

Application of compressive sensing theory for the reconstruction of signals in polymer scintillators

Lech Raczyński, Paweł Kowalski

Lech.Raczynski@ncbj.gov.pl
Pawel.Kowalski@ncbj.gov.pl

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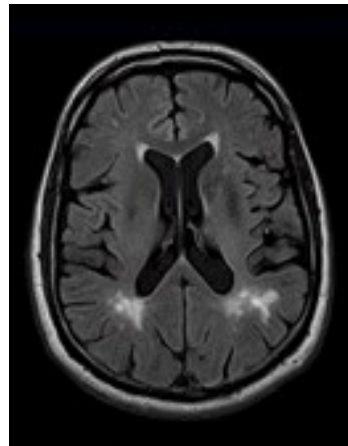
1. Introduction

Medical Imaging

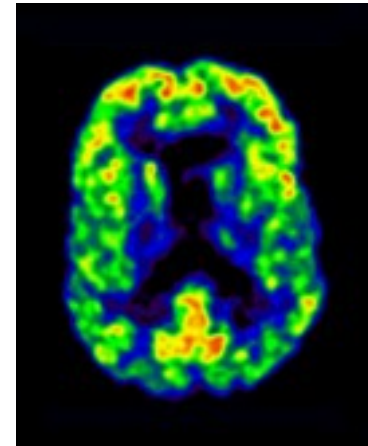
- Medical imaging starts in **1895** with the discovery of X-rays by Roentgen
- Medical imaging is a routine and one of the most important part of a today's medicine
- Providing an objective diagnosis is possible (based not only on symptoms)
- Supporting the surgery with medical imaging



X-ray radiography



MRI image [1]

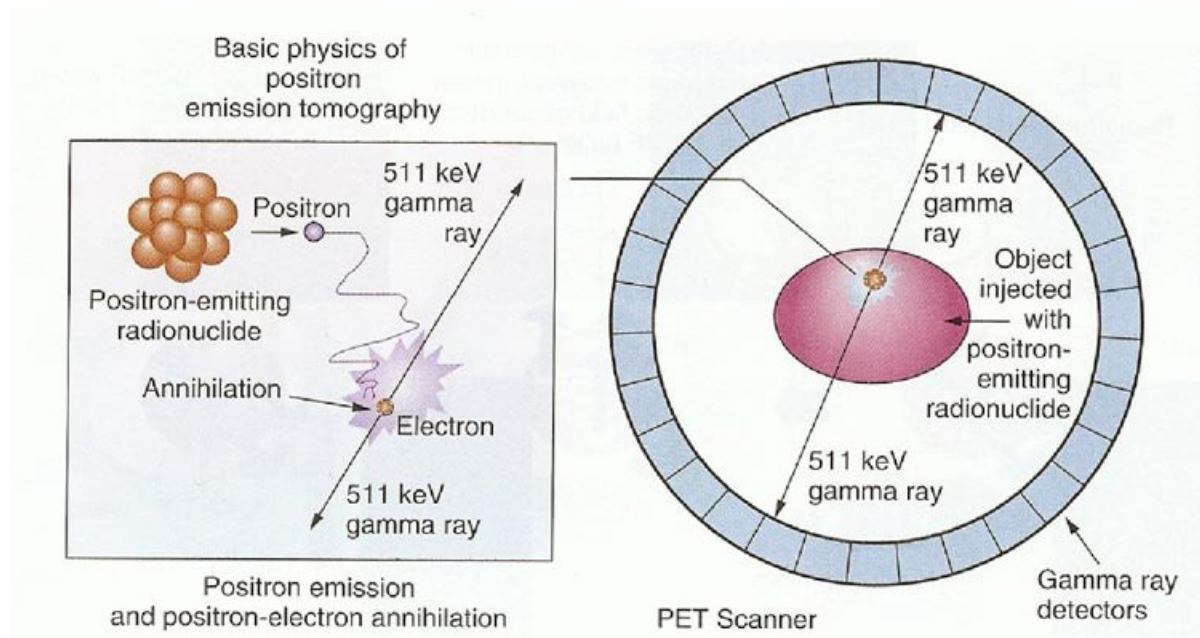


PET image [1]

1. Introduction

PET

- Positron Emission Tomography (PET) is one of the most prominent imaging techniques
- Visualisation of functional processes in the body



