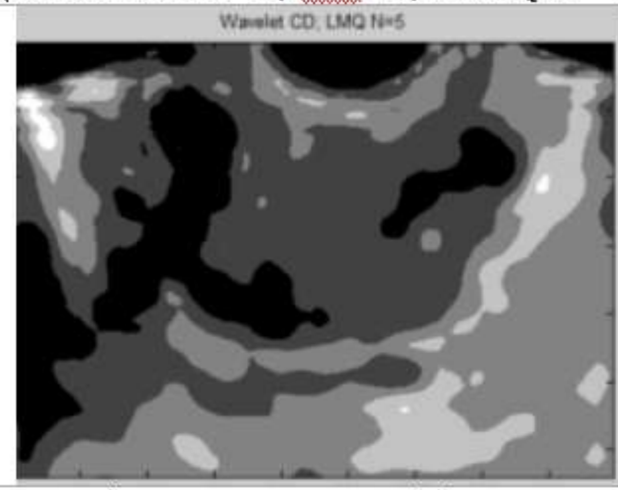
a) Original ultrasound image



b) Processed image (Gaussian N=1, nw=3, LMQ L=4)



c) Processed image (Gaussian N=5, nw=5, LMQ L=5)



d) Processed image (Wavelet C2D, LMQ L=5)

Superresolution


Channel

Superresolution

Let denote signal by $f \in R_n$. This signal can be decomposed in an arbitrary orthonormal basis $\Psi = [\psi_1 \psi_2 \ldots \psi_n]$ as follow:

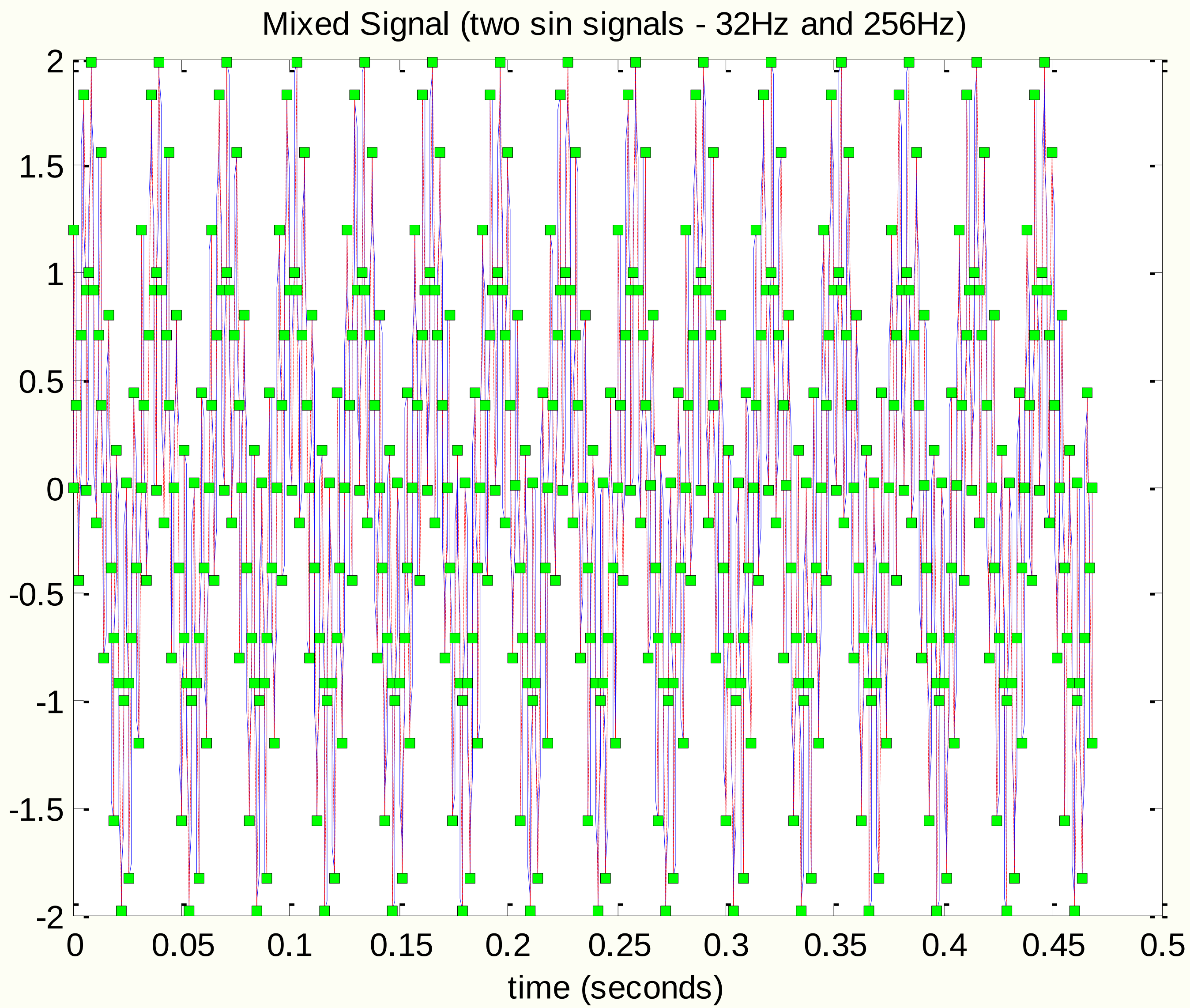
$$f(t) = \sum_{i=1}^{n} x_i \psi_i(t)$$,

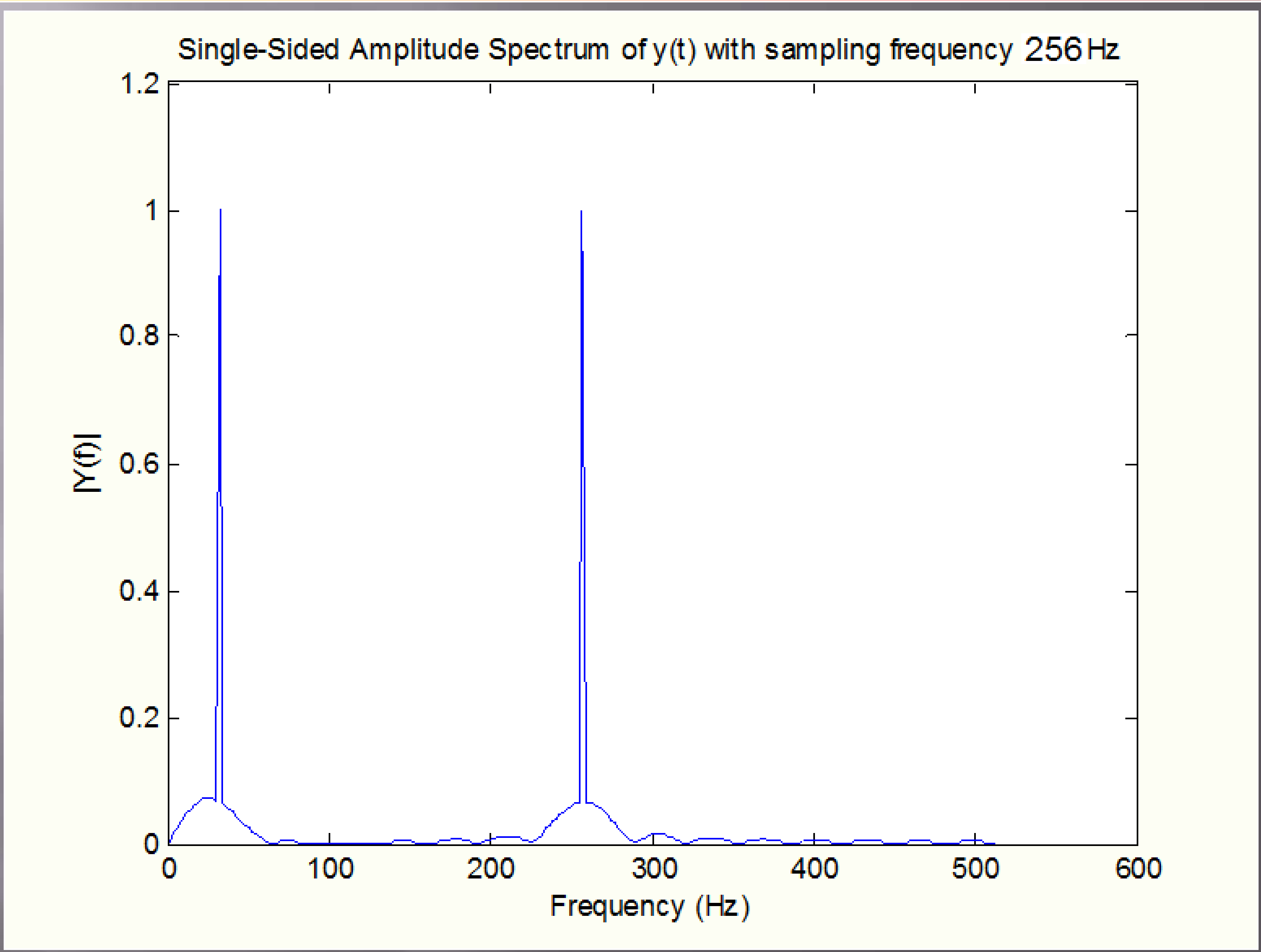
where $x_i = \langle f, \psi_i \rangle$ are the coefficients of the corresponding orthonormal functions.

