Course Introduction and Logistics

Mathematical Models and Methods for Image Processing

Giacomo Boracchi

https://boracchi.faculty.polimi.it/

February 24th 2026

The Team

Giacomo Boracchi

Mathematician (Università Statale degli Studi di Milano 2004),

PhD in Information Technology (DEIB, Politecnico di Milano 2008)

Associate Professor since 2019 at DEIB (Computer Science), Polimi

Research Interests are mathematical and statistical methods for:

- Image / Signal analysis and processing
- Unsupervised learning, change / anomaly detection

Contact: giacomo.boracchi@polimi.it

Stefano Bertolasi

MSc in Mathematics (UniTN 2025),

Currently PhD student in Information Technology (since 2025)

Research Interests are mainly focused on:

- Mathematical models for Image Denoising
- Online and Reinforcement Learning
- Adaptive Sampling, HDR

Contact: stefano.bertolasi@polimi.it

The Course

The Goal

*The primary **goal** of this laboratory course is to **let the students design, implement and practice algorithms** based **on***

- ***simple mathematical models** from **linear algebra and convex optimization,***
- ***solve** challenging inverse **problems in image processing** (denoising, deblurring, inpainting, anomaly detection)*
- *Understand the most important aspects of **sparse representations** and of sparsity as a form of **regularization in learning problems**.*

What you get

- *An* ***excellent opportunity to practice*** *and gain better insights on fundamental principles and techniques (linear algebra, convex optimization)*

- *Gain the* ***fundamental notions*** *and expertise to approach many* ***image processing problems*** *and take advantage your mathematical background*

The Outline

The course **topics include**:

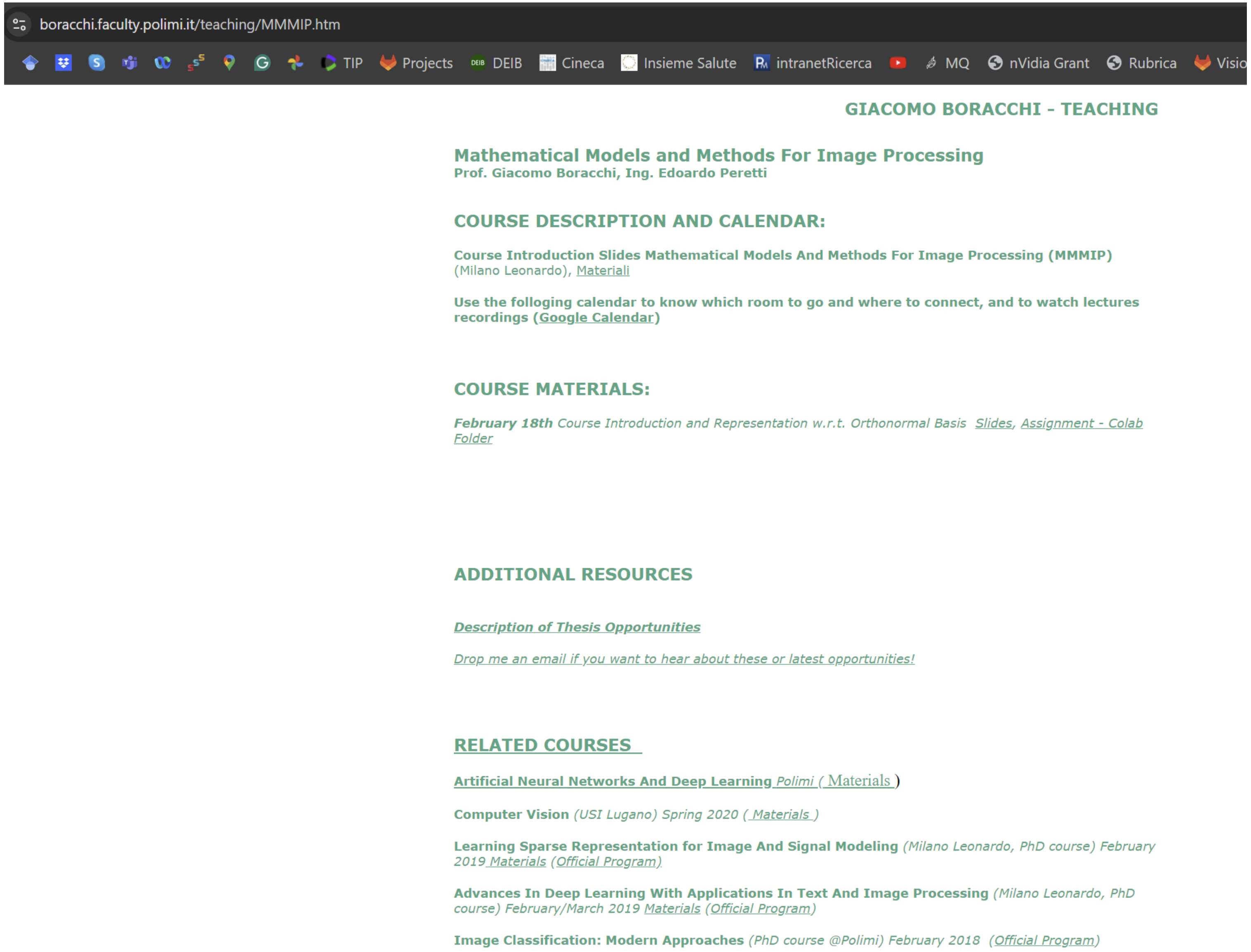
- **Image models based on orthonormal bases** (Discrete Cosine Transform), **data-driven basis** (PCA, Gram-Schmidt) and **local polynomial approximation**.
- **Sparsity and redundancy**.
  - Away from Orthonormal Basis, redundant set of generators
  - Sparse coding with ℓ^0 (OMP) or ℓ^1 norm (convex optimization ISTA, IRLS, LASSO)
  - Dictionaries yielding sparse representations and dictionary learning (KSVD)
- **Applications of sparse models** to image denoising, inpainting, anomaly detection.