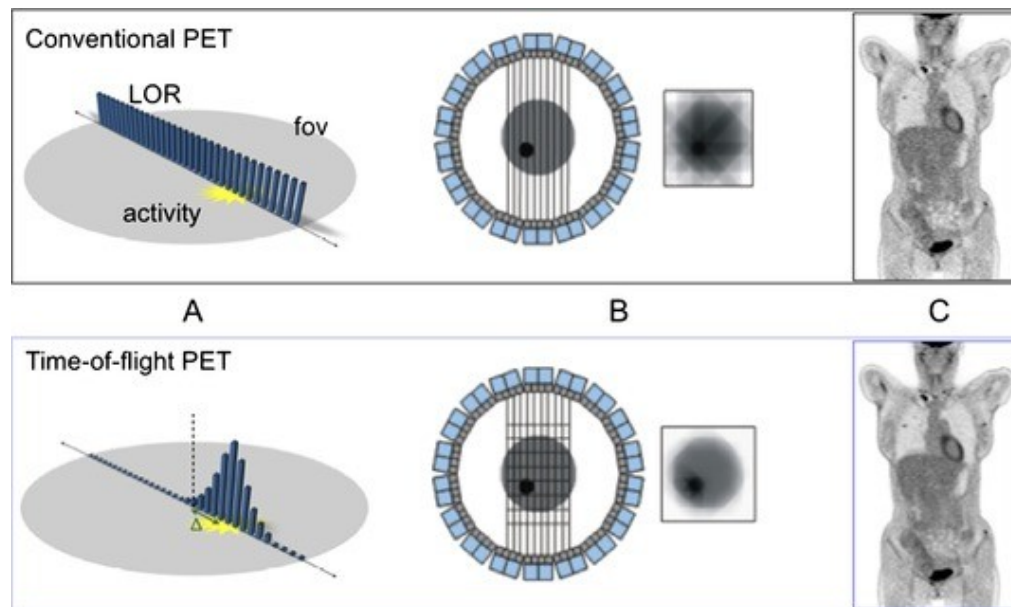
Working principle of PET scanner [2]

1. Introduction

TOF PET

- Time of Flight (TOF) information improves the image reconstruction in PET
- In conventional PET, only a line through the patient's body is detected by two detectors

- In Time of Flight PET, the faster detectors enable the measurement of the difference in the arrival time to the two detectors

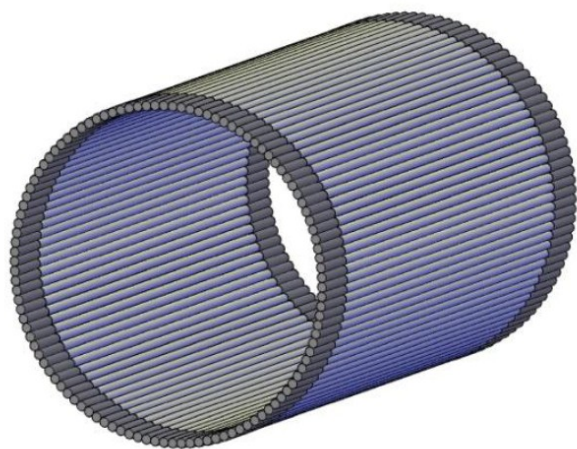


Time of Flight information [3]

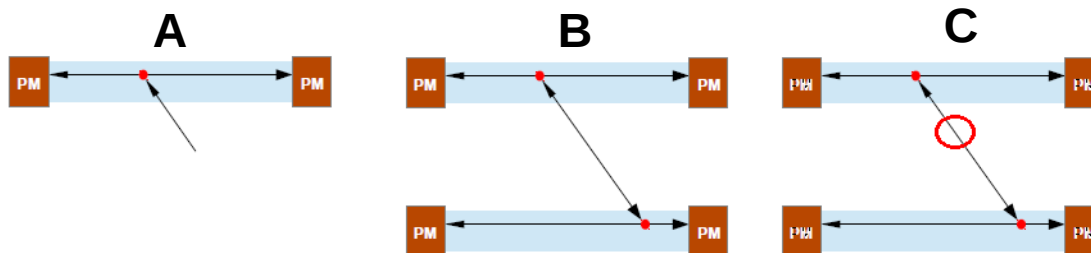
1. Introduction

Striped TOF PET

- Detectors built from one plastic scintillator and two photomultipliers
- Double time-of-flight method