„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:

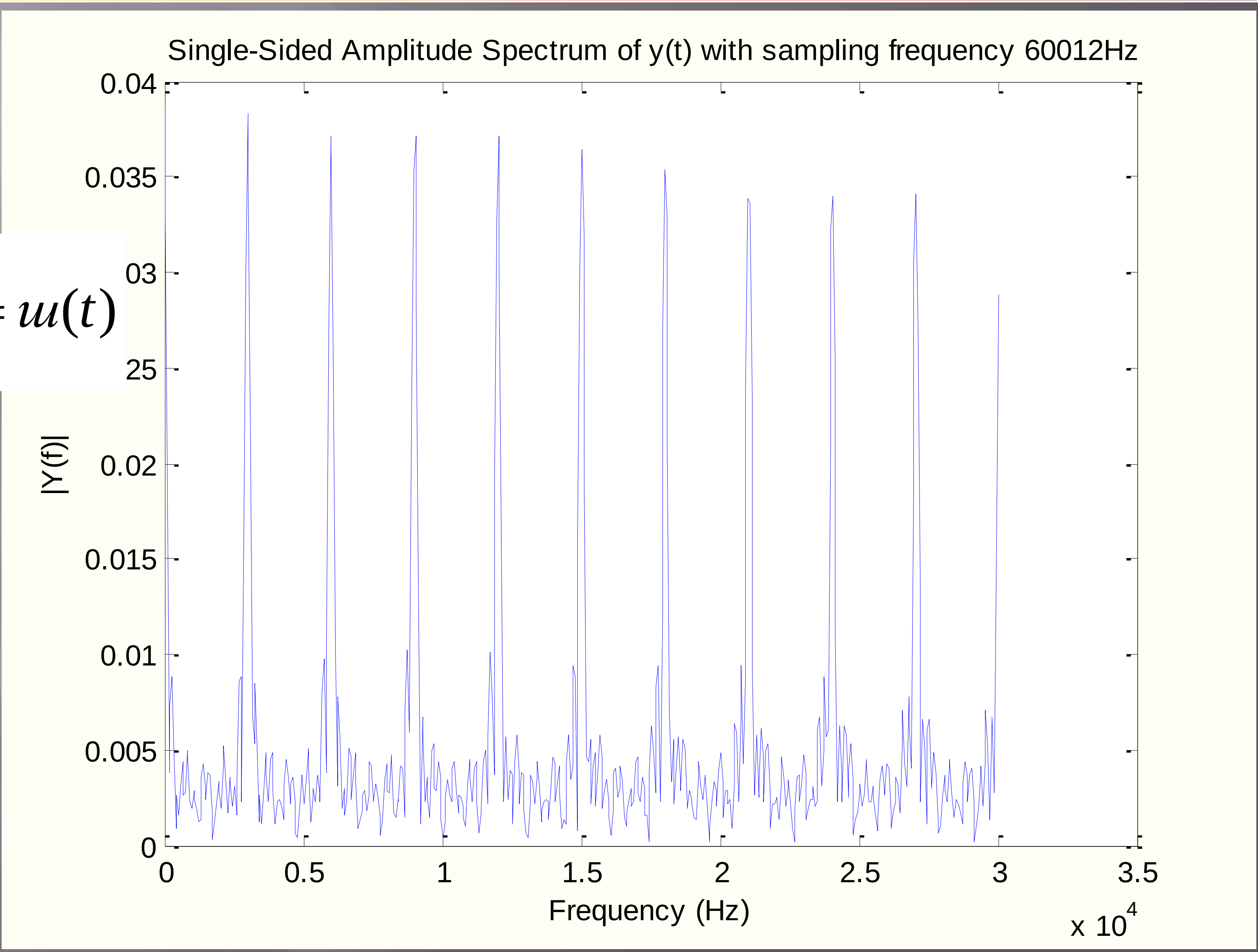
$$f_S(t) = \sum_{i \in S} x_i \psi_i(t)$$

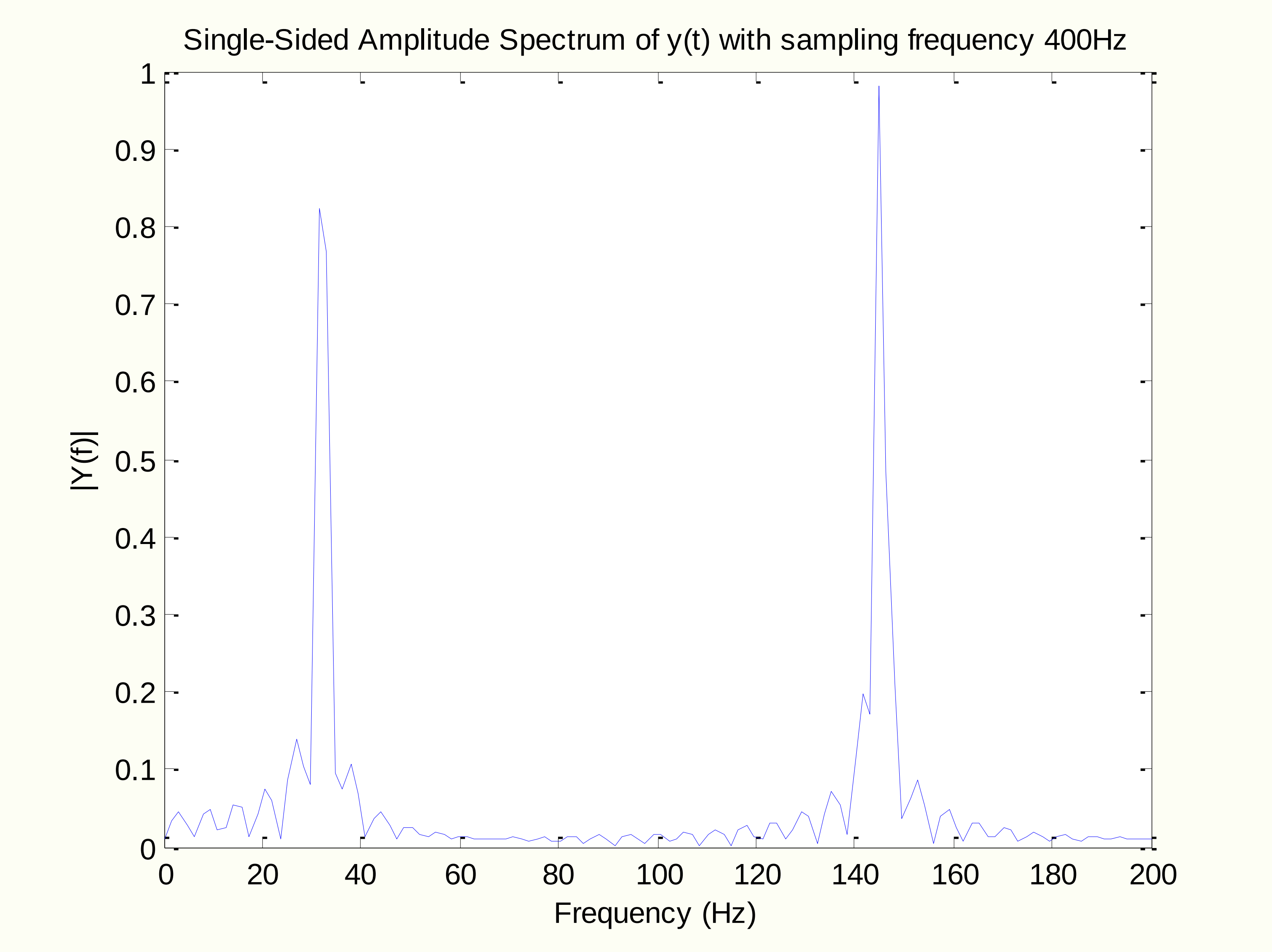
The signal $f \in R_n$ will be called *S* sparse, if f_S approximate very good f and the approximation error $\varepsilon = \| f - f_S \|_{l_2}$ is small enough. For audio- and video- signals it is well-known that only about 2.5% of the biggest coefficients may be used for signal recovery and the discrimination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

