

Metodi di regolarizzazione innovativi per dati telerilevati

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Outline

- 1 Motivations
- 2 Mathematical problem
- 3 Numerical Experiments

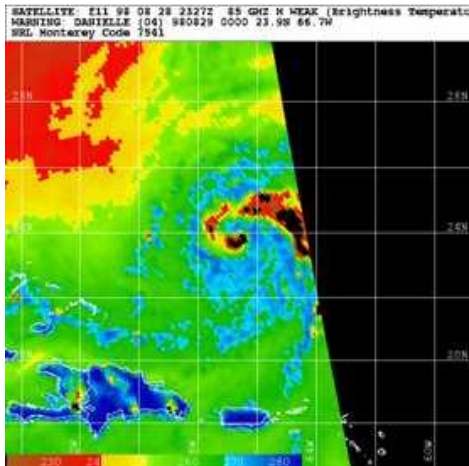
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Spatial Resolution: a limiting factor

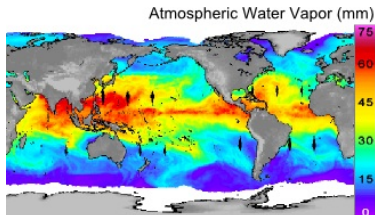
- 1 **Small but significant features are to be observed**

Thunderstorm



Spatial Resolution: a limiting factor

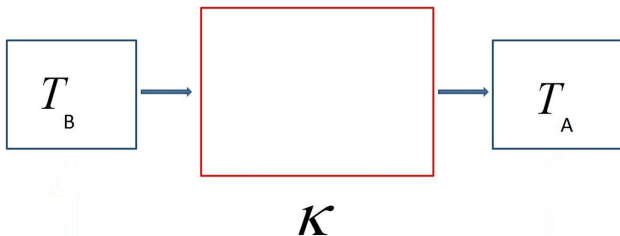
- 1 Small but significant features are to be observed
- 2 **Data fusion among various sensor channels**



Atmospheric water vapor maps generated by combining of 19V and 22V measurements

SSM/I channel's	3 dB Footprint	Spacing (km)
19.35V/H	69 × 43	25
22.235V	50 × 40	25
37.0V/H	37 × 28	25
85.5V/H	15 × 13	12.5

Measurements

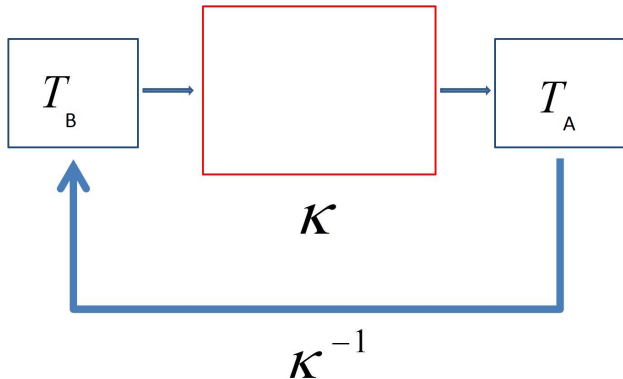


In formula:

