

Motivation and goals

CS-ICT project aimed at developing of **advanced signal processing algorithms and methods**, which are used in practical signal processing application. The idea was to design interesting applications in order to become the most attractive and competitive laboratory for considered research field.

The project was focused to the development of new algorithms and techniques for **compressive sampling/sensing and spectral analysis of signals**.

The number of measurement per time or space unit is defined by the fundamental theorem in the communications which has been known as the **Sampling Theorem**. Very often in real situations we are faced with the great amount of data which requires the complex and demanding algorithms for data compression.

Compressive sensing is a concept that opens the possibility to **acquire a significantly smaller amount of data**, but to be able to achieve the same quality of the final information as it is the case when the entire physical phenomenon is sensed. The research efforts are made to simplify the very expensive devices and apparatus for data recording, imaging, sensing (for instance **MRI scanners**, **PET scanners** for Computed tomography, **high resolution cameras**, etc.).

Theory/Approach/ Methodology

Compressive Sensing (CS)

CS is method that **allows reconstruction of sparse signals by using a small set of available samples** (incomplete dataset). The incomplete dataset can be described by a measurement vector \mathbf{y} and matrix Φ that models a random selection of the signal samples: $\mathbf{y} = \Phi \mathbf{x}$

Sparsity condition is assumed to be satisfied in a certain transform domain Ψ . The signal \mathbf{x} is represented as $\mathbf{x} = \Psi \mathbf{X}$, where \mathbf{X} are transform domain coefficients:

$$\mathbf{y} = \Phi \Psi \mathbf{X} = \mathbf{A} \mathbf{X} \quad \text{CS matrix}$$

The **sparsest solution** of the undetermined equation can be found by using **optimization algorithms (e.g l1 norm minimization)**.

$$\min \|\mathbf{X}\|_{\ell_1} \quad \text{subject to } \mathbf{y} = \mathbf{A} \mathbf{X} \quad \leftarrow \text{L1 minimization}$$

New algorithms developed: Adaptive gradient based algorithm (GA)

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1: Set  $i=0$  and  $y^{(0)}(n) \leftarrow y(n)$ 
2: Set  $\Delta \leftarrow \max |y^{(0)}(n)|$ 
5: repeat
6:   Set  $y_p(n) = y^{(i)}(n)$ 
7:   repeat
8:      $i \leftarrow i+1$ 
9:     for  $n_s \leftarrow 0$  to  $N-1$  do
10:      if  $n_s \in \mathbf{N} \setminus \mathbf{N}_M$  then
11:         $x^+(k) \leftarrow \text{DFT} \{y^{(i)}(n) + \Delta \delta(n - n_s)\}$ 
12:         $x^-(k) \leftarrow \text{DFT} \{y^{(i)}(n) - \Delta \delta(n - n_s)\}$ 
13:         $G^{(i)}(n_s) \leftarrow \frac{1}{N} \sum_{k=0}^{N-1} |x^+(k)| - |x^-(k)|$ 
14:      else
15:         $G^{(i)}(n_s) \leftarrow 0$ 
16:      end if
17:       $y^{(i+1)}(n_s) \leftarrow y^{(i)}(n_s) - G^{(i)}(n_s)$ 
18:    end for
19:     $\beta_i = \arccos \frac{\langle \mathbf{G}^{i-1}, \mathbf{G}^i \rangle}{\|\mathbf{G}^{i-1}\|_2 \|\mathbf{G}^i\|_2}$ 
20:    until  $\beta_i < 170^\circ$ 
21:     $\Delta \leftarrow \Delta / \sqrt{10}$ 
22:     $\Xi = 10 \log_{10} \frac{\sum_{n \in \mathbf{N} \setminus \mathbf{N}_M} |y_p(n) - y^{(i)}(n)|^2}{\sum_{n \in \mathbf{N} \setminus \mathbf{N}_M} |y^{(i)}(n)|^2}$ 
23:  until  $\Xi < \Xi_{\max}$ 
24: return  $y^{(i)}(n)$ 
return: reconstructed signal  $y^{(i)}(n)$ 