- **Robust fitting** methods (RANSAC, LMEDS, HOUGH) and their sequential counterparts for object detection in images.

The Materials

- Very few slides, lectures at the backboard!
  - Yes, you need to take notes…
- Code snippets to be filled in will be provided
  - Python is the only accepted programming language for assignment.
- Please refer to the website

https://boracchi.faculty.polimi.it/teaching/MMMIP.htm



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TIP Projects DEIB Cineca Insieme Salute intranetRicerca MQ nVidia Grant Rubrica Visio

GIACOMO BORACCHI - TEACHING

Mathematical Models and Methods For Image Processing
Prof. Giacomo Boracchi, Ing. Edoardo Peretti

COURSE DESCRIPTION AND CALENDAR:

Course Introduction Slides Mathematical Models And Methods For Image Processing (MMMIP) (Milano Leonardo), Materiali

Use the folloging calendar to know which room to go and where to connect, and to watch lectures recordings (Google Calendar)

COURSE MATERIALS:

February 18th *Course Introduction and Representation w.r.t. Orthonormal Basis Slides, Assignment - Colab Folder*

ADDITIONAL RESOURCES

Description of Thesis Opportunities

Drop me an email if you want to hear about these or latest opportunities!

RELATED COURSES

Artificial Neural Networks And Deep Learning *Polimi* (Materials)