$$T_A(s, t) = \int \int_{\Omega} K(x, y, s, t) T_B(x, y) dx dy$$

Equation of Fredholm of the first kind

Inverse Problem



Resolution Enhancement

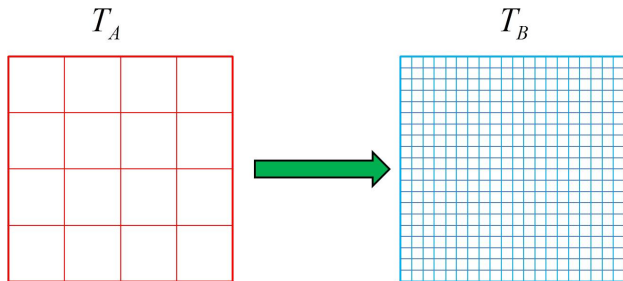
Metodi di
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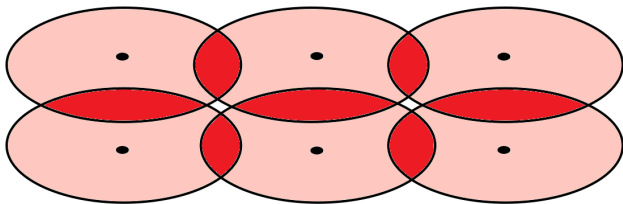
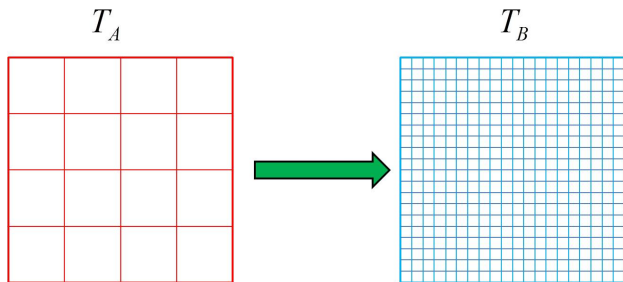
Motivations

Mathematical
problem

Numerical
Experiments



Resolution Enhancement



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Discretization

The continuous model is mainly of theoretical interest since in practice, data are collected at discrete values

- Data provided by the problem $\rightarrow B \in \mathbf{R}^{m_1 \times m_2}$ of observables data
- Discretization of the solution $\rightarrow X \in \mathbf{R}^{n_1 \times n_2}$ of unknown brightness field
- Discretization of the integral $\rightarrow L : \mathbf{R}^{m_1 \times m_2} \rightarrow \mathbf{R}^{n_1 \times n_2}$



$$L(X) = B$$

Ill- conditioned problem

Approach to solution

$$L(X) = B$$

Regularization of the problem

- Vectorize X and B
Cast the problem in standard matrix form
Apply standard procedure
- Approach based on Fredholm integral equation with separable kernel.

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Regularization of the problem

- Vectorize X and B
Cast the problem in standard matrix form
Apply standard procedure
- Approach based on Fredholm integral equation with separable kernel.

$$K(x, y, s, t) = K_1(x, s)K_2(y, t)$$

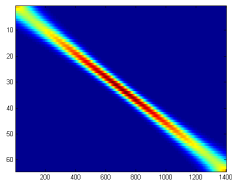
Discretization of Fredholm integral equation with separable kernel

$$T_A(s, t) = \int_{\Omega_2} K_2(y, t) \int_{\Omega_1} K_1(x, s) T_B(x, y) dx dy$$

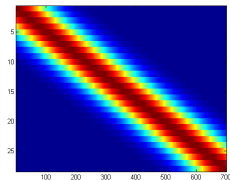


$$A_1 X A_2^T = B$$

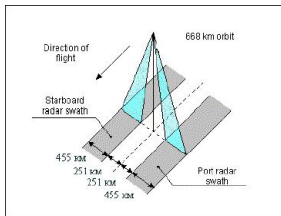
A_1



A_2



Linear Scansion

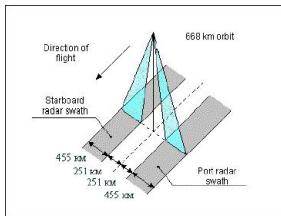


$$A_1(i, j) = Ce^{(-2\pi C_2(\arctg(\frac{x_i}{r}) - \arctg(\frac{s_j}{r}))^2)}$$

with $x_i = \frac{1400}{n_1} * i, i = 1, \dots, n_1$ and
 $s_j = \frac{1400}{m_1} * j, j = 1, \dots, m_1$

Matrix A_1

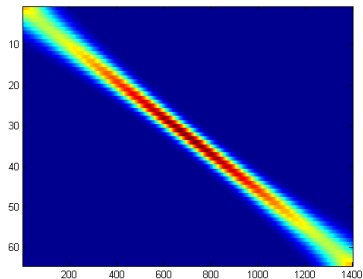
Linear Scansion



It is not a Toeplitz matrix but it is structured. By means of a coordinates transformation, it can be transformed into a Toeplitz one.