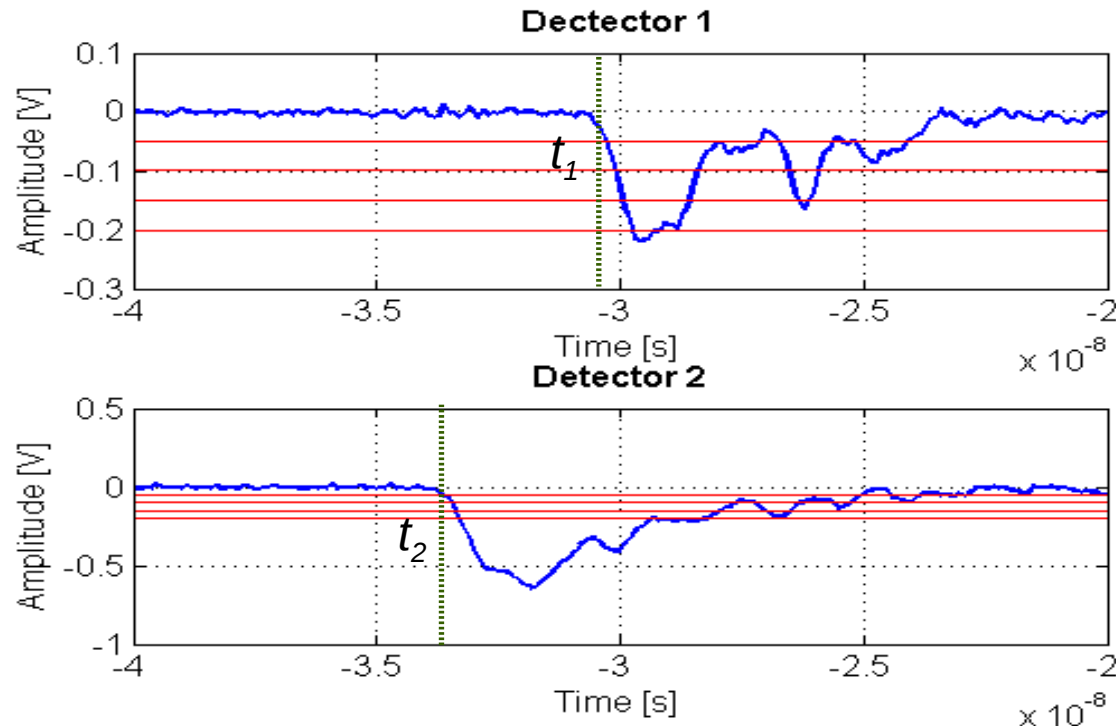
Striped TOF PET



Time of Flight method
fo Striped TOF PET

1. Introduction

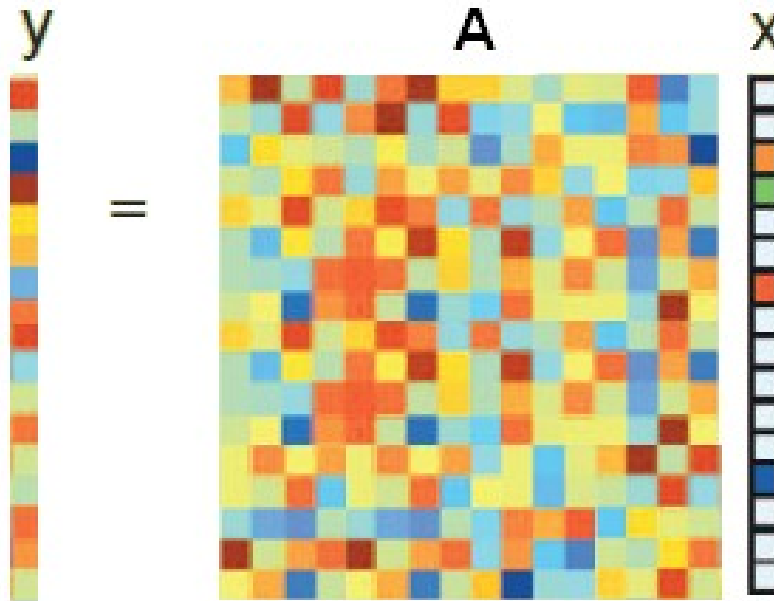
Striped TOF PET



- Constant multi-level discriminator is used to sample a time domain signal
- The goal of this work was to investigate the possibilities of reconstruction of the original signal with a small number of measurements based on Compressive Sensing theory

2. Compressive Sensing

- The discrete signal measured by an oscilloscope is denoted by \mathbf{y}
- The **K -sparse** representation, denoted by \mathbf{x} , contains only K non-zero coefficients (where $K \ll M$)
- The relation between \mathbf{x} and \mathbf{y} is depicted by the transform matrix \mathbf{A}