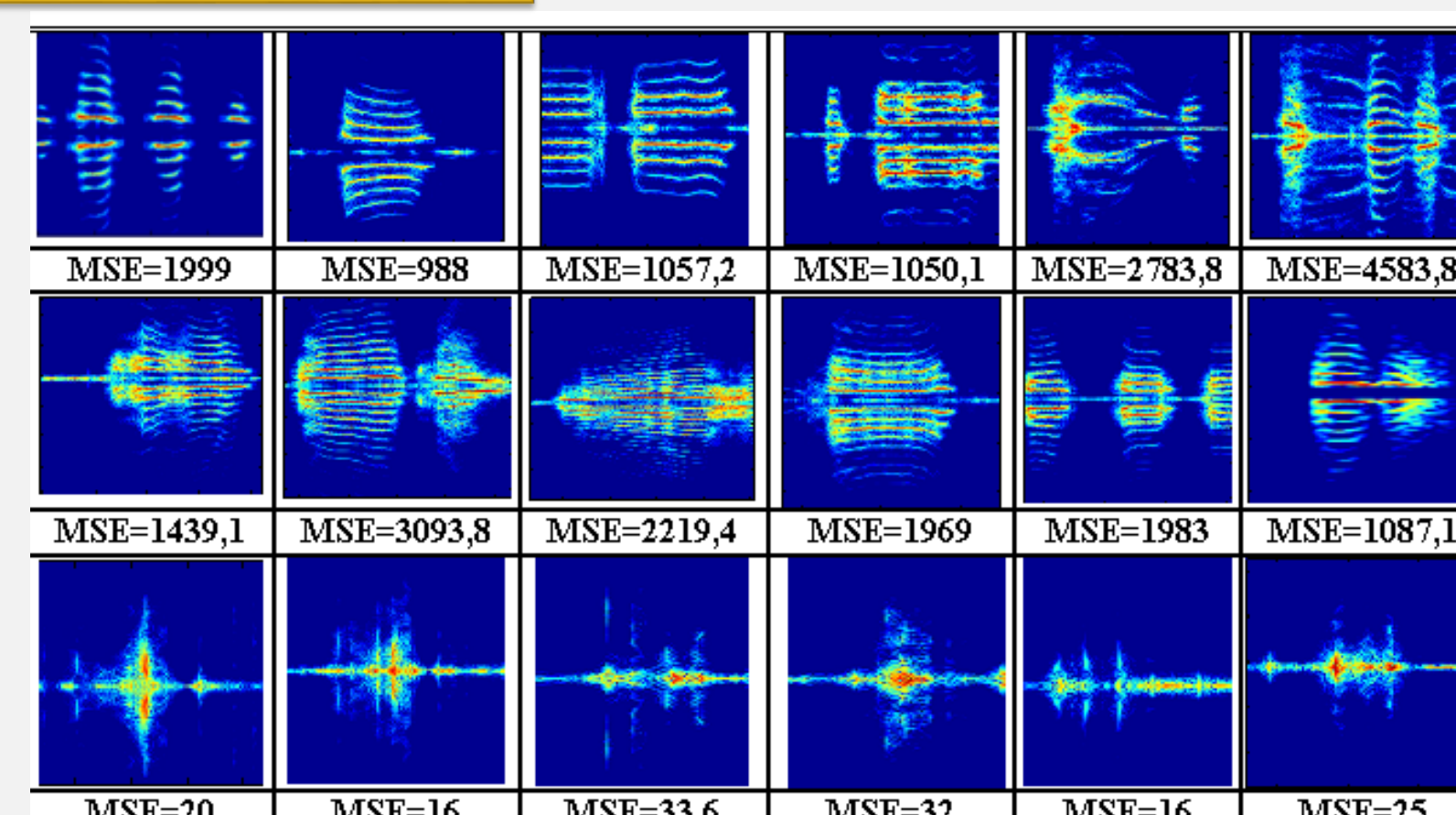
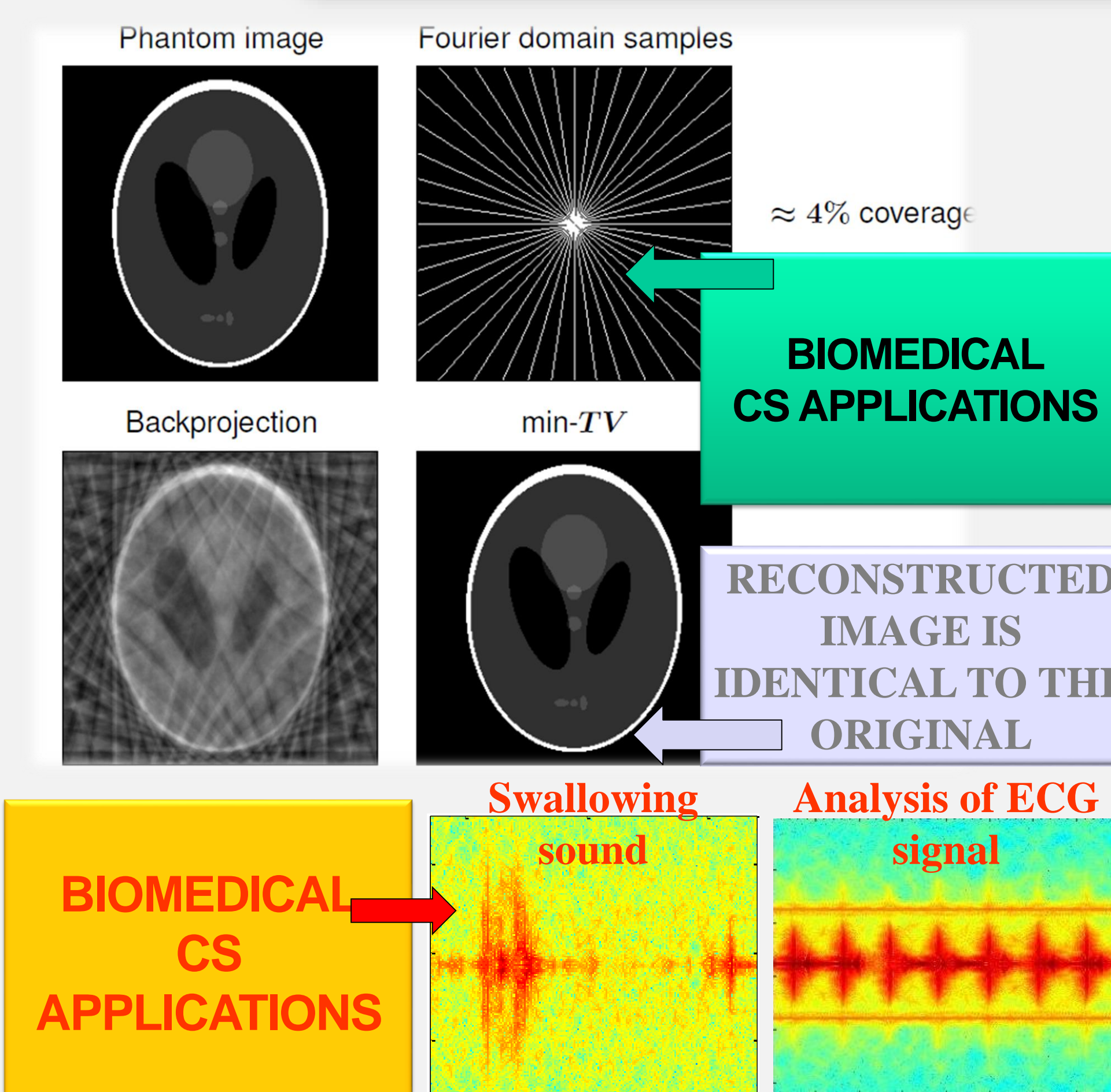
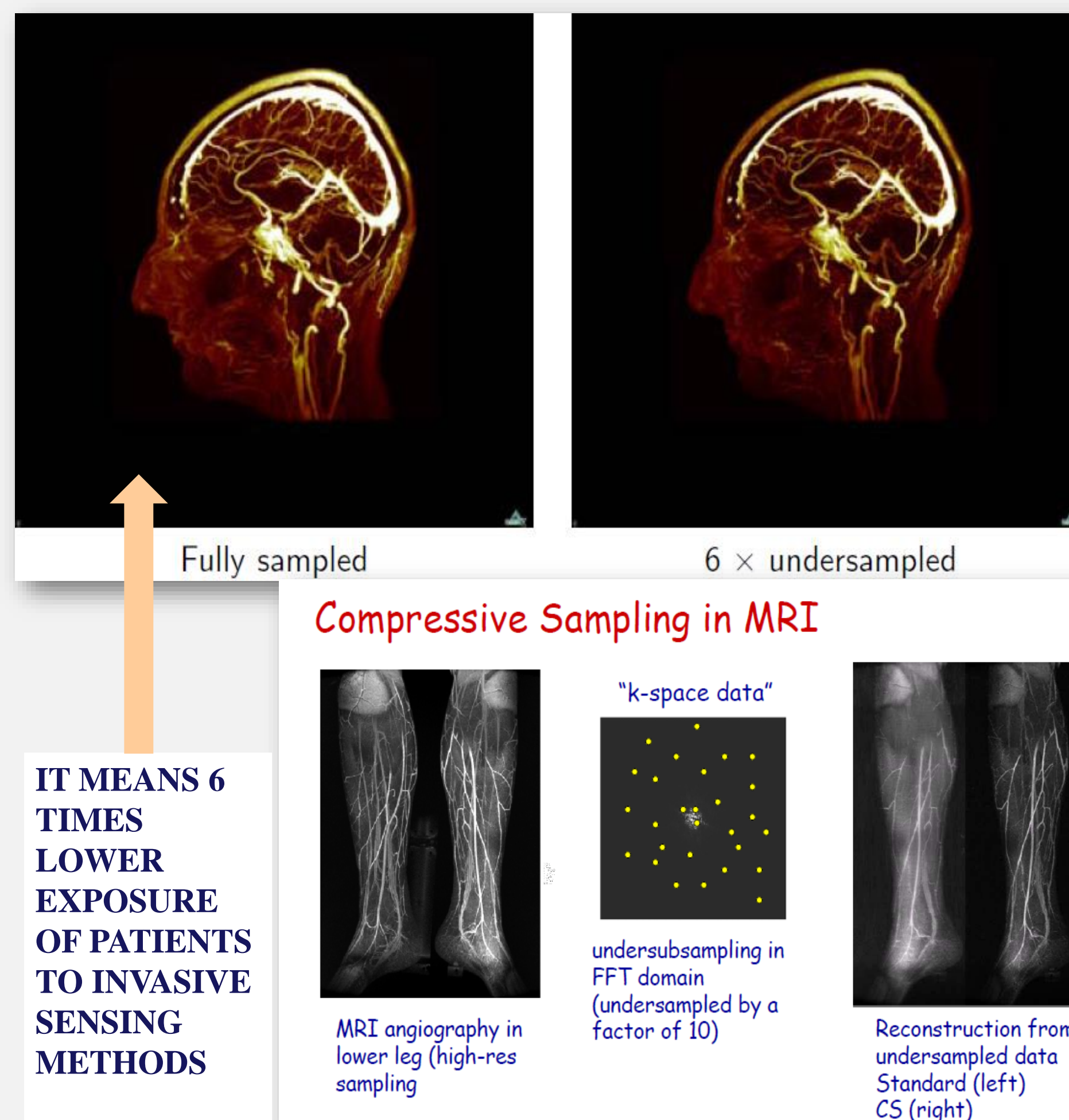
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Adaptive gradient-based algorithm belongs to the group of convex optimization approaches. The algorithm iteratively varies values of the available signal samples, improving the concentration in the sparsity domain. Namely, the initial value of the available sample is changed for adaptable step $\pm \Delta$, approaching its exact value. The missing signal values are updated by the gradient vector, obtained as a difference between the ℓ_1 -norms of the vectors changed for $+\Delta$ and $-\Delta$. This gradient value is used to update the values of the missing samples.