$$A_1(i, j) = Ce^{(-2\pi C_2(\arctg(\frac{x_i}{r}) - \arctg(\frac{s_j}{r}))^2)}$$

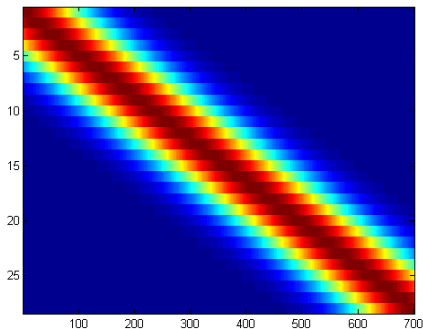
with $x_i = \frac{1400}{n_1} * i, i = 1, \dots, n_1$ and
 $s_j = \frac{1400}{m_1} * j, j = 1, \dots, m_1$



Matrix A_2

$$A_2(i, j) = Ce^{-2\pi C_2(y_i - t_j)^2}$$

with $y_i = \frac{700}{n_2} * i$, $i = 1, \dots, n_2$ and $t_j = \frac{700}{m_2} * j$, $j = 1, \dots, m_2$



It is a **G-Toeplitz**. It is:

$$A_2(i, j) = \mathbf{a}\left(\frac{n_2}{m_2} * i - j\right)$$

Reconstruction Algorithms

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Motivations

Mathematical
problem

Numerical
Experiments

- Truncated Singular Value Decomposition
- Landweber Method in Hilbert Space
- Landweber Method in Banach Space

TSVD

$$A_1 X A_2^T = B$$



$$A \mathbf{x} = \mathbf{b}$$

TSVD

$$A_1 X A_2^T = B$$



$$A \mathbf{x} = \mathbf{b}$$

$$(A_2 \otimes A_1) \mathbf{x} = \mathbf{b}$$

TSVD

$$A_1 X A_2^T = B$$



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SVD SVD

TSVD

$$A_1 X A_2^T = B$$



$$A \mathbf{x} = \mathbf{b}$$

$$(A_2 \otimes A_1) \mathbf{x} = \mathbf{b}$$



SVD SVD

TSVD solution

$$X_k = \sum_{j=1}^k v_{l(j),1} \frac{u_{l(j),1}^T B v_{h(j),2}}{\sigma_{l(j),1} \sigma_{h(j),2}} v_{h(j),2}^T$$

Landweber Method in Hilbert Space

Gradient Method

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \lambda \nabla \left(\frac{1}{2} \|A\mathbf{x}_k - \mathbf{b}\|_2^2 \right) = \mathbf{x}_k - \lambda A^*(A\mathbf{x}_k - \mathbf{b})$$

Formally, A^* is the dual operator of A :

$$A : X \rightarrow Y, \quad A^* : Y^* \rightarrow X^*$$

where X^* and Y^* are the dual spaces of X and Y .

Landweber Method in Hilbert Space

Gradient Method

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \lambda \nabla \left(\frac{1}{2} \| \mathbf{A} \mathbf{x}_k - \mathbf{b} \|_2^2 \right) = \mathbf{x}_k - \lambda \mathbf{A}^* (\mathbf{A} \mathbf{x}_k - \mathbf{b})$$

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Riesz Theorem

If X is Hilbert space, X^* is isometrically isomorph to X

Landweber Method in Hilbert Space

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Riesz Theorem

If X is Hilbert space, X^* is isometrically isomorph to X

The Landweber method is well-defined in Hilbert Space

From Hilbert to Banach space

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \lambda A^* (A \mathbf{x}_k - \mathbf{b})$$

- $A \mathbf{x}_k - \mathbf{b} \in Y, A^* : Y^* \rightarrow X^* \Rightarrow A^* (A \mathbf{x}_k - \mathbf{b})$ is **not** correct
- $\mathbf{x}_k \in X, A^* \phi \in X^* \Rightarrow \mathbf{x}_k - A^* \phi$ is **not** correct

From Hilbert to Banach space

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- $\mathbf{x}_k \in X, A^* \phi \in X^* \Rightarrow \mathbf{x}_k - A^* \phi$ is **not** correct

$$\mathbf{x}_{k+1}^* = \mathbf{x}_k^* - \lambda \Phi_A(\mathbf{x}_k, \mathbf{b})$$

where $\Phi_A(\mathbf{x}_k, \mathbf{b})$ is the generalization of the gradient of the functional $\frac{1}{r} \|A \mathbf{x}_k - \mathbf{b}\|_Y^r$.