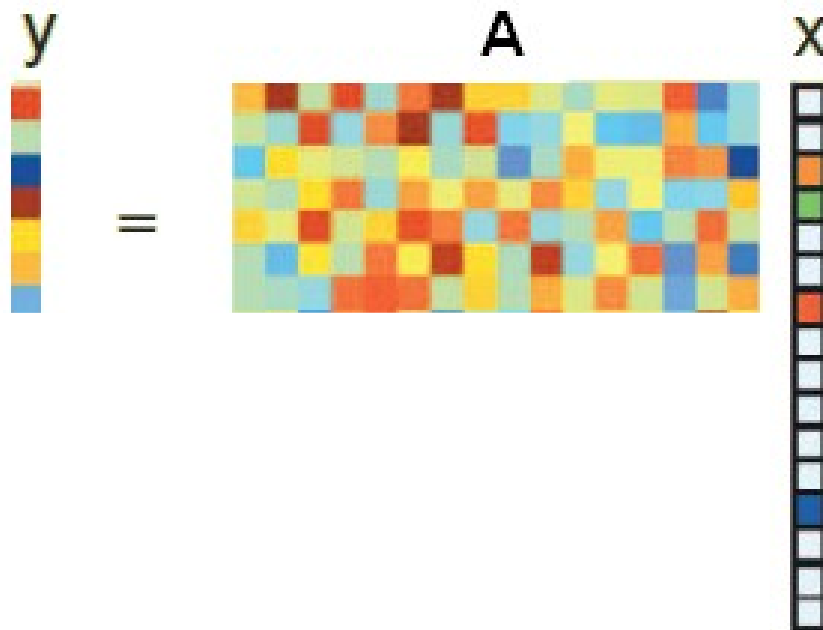


$\mathbf{y} = \mathbf{A} \cdot \mathbf{x}$

$x \in R^M$
 $y \in R^M$
 $y = A \cdot x$

2. Compressive Sensing

- The reconstruction of x does not require the full information about y
- In general it can be shown that the N random measurements of y are required, where $N > 2K$ and K is the sparsity of the x



$$x \in R^M$$

$$y \in R^N$$

$$N < M$$

$$y = A \cdot x$$

2. Compressive Sensing

Optimization problem:

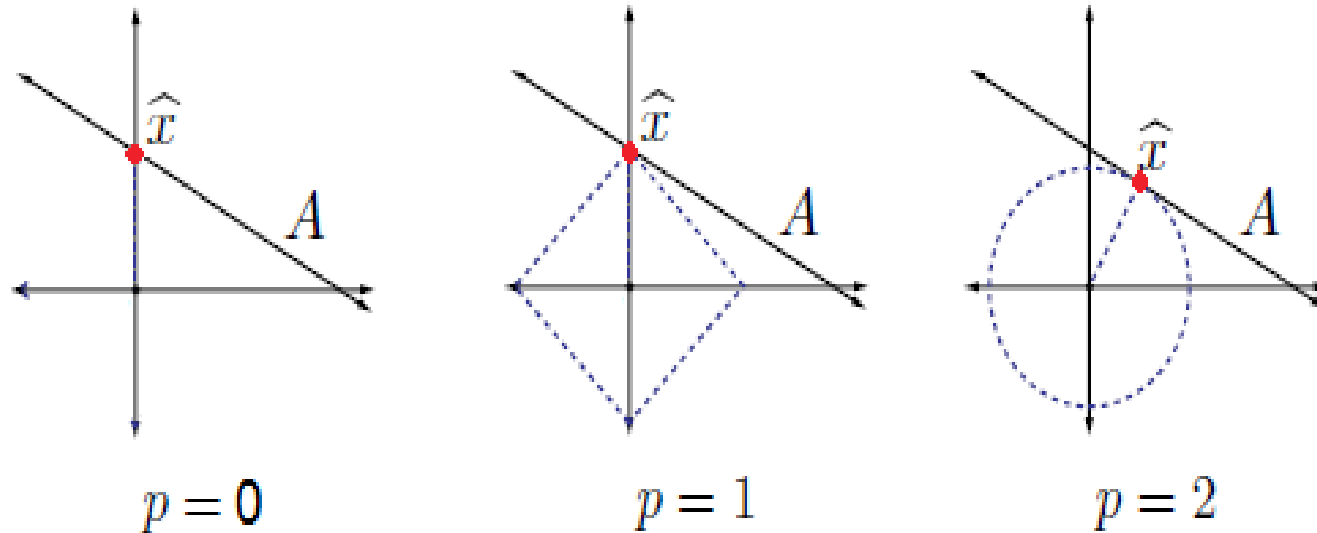
- l_0 minimization problem

$$\hat{x} = \arg(\min \|x\|_0) \quad \wedge \quad y = A \cdot x$$
$$\|x\|_0 = K, \quad K - \text{nr of non-zero elements of } x$$