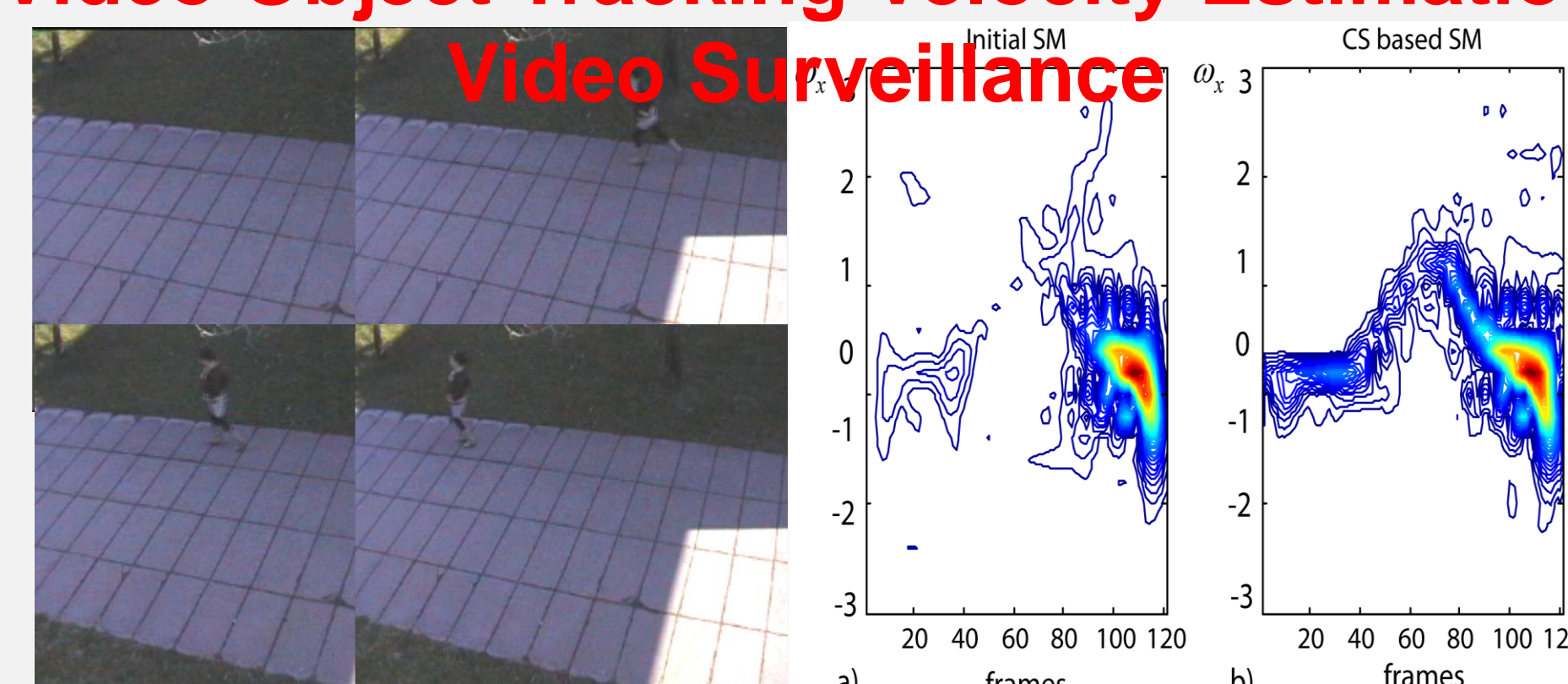
Results

New practical applications

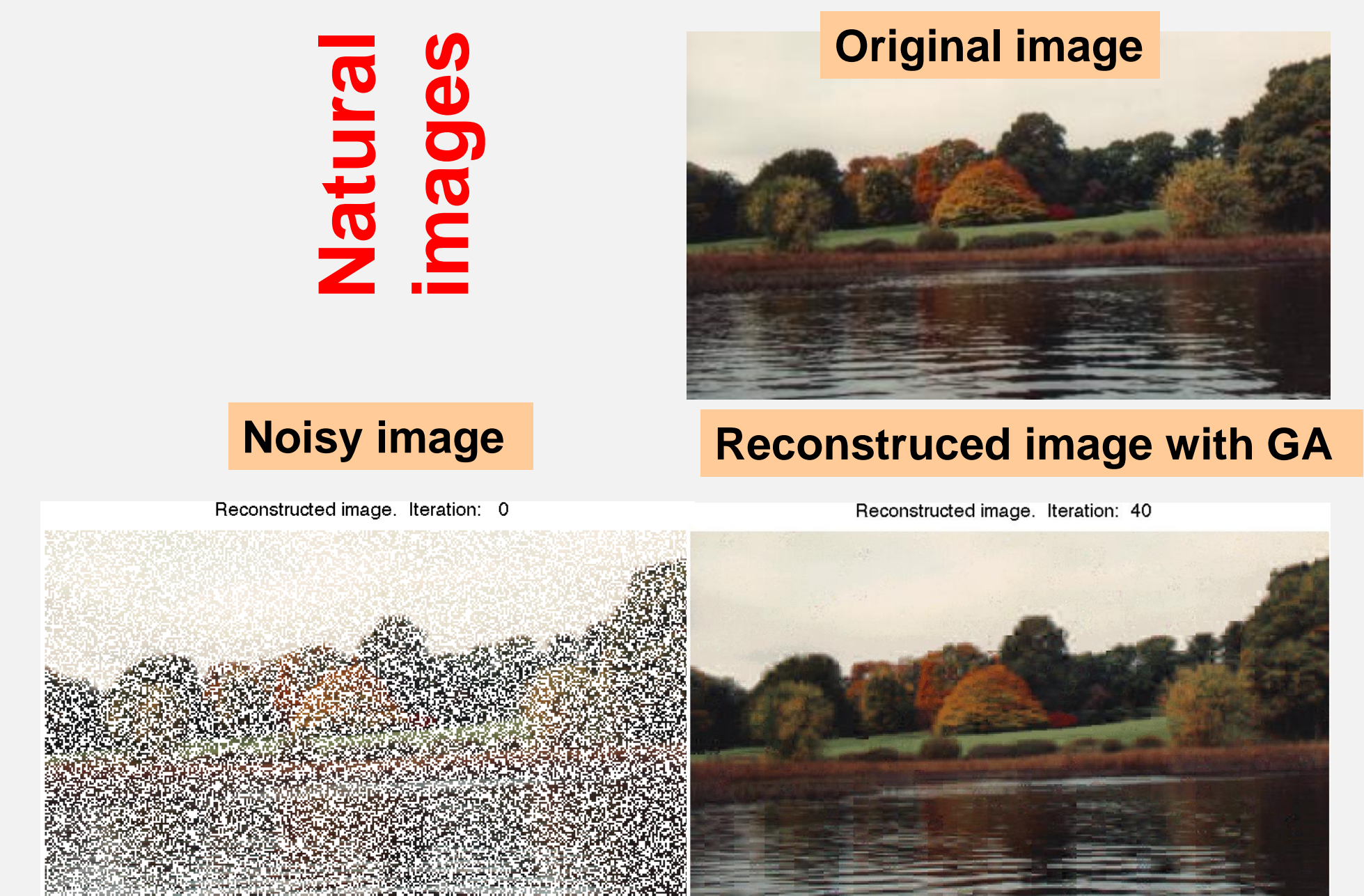