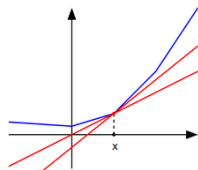
The key point: To generalize from Hilbert to Banach spaces we have to consider the so-called **subdifferential**

From Hilbert to Banach spaces (2)

Let f be a convex functional
 $f : X \rightarrow \mathbf{R}$.

The subdifferential of f is the
operator $\delta f : X \rightarrow 2^{X^*}$:

$$x^* \in \delta f(x) \leftrightarrow f(y) \leq f(x) + x^*(y - x)$$



In Banach space l^p the subgradient of the functional $1/r \| \mathbf{A} \mathbf{x}_k - \mathbf{b} \|_p^r$
is given by:

$$\begin{aligned} \delta \left(\frac{1}{r} \| \mathbf{A} \mathbf{x}_k - \mathbf{b} \|_p^r \right) &= \| \mathbf{A} \mathbf{x}_k - \mathbf{b} \|_p^{r-p} \mathbf{A}^* (| \mathbf{A} \mathbf{x}_k - \mathbf{b} |^{p-1} \text{sgn}(\mathbf{A} \mathbf{x}_k - \mathbf{b})) = \\ &= \mathbf{A}^* J_r^{l^p} (\mathbf{A} \mathbf{x}_k - \mathbf{b}) \end{aligned}$$

Landweber method in Banach space

$$Y = l^p \Rightarrow \mathbf{x}_{k+1}^* = \mathbf{x}_k^* - \lambda A^* J_r^{l^p}(A\mathbf{x}_k - \mathbf{b})$$

The duality map is a function which allows us to associate an element of a Banach Space X with an element of its dual X^* :

$$J_r^X : X \rightarrow 2^{X^*} \quad J_{r^*}^{X^*} : 2^{X^*} \rightarrow X$$

$$\text{with } r^* : \frac{1}{r} + \frac{1}{r^*} = 1.$$

$$\mathbf{x}_{k+1} = J_{r^*}^{X^*}(J_r^X(\mathbf{x}_k) - \lambda A^* J_r^Y(A\mathbf{x}_k - \mathbf{b}))$$

Landweber method in Banach space

$$Y = l^p \Rightarrow \mathbf{x}_{k+1}^* = \mathbf{x}_k^* - \lambda A^* J_r^{l^p}(A\mathbf{x}_k - \mathbf{b})$$

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$$\mathbf{x}_{k+1} = J_{r^*}^{X^*}(J_r^X(\mathbf{x}_k) - \lambda A^* J_r^Y(A\mathbf{x}_k - \mathbf{b}))$$

$$A : l^p \rightarrow l^p \quad 1 \leq p \leq 2 \Rightarrow \mathbf{x}_{k+1} = J_{r^*}^{l^p}(J_r^{l^p}(\mathbf{x}_k) - \lambda A^* J_r^{l^p}(A\mathbf{x}_k - \mathbf{b}))$$

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Real Radiometer Data

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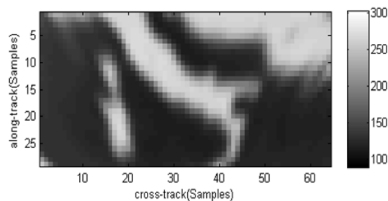
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Motivations

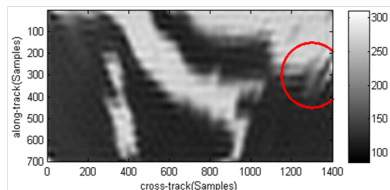
Mathematical
problem

Numerical
Experiments

19 GHz V-polarized brightness
temperature at non-enhanced
resolution



19 GHz V-polarized brightness
temperature at enhanced
resolution



Real Radiometer Data

Metodi di
regolarizzazione
innovativi per dati
telerilevati

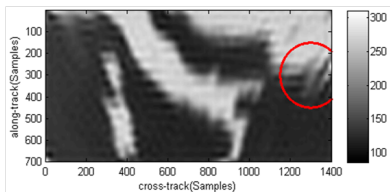
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Motivations