- l_1 minimization problem

$$\hat{x} = \arg(\min \|x\|_1) \quad \wedge \quad y = A \cdot x$$
$$\|x\|_1 = \sum_i^M |x_i|, \quad M - \text{size of vector } x$$

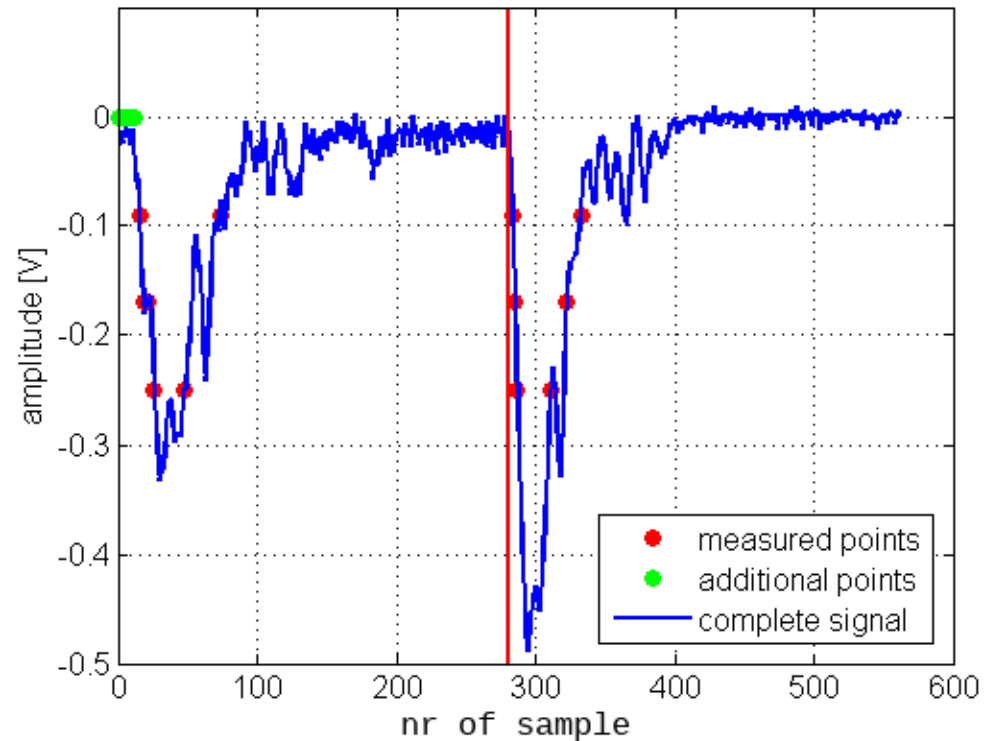
2. Compressive Sensing



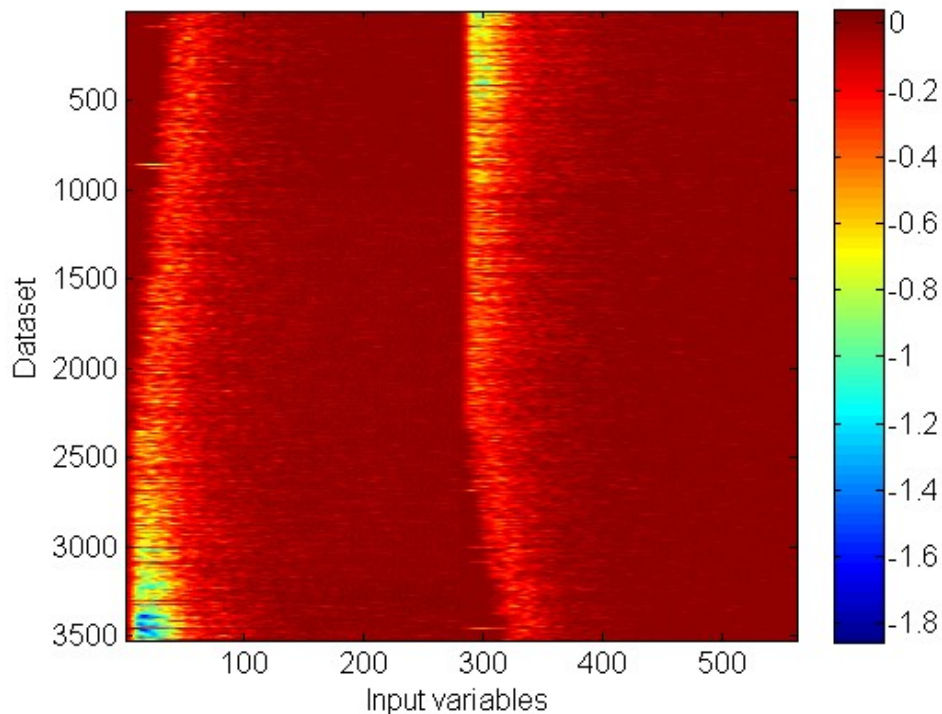
- Searching for the sparse solution of $\mathbf{y} = \mathbf{A}\mathbf{x}$ with different p norms
- Minimizing of p norm is adequate to finding the first intersect of p sphere with line $\mathbf{y} = \mathbf{A}\mathbf{x}$ when p sphere grows from $(0, 0)$
- It can be shown that for $p \leq 1$ sparse solution might be found