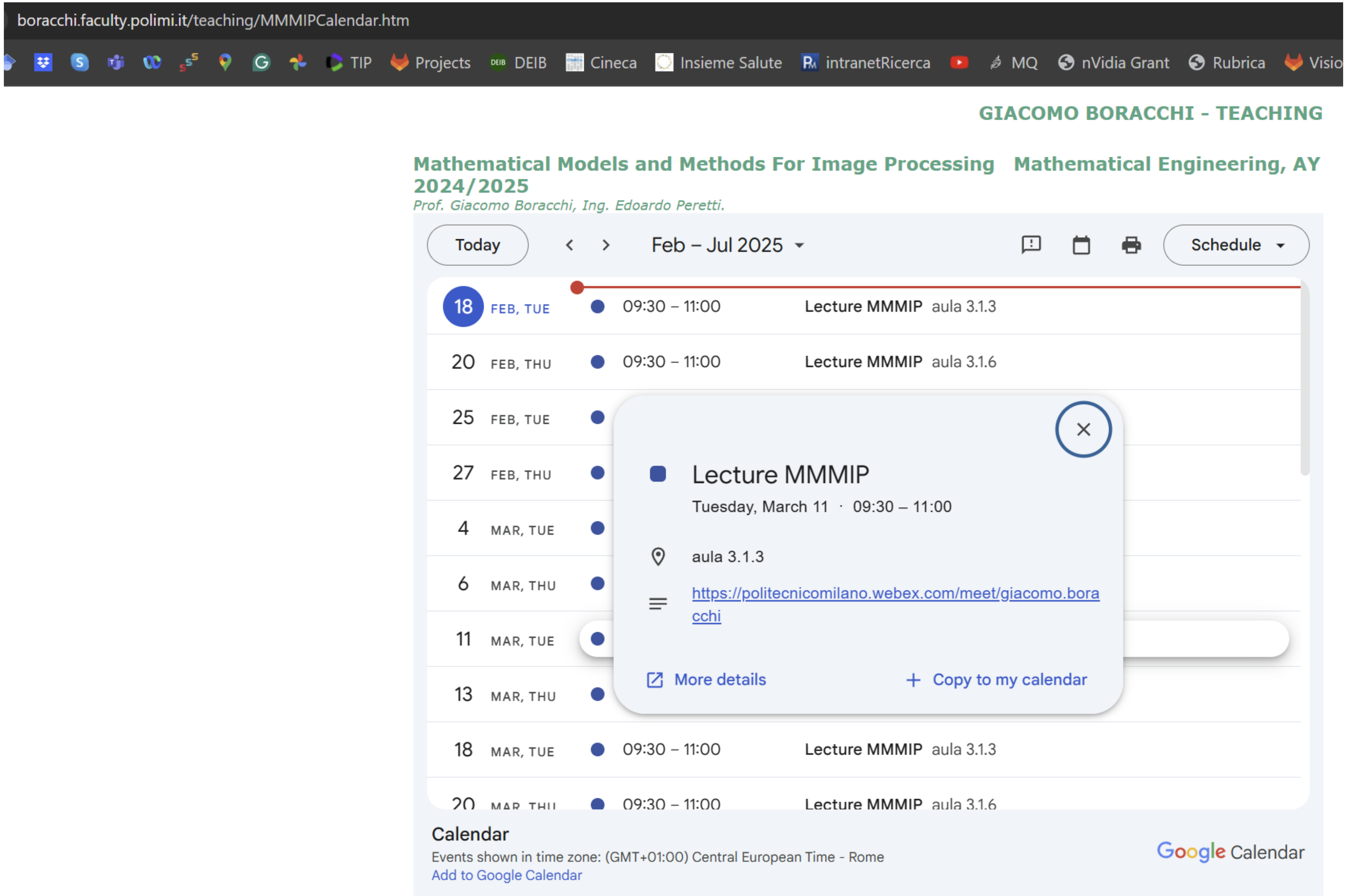
Computer Vision *(USI Lugano) Spring 2020 (Materials)*

Learning Sparse Representation for Image And Signal Modeling *(Milano Leonardo, PhD course) February 2019 Materials (Official Program)*

Advances In Deep Learning With Applications In Text And Image Processing *(Milano Leonardo, PhD course) February/March 2019 Materials (Official Program)*

Image Classification: Modern Approaches *(PhD course @Polimi) February 2018 (Official Program)*

https://boracchi.faculty.polimi.it/teaching/MMMIPCalendar.htm



The Lectures & Lab