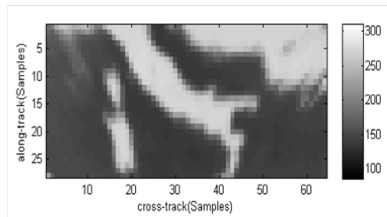
Mathematical
problem

Numerical
Experiments

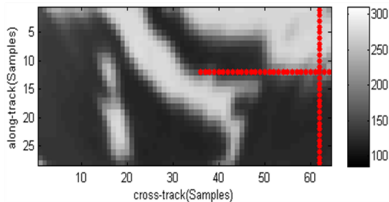
19 GHz V- polarized brightness
temperature at enhanced
resolution



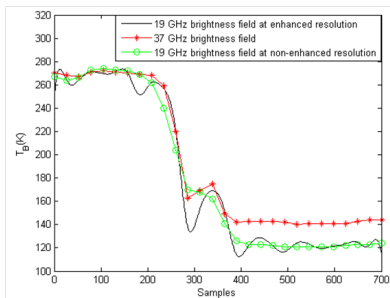
37 GHz V-polarized brightness
temperature



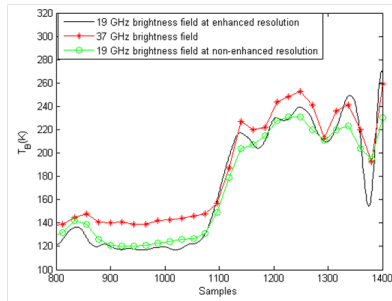
Real Radiometer Data



Along-track



Cross-track



Simulation Parameters for one-dimensional case

- Simulation of Reference Field/ Measurements

SSM/I parameters:

Area 1400 *km*

Resolution 69 *km*

Measurements 64

- Noise

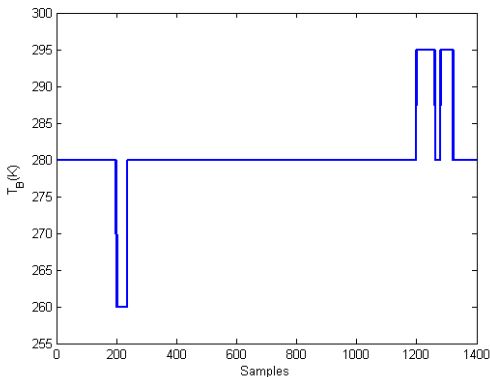
$$E = \mathcal{N}(0, 1.06)$$

- Antenna Gain

Gaussian

First Landweber experiment

The reference field includes three hot spots characterized by different brightness temperature and by different dimension. The simulated measurements are obtained by using Gaussian gain and a noise $N(0,1.06)$.



First Landweber experiment

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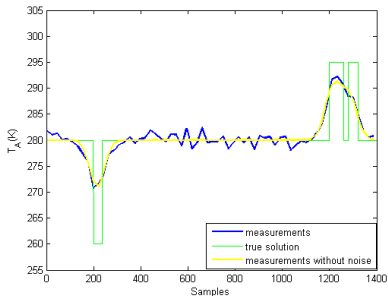
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Motivations