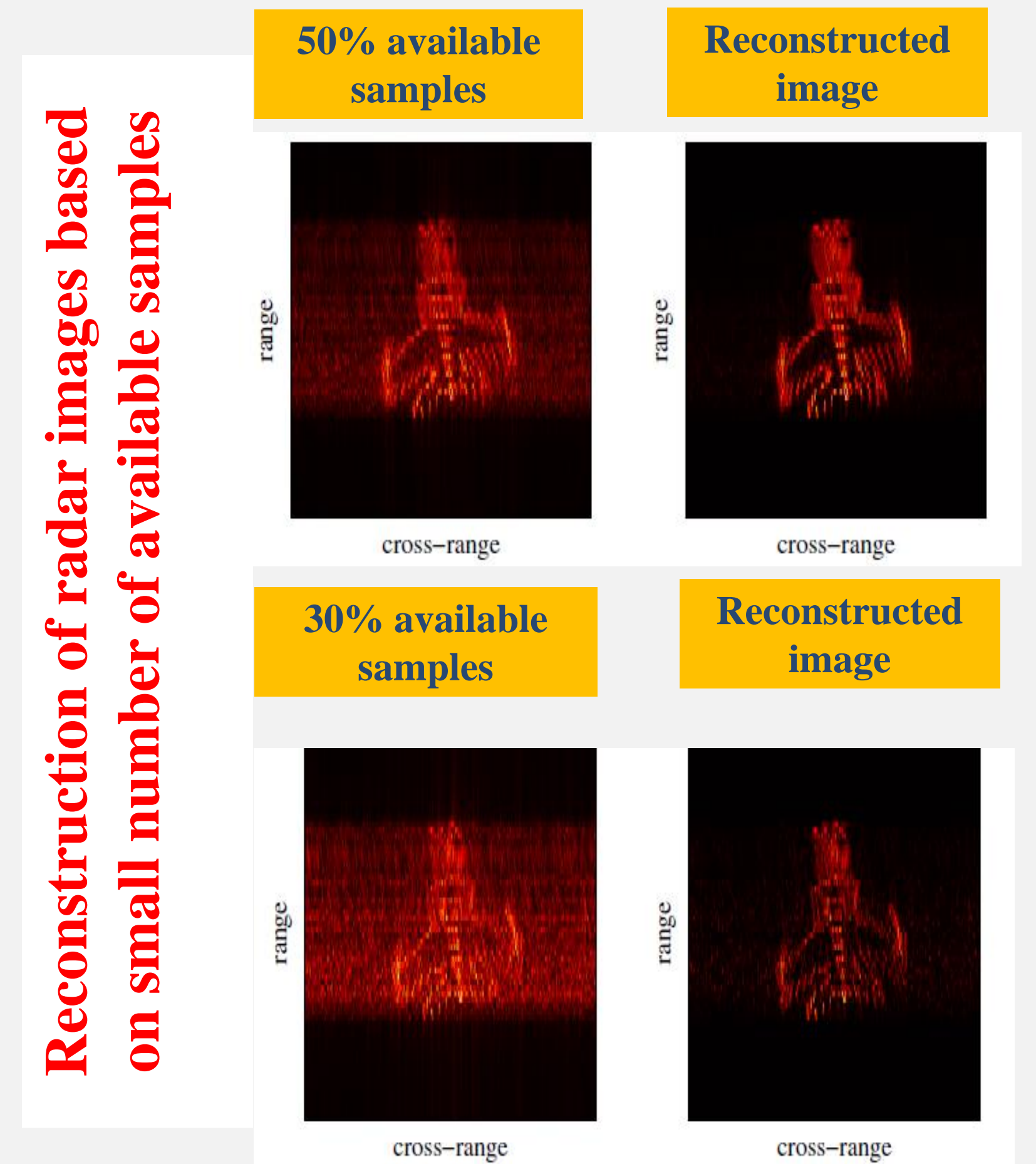
WE WILL NEED 6 TIMES LESS MEASUREMENTS FOR THE SAME IMAGE QUALITY