3. Signal representation

- Single data y is a concatenation of a two measured signals (place marked in red)
- This approach enable to take into account the time difference (additional points marked in green)
- The registration starts after one of the signals reach the amplitude of -0.05 V (in the example a second one)
- Data sampling: 10 GHz (100 ps between samples)
- Data dimension: $M = 560$
 $N = 21$ (12+9)

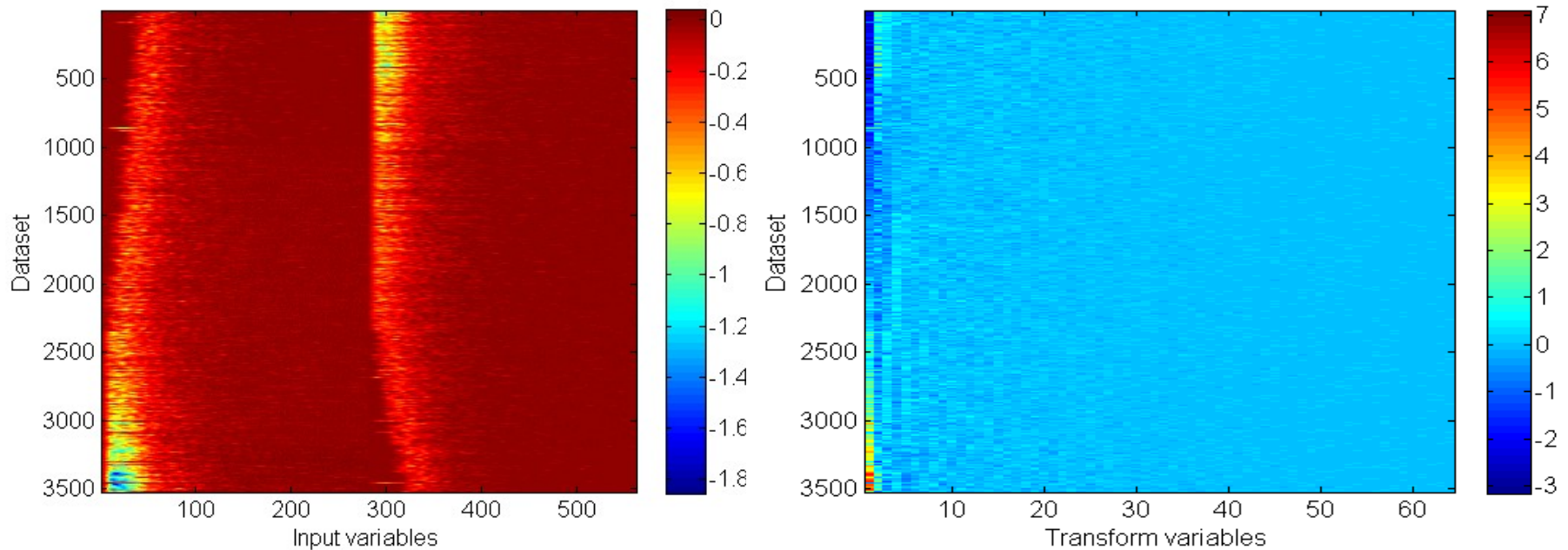


3. Signal representation



- The complete data set used in this study with about 3500 signals
- The signals y are present in the rows
- The amplitude of a signals is indicated by a color in the image
- High correlation of the signals y in the data set