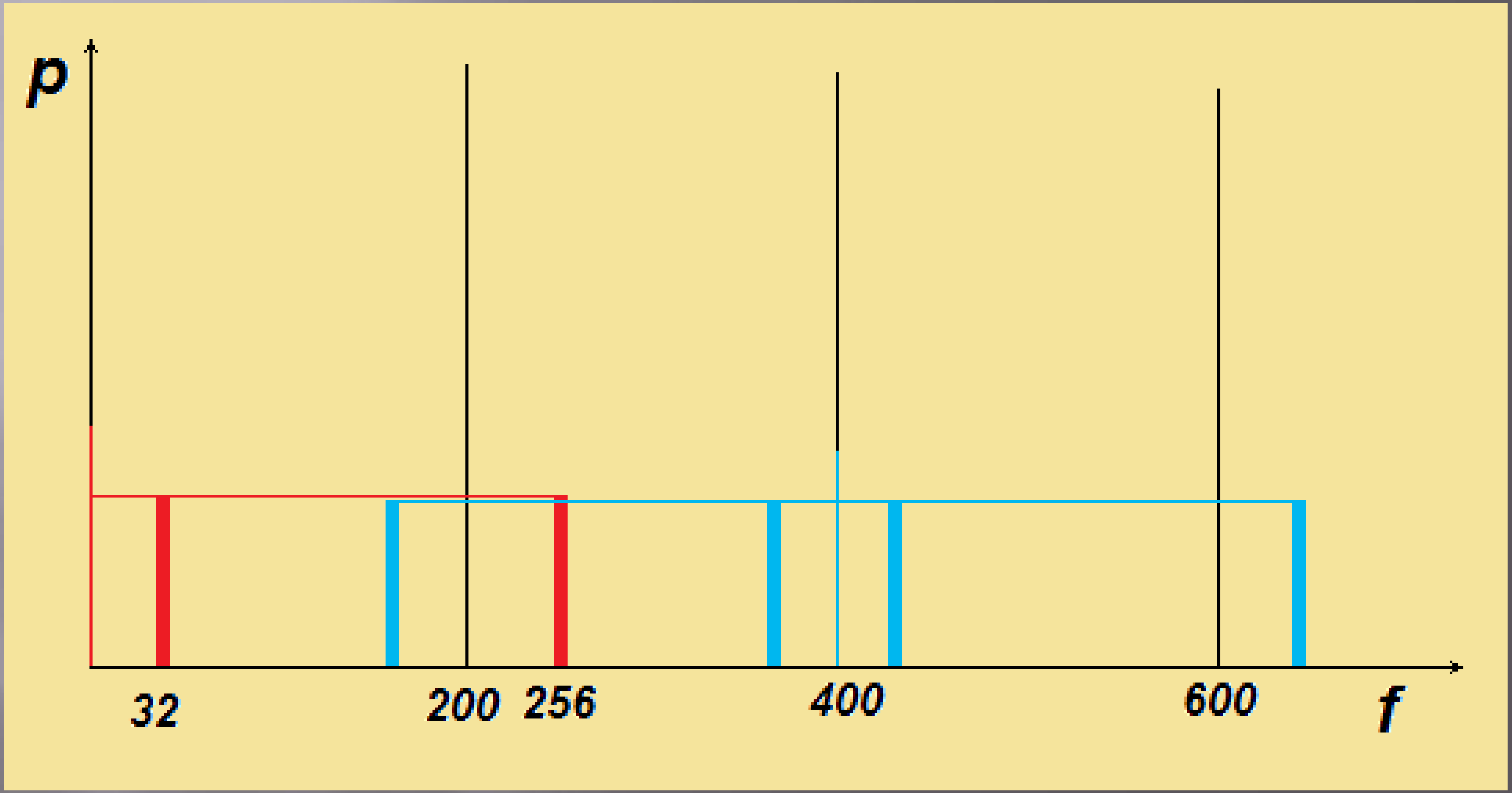

Mixed Signal (two sin signals - 32Hz and 256Hz)
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
time (seconds)


Single-Sided Amplitude Spectrum of y(t) with sampling frequency 256 Hz
|Y(f)|
Frequency (Hz)
1.2
1
0.8
0.6
0.4
0.2
0
0
100
200
300
400
500
600

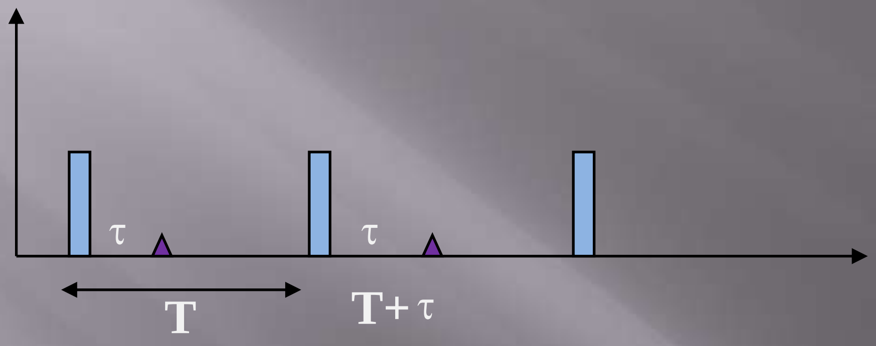
$$\sum_{i=-\infty}^{\infty} \delta(t - iT) = u(t)$$




Single-Sided Amplitude Spectrum of y(t) with sampling frequency 400Hz
|Y(f)|
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
20
40
60
80
100
120
140
160
180
200
Frequency (Hz)


p
32
200
256
400
600
f

How to use alias information?



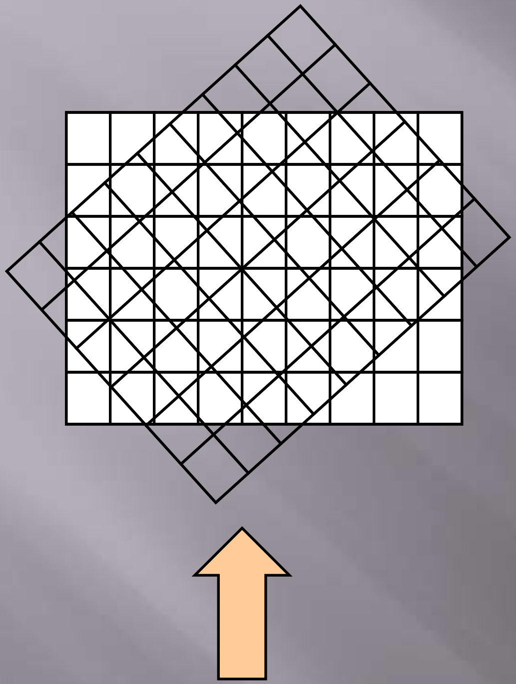
Solution (from radars): create second sampling pulse with different sampling rate

How to use alias information?