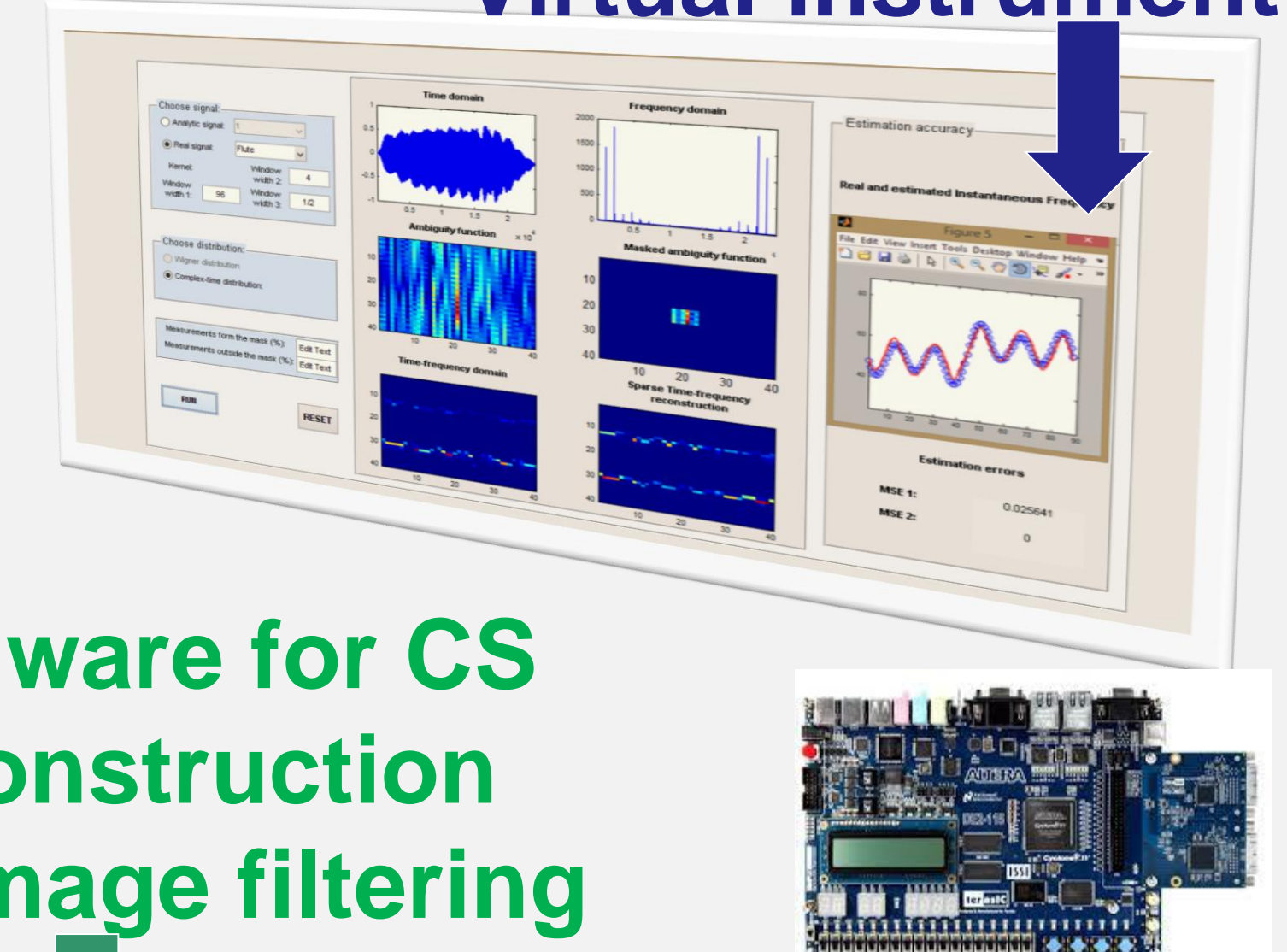
Video Object Tracking Velocity Estimation