Mathematical
problem

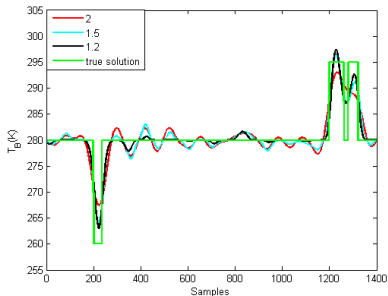
Numerical
Experiments

INPUT



Correlation coefficient
0.7626

RECONSTRUCTED FIELD



Correlation coefficient

$p = 2$	$p = 1.5$	$p = 1.2$
0.7745	0.8094	0.8455

First Landweber experiment

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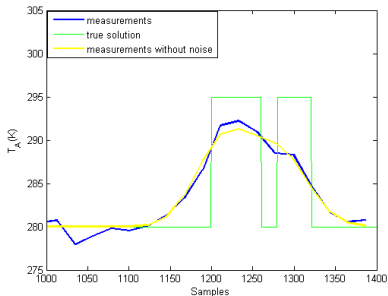
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Motivations

Mathematical
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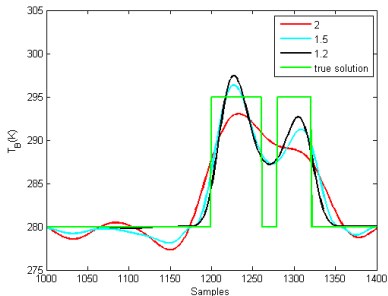
Numerical
Experiments

INPUT



Correlation coefficient
0.7626

RECONSTRUCTED FIELD

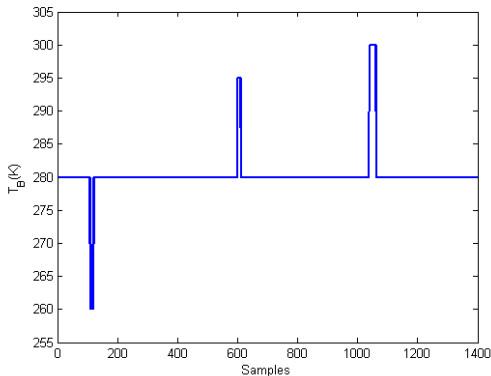


Correlation coefficient

$p = 2$	$p = 1.5$	$p = 1.2$
0.7745	0.8094	0.8455

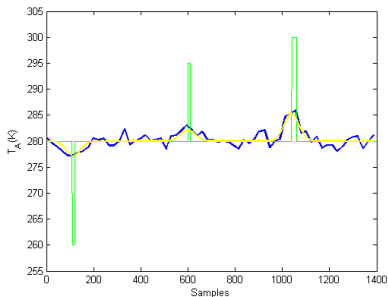
Second Landweber experiment

The reference field includes three hot spots characterized by very small dimension. The simulated measurements are obtained by using Gaussian gain and a noise $N(0,1.06)$.



Second Landweber experiment

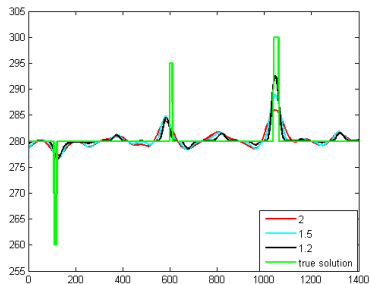
INPUT



Correlation coefficient

0.4108

RECONSTRUCTED FIELD

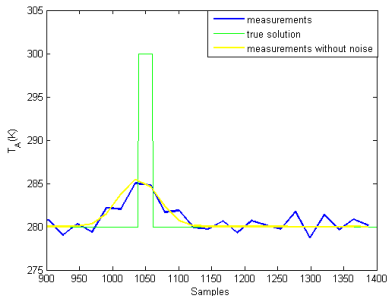


Correlation coefficient

$p = 2$	$p = 1.5$	$p = 1.2$
0.4584	0.5309	0.6186

Second Landweber experiment

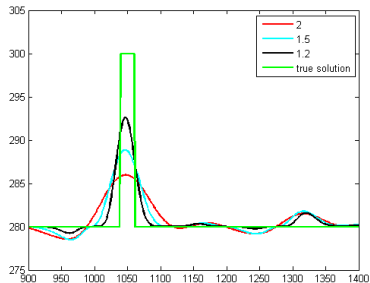
INPUT



Correlation coefficient

0.4108

RECONSTRUCTED FIELD



Correlation coefficient

$p = 2$	$p = 1.5$	$p = 1.2$
0.4584	0.5309	0.6186

Thank you