3. Signal representation

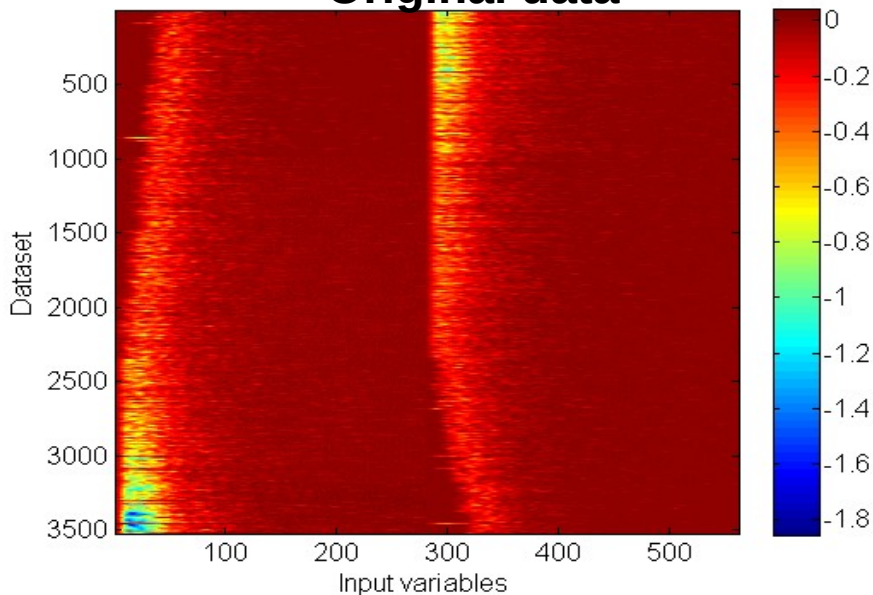


- Decorrelation of the data set with Singular Value Decomposition (SVD)
- Signal \mathbf{x} , in the new SVD space, is sparse: the information is concentrated in a first few coefficients (right image)
- The number of signal \mathbf{y} measurements is greater than the sparsity of \mathbf{x}

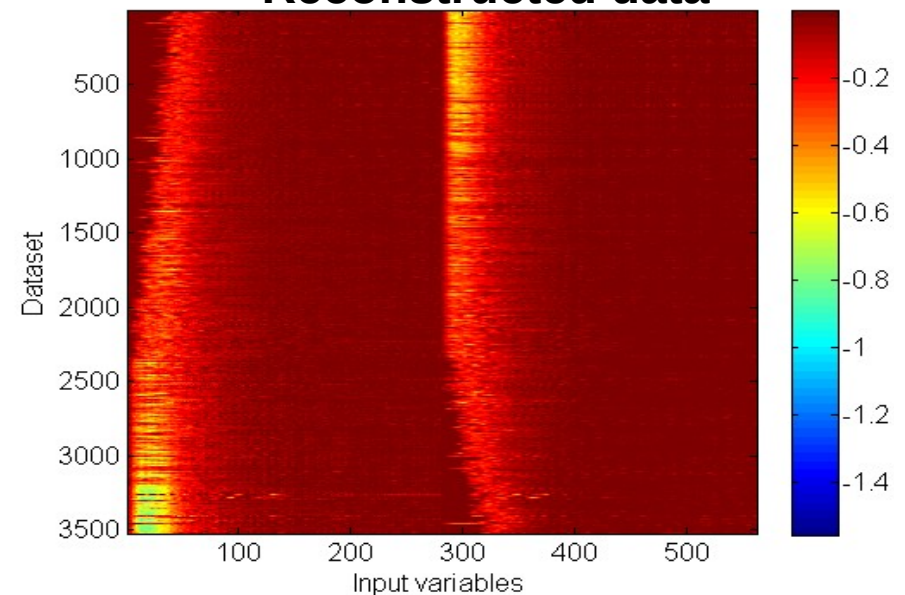
4. Results

- Original, measured signals y are stored in the matrix shown on the left
- Estimation of y based on measurements is 2 step process:
 - Step 1: reconstruction of x based on N random measurements of y
 - Step 2: estimation of y based on x (presented on the right)
- The mean RMSE (between original and reconstructed signal) is c.a. 0.05 V