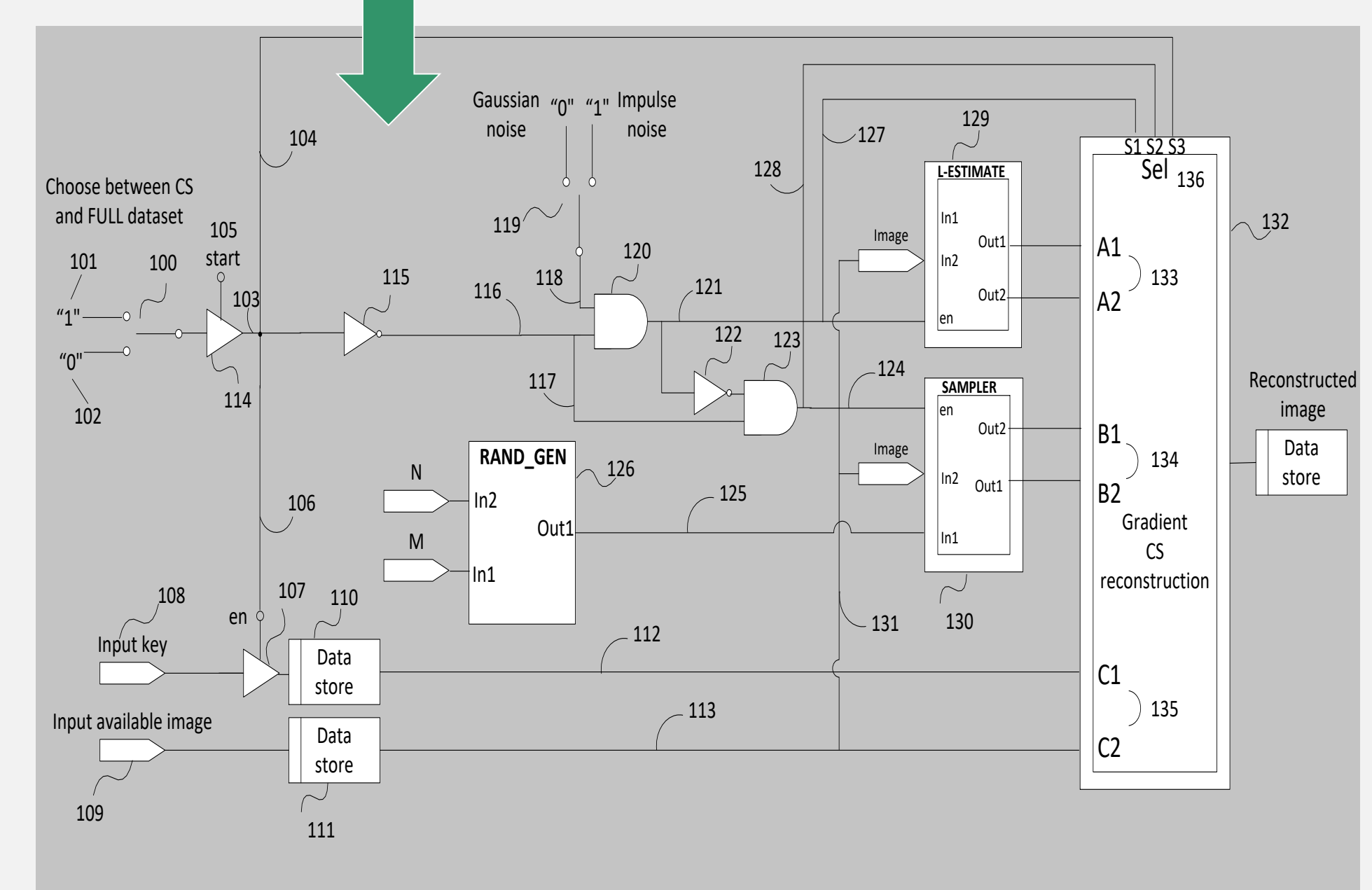
26 researchers involved in project
implementation: **6 PhDs**, **2 Msc students**,
2 Postdoctoral Research



Virtual instrument



Hardware for CS reconstruction and image filtering



Partners

- University of Montenegro, Faculty of Electrical Engineering
- Institute polytechnic Grenoble
- ALPMEDIA, Slovenia & LTFE, University Ljubljana
- S&T Montenegro
- University of Pittsburgh