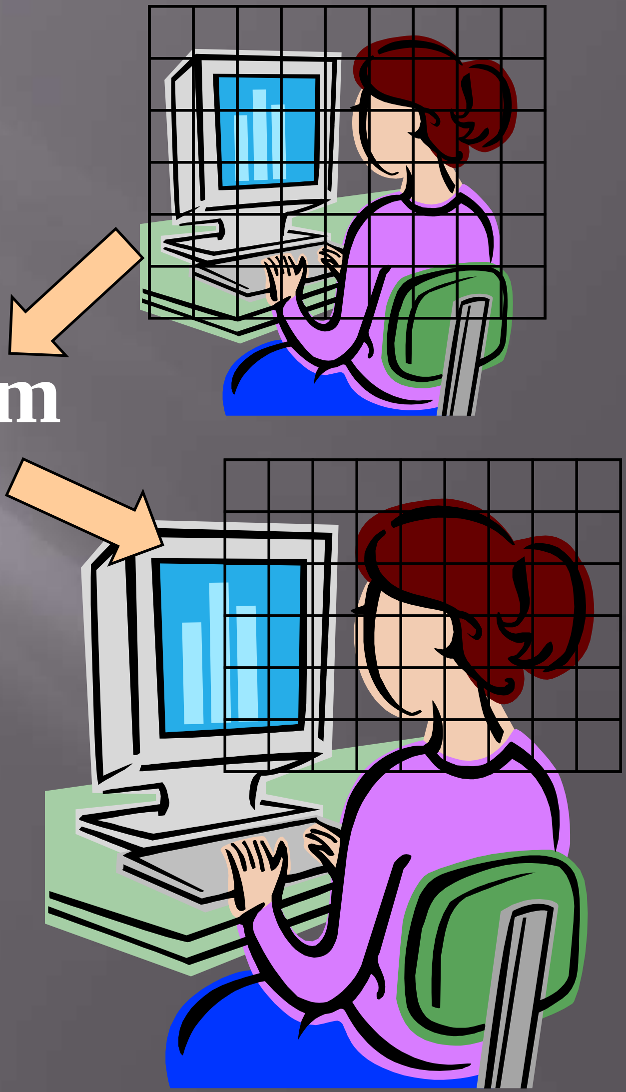
1. **Generate „in plane" camera rotation on random angle**

   (angle $\neq k\dfrac{\pi}{2}, \quad k = 1, 2, \ldots$ **). When such images are registered, the sampling rate is changed.**

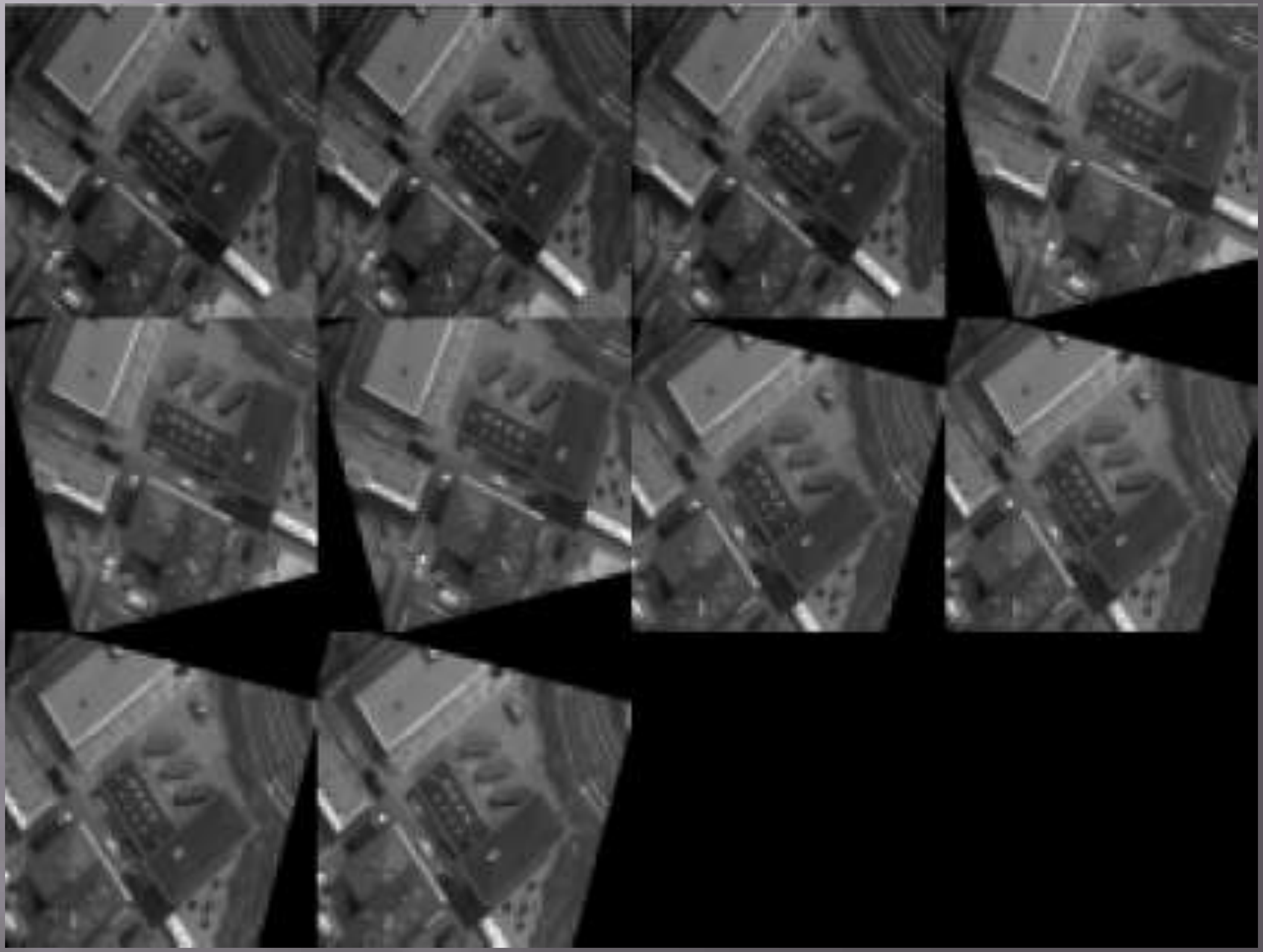
2. Using camera "zoom". The change of zoom rescale the scene in the same sampling rate, hence the sampling rate of one and same scene element is changed.



In plane rotation



Low-resolution images



Enhanced image

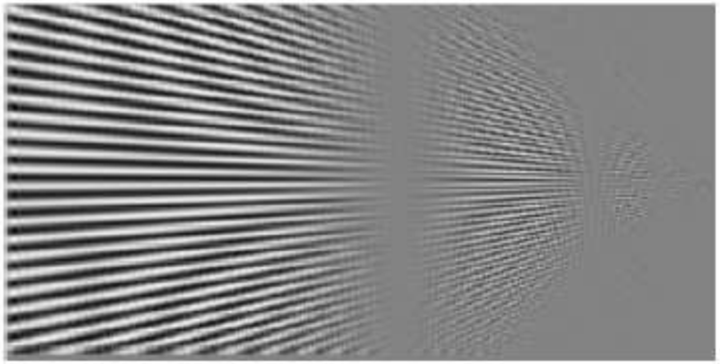


Figure 7: Restored 400x200 HR resolution test target image, no camera rotation

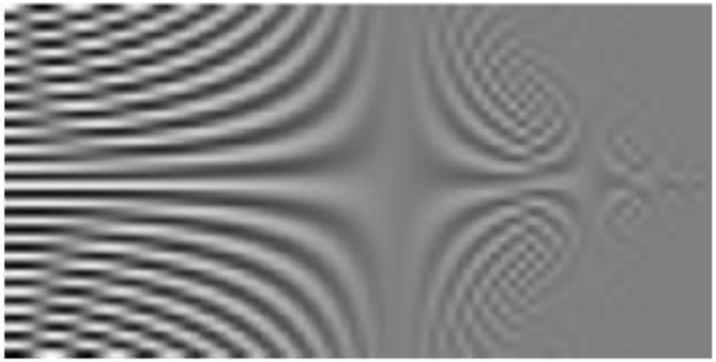


Figure 5: An 80x40 simulated LR resolution test target image

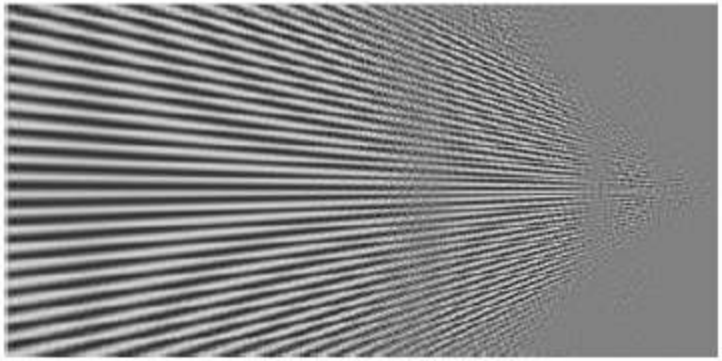


Figure 8: Restored 400x200 HR resolution test target image with camera rotation

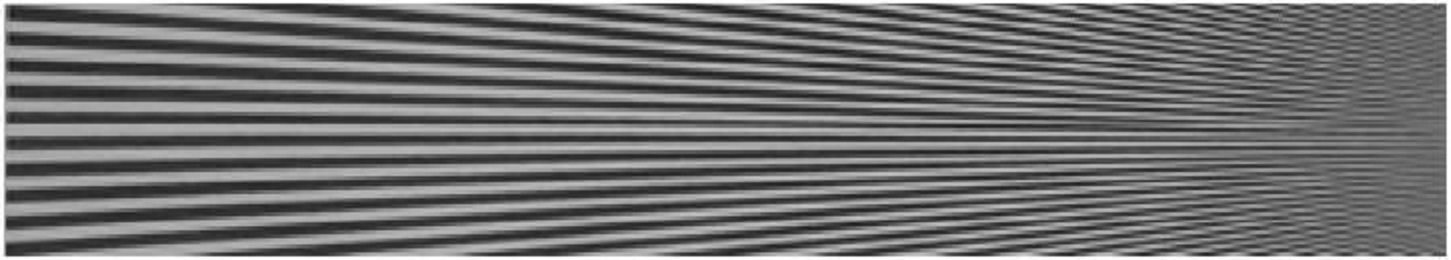


FIGURE 4. Very high resolution photo of a resolution test target (detail)

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

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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.

RELATED NEWS

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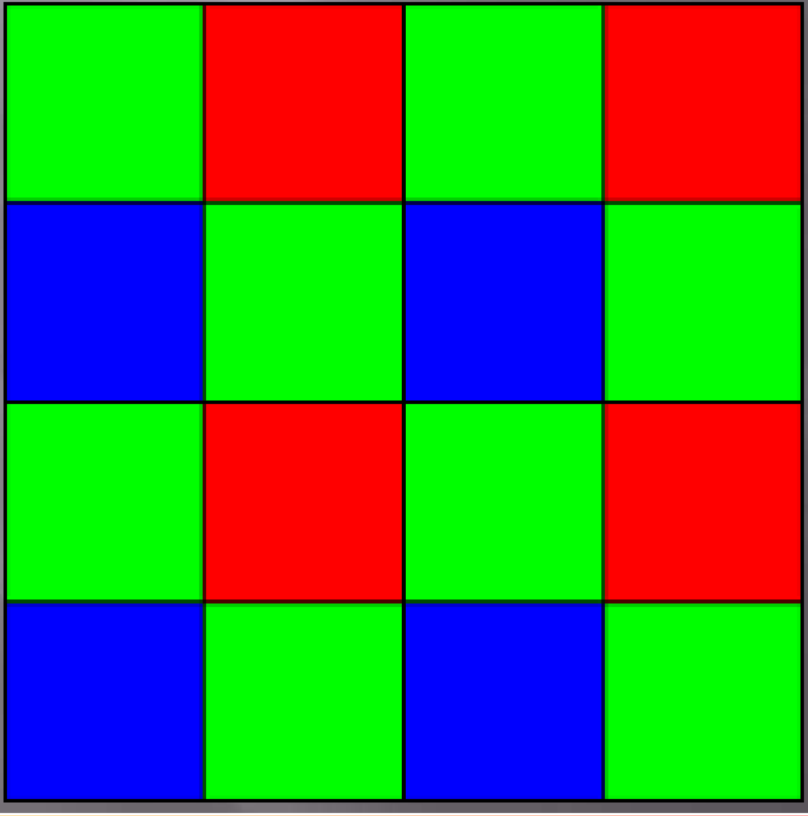
"We are creating aliasing—just what we teach EEs not to do," said Eldar. "We are folding the high-frequency signal into the lower-frequency domain, all aliased, but modulated by a known high-frequency signal. The key to the post-processing step is to recognize that all the information is still there,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

Bayer Filter

- Invented in 1976 by Bryce Bayer (Eastman Kodak);
- The most popular color filter array for cheaper systems



Compressive sensing

- David Donoho 2004 – 2006;
- Emamnuel J. Candès, Terry Tao 2004 - 2006;
- Richard G. Baraniuk 2007.

$$\mathrm{x} = \sum_{i=1}^{N} s_i \psi_i$$

If K coefficiens of s_i are nonzero and K<<N the signal x is called K-sparse and it is compressible.

THEOREM 1 [10]

Fix $f \in \mathbb{R}^n$ and suppose that the coefficient sequence x of f in the basis Ψ is S-sparse. Select m measurements in the Φ domain uniformly at random. Then if

$$m \geq C \cdot \mu^2(\Phi, \Psi) \cdot S \cdot \log n \qquad (6)$$

for some positive constant C, the solution to (5) is exact with overwhelming probability. (It is shown that the probability of success exceeds $1 - \delta$ if $m \geq C \cdot \mu^2(\Phi, \Psi) \cdot S \cdot \log(n/\delta)$. In addition, the result is only guaranteed for nearly all sign sequences x with a fixed support, see [10] for details.)

1) The role of the coherence is completely transparent; the smaller the coherence, the fewer samples are needed, hence our emphasis on low coherence systems in the previous section.

IEEE SIGNAL PROCESSING MAGAZINE [21] MARCH 2008 comparably small). We do not know which frequencies are active nor do we know the amplitudes on this active set. Because the active set is not necessarily a subset of consecutive integers, the Nyquist/Shannon theory is mostly unhelpful (since one cannot restrict the bandwidth a priori, one may be led to believe that all n time samples are needed). In this special instance, Theorem 1 claims that one can reconstruct a signal with arbitrary and unknown frequency support of size S from on the order of $S \log n$ time samples, see [1]. What is more, these samples do not have to be carefully chosen; almost any sample set of this size will work. An illustrative example is provided in Figure 2. For other types of theoretical results in this direction using completely different ideas see [11]–[13].

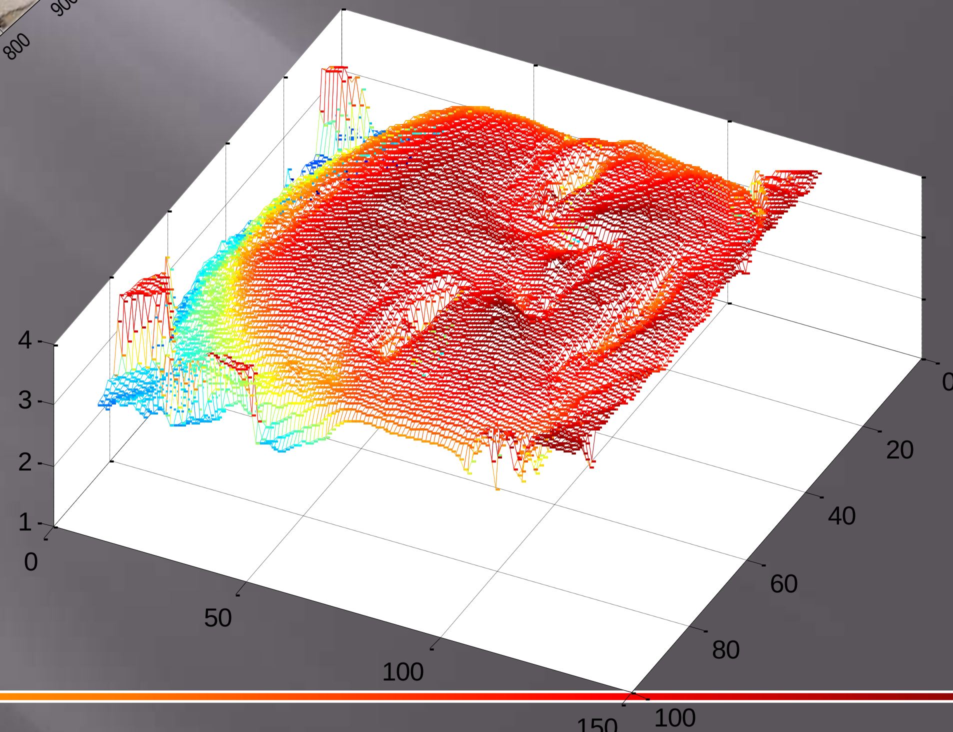
Laurent Condat
A NEW RANDOM COLOR FILTER ARRAY WITH GOOD SPECTRAL PROPERTIES

3D scene reconstruction is important for:

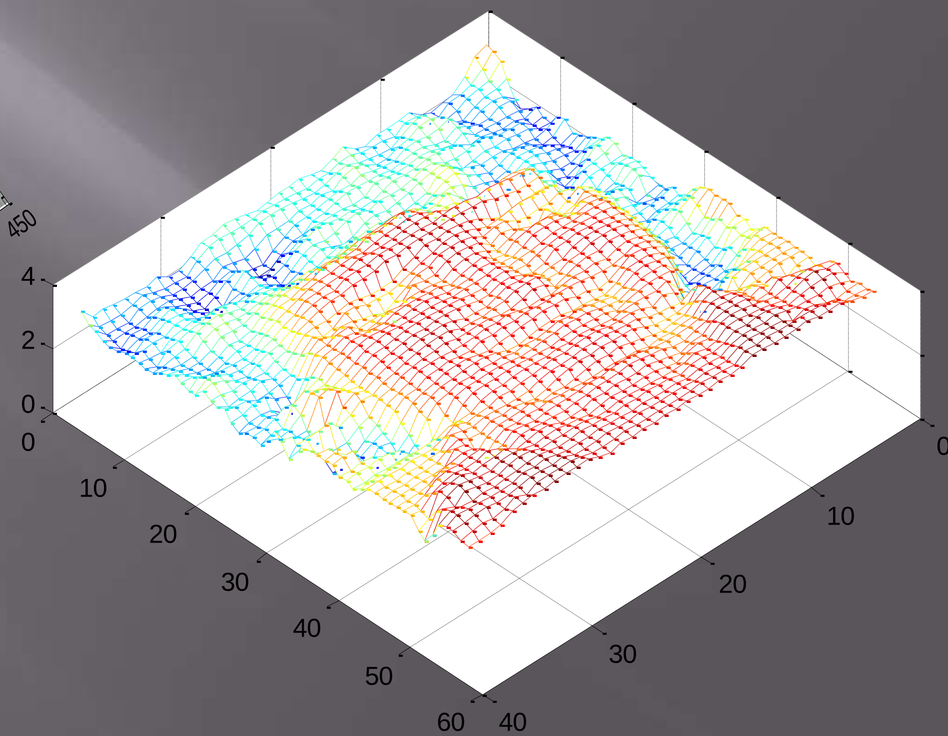
- Object localization;
- Object tracking;
- Discovering space-time relations between participants in the scene;
- Object behavior estimation;
- Future events prediction.

3D scene recovery

Depth recovery from texture



Depth recovery from texture



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

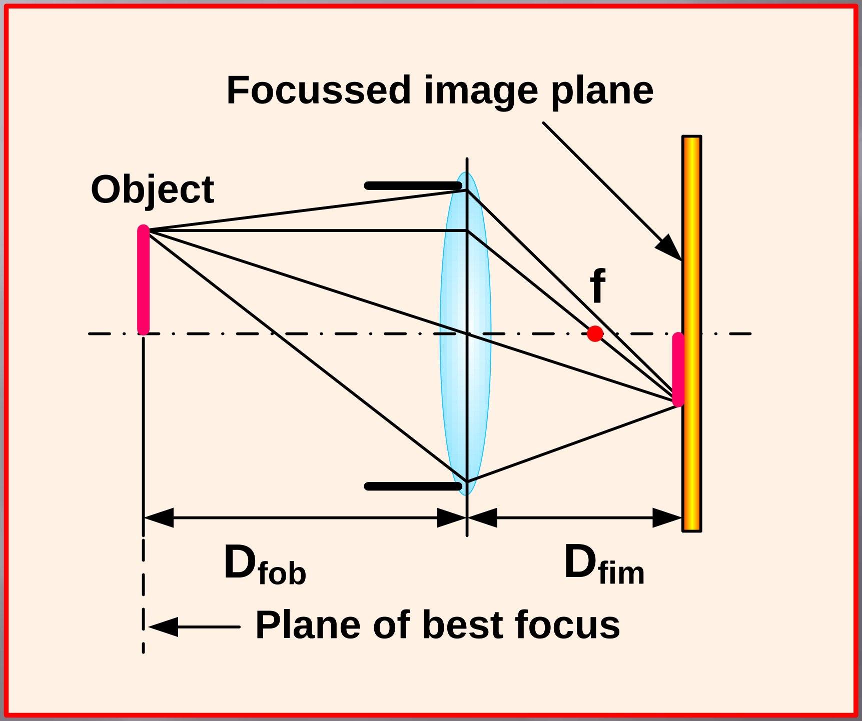
The algorithm steps:

- Several frames (2-8) are required from camera on one and same scene. Each frame is acquired for a different camera focus;
- 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).

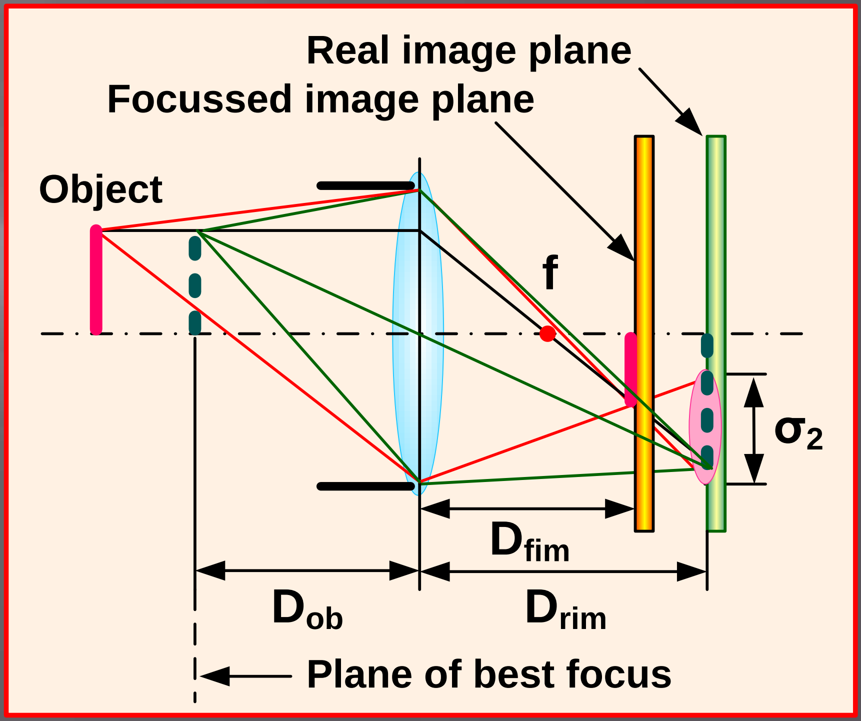
Blur spot diameter estimation

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.

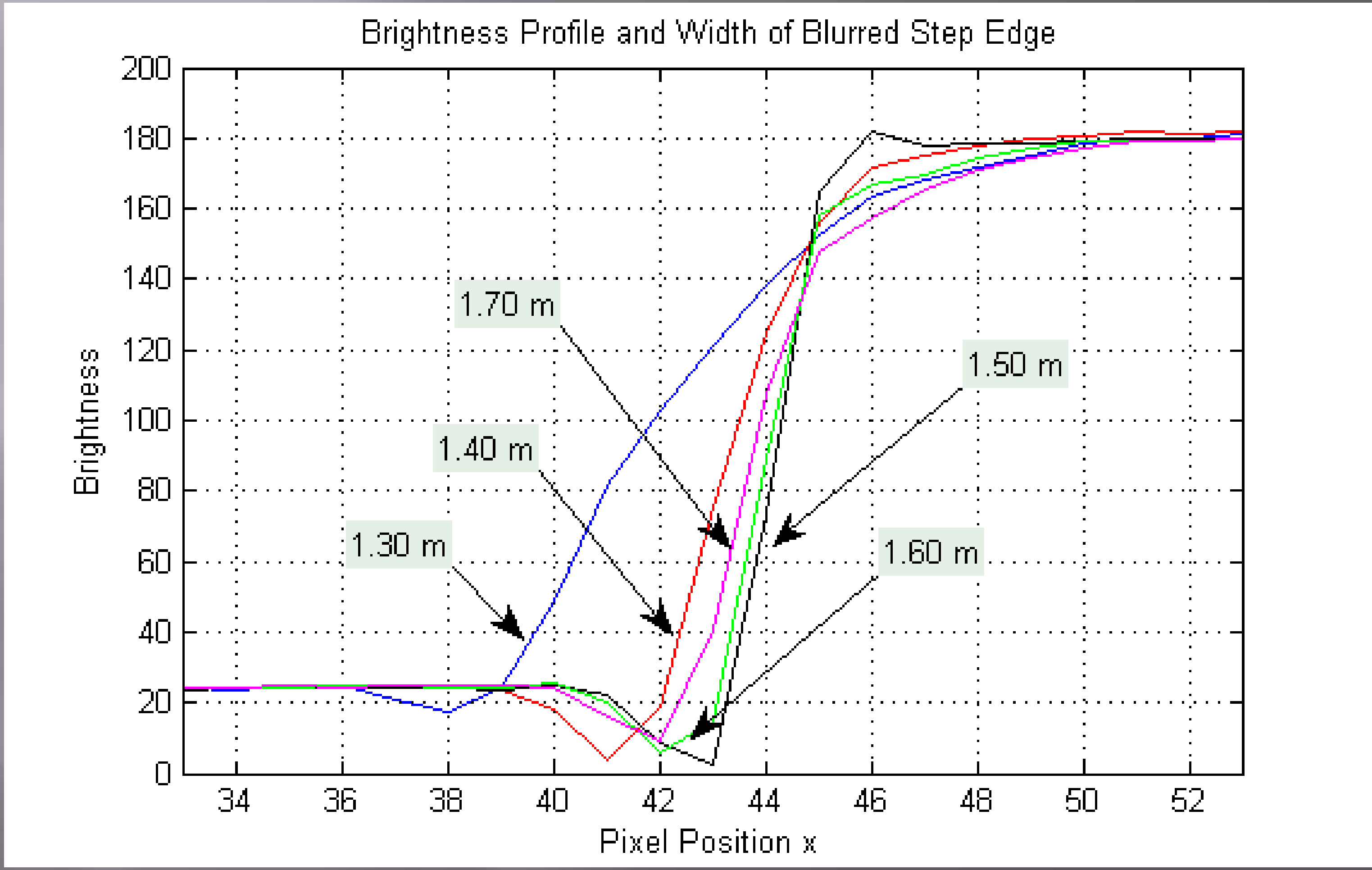
Focused object



Object out of focus



Blur spot diameter estimation



Mathematical model of defocus blur

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

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

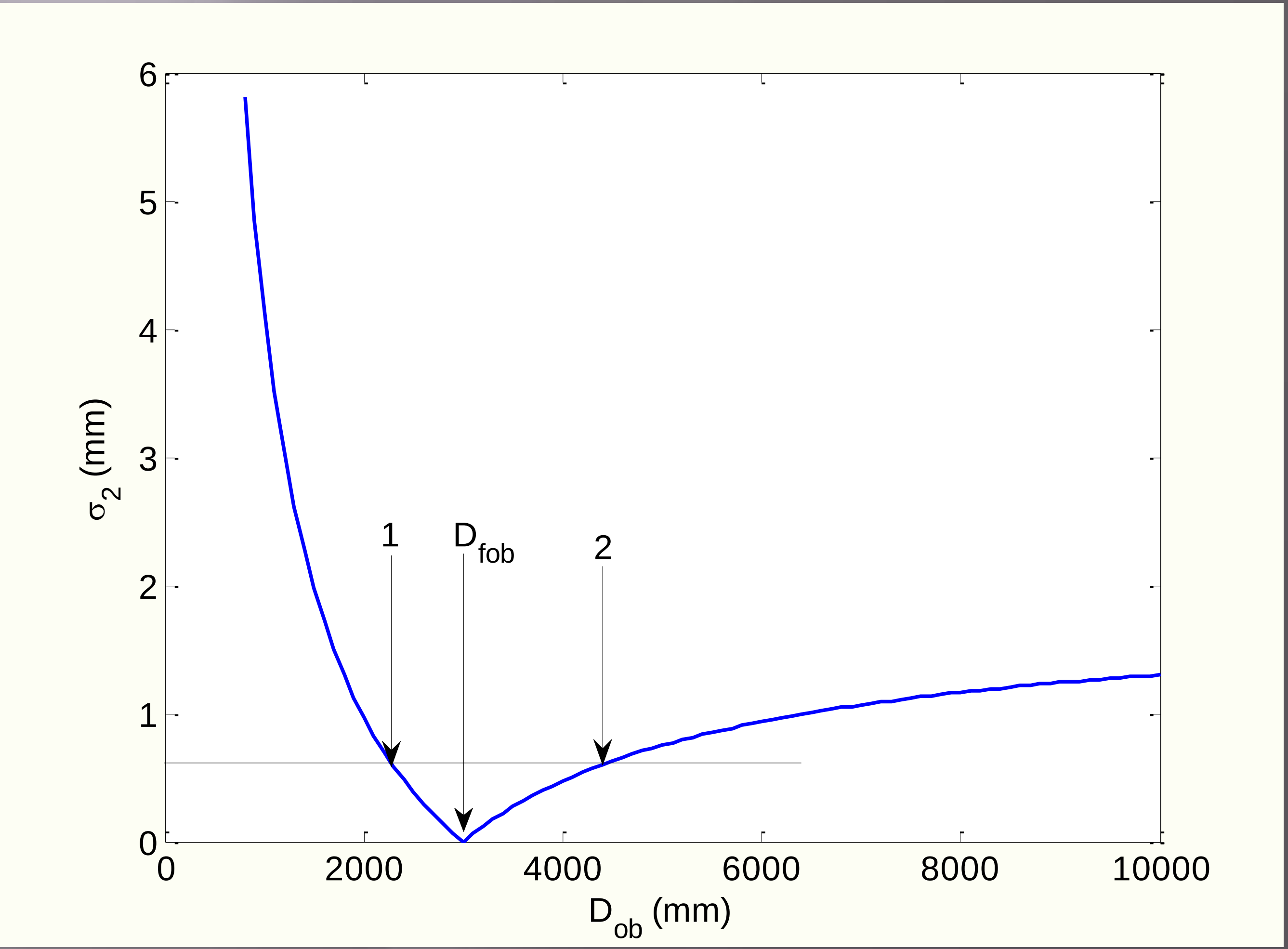
$$D_{fim} = \frac{fD_{fob}}{D_{fob} - f}$$

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

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

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

Mathematical model of defocus blur



Experimental results

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		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Face detection and recognition

- Viola-Jones face detection algorithm [1];
- Principal Component Analysis (PCA) or Eigenvalue method for face recognition.

[1] Paul Viola, Michael Jones, “Robust Real-time Object Detection”, Second International Workshop on Statistical and Computational Theories of Vision - Modeling, Learning, Computing, and Sampling.
[2] M. Turk and A. Pentland, “Eigenfaces for Recognition”, Journal of Cognitive Neuroscience, vol. 3, No 1, 1991.
[3] Javier Ruiz-del-Solar, P. Navarrete, “Eigenspace-based Face Recognition: A comparative study of different approaches”, IEEE Transactions on Systems, Man & Cybernetics, Part C., Vol. 16, No. 7, 817-830, 2002.
[4] B. A. Draper, K. Baek, M. S. Bartlett, J. R. Beveridge, “Recognizing faces with PCA and ICA”, Computer Vision and Image Understanding, vol. 91 , Issue 1-2, July, 2003.

Viola-Jones Detection Algorithm

Viola-Jones algorithm decompose the image in Haar-like wavelet space and determine the closeness to the searched object. The typical Voila-Jones features are displayed on fig. 1. A cascade algorithm is used to speed up the algorithm (fig. 2). A variant of AdaBoost learning algorithm is implemented to select the best features and to train classifier to use them.

Fig.1 Voila-Jones features

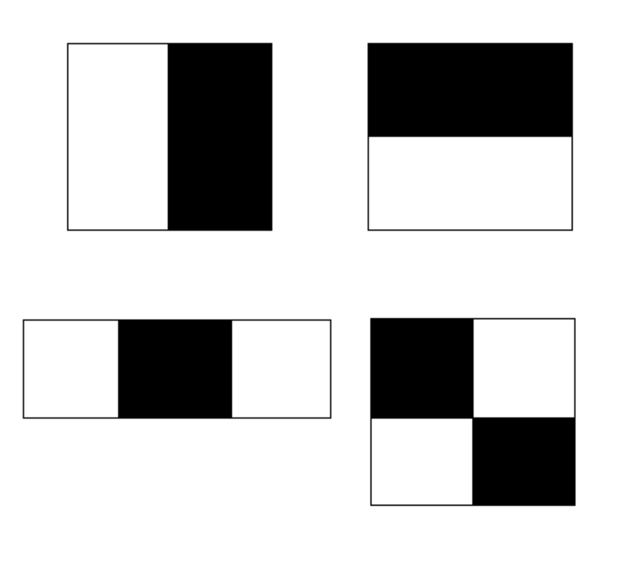
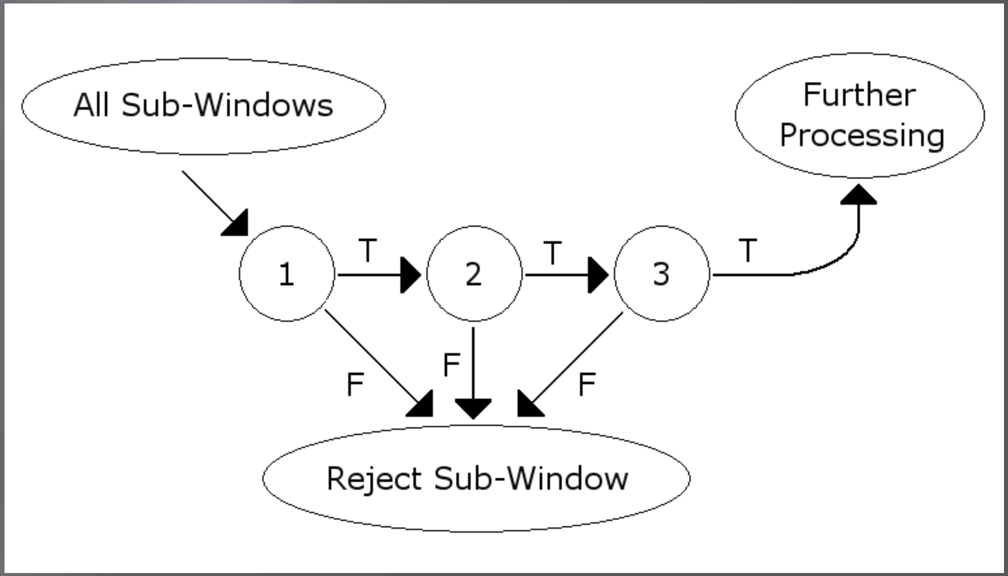


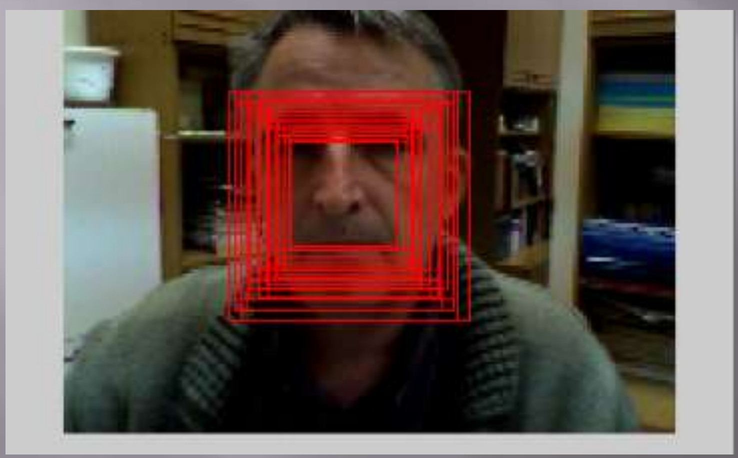
Fig.2 Voila-Jones cascade algorithm



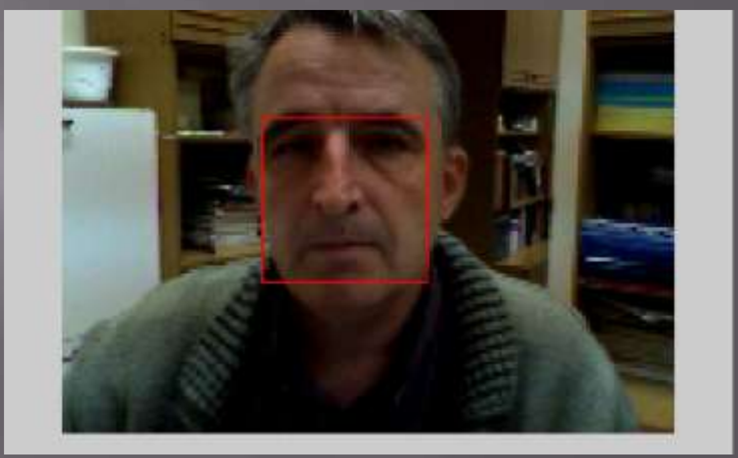
Face Detection Algorithm

Multiple object detection

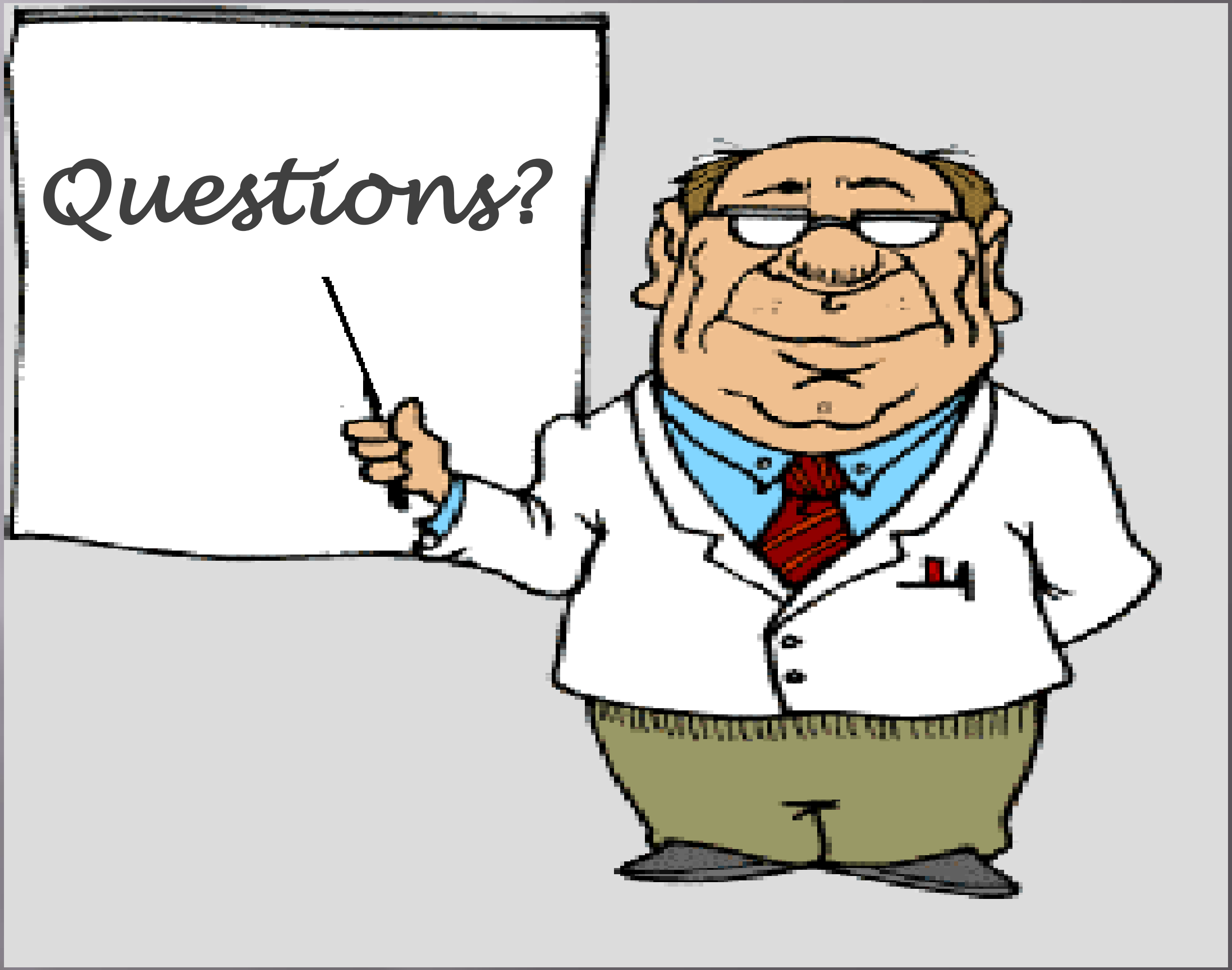
Face Detection Algorithm



a) Multiple detections of one face



b) Finally detected face


Questions?