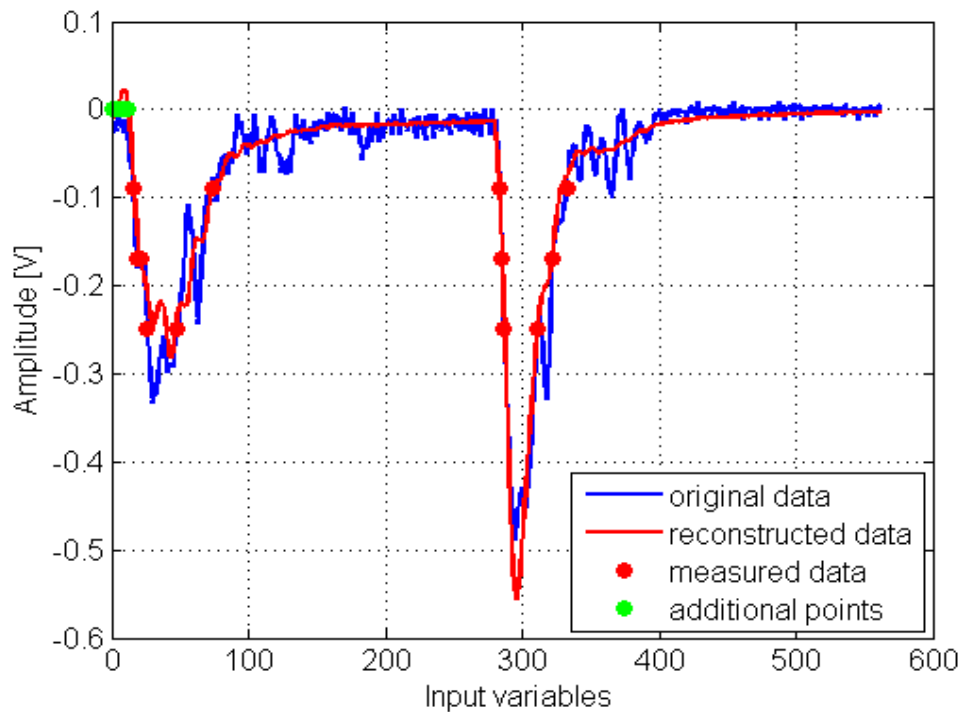
Original data



Reconstructed data



4. Results



N – nr of measurements

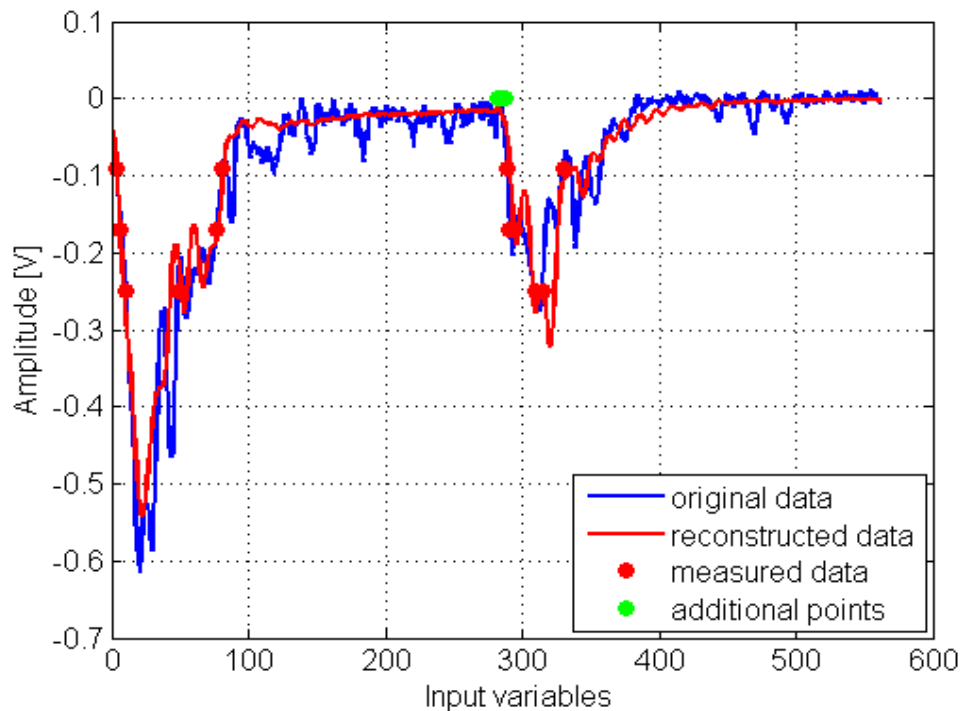
M – length of vector

Example 1:

$N = 21 (12 + 9)$

$M = 562$

4. Results



N – nr of measurements

M – length of vector

Example 2:

$N = 18 (12 + 6)$

$M = 562$

5. Conclusions

- It is possible to believably reconstruct full time series of the voltage signal using just several measurements
- Reconstruction of signals from the photomultipliers using presented scheme is fast. It should be stressed that this is the case of using a SVD transform and for another transformation it could last much longer
- The analysis of shapes of reconstructed signals may be used to reduce random coincidences and the background
- The conception of the *compressive sensing* is very general and it may be used in solving other problems, where it is possible to find the sparse representation for the original representation of the data

References

www.cis.gov.pl

- [1] <http://www.gch.org/Services/Imaging/PET-CT.aspx>
- [2] <http://www.cellsighttech.com/technology/pet.html>
- [3] http://www.springerimages.com/Images/RSS/1-10.1007_s13244-011-0069-4-4

Thank you for
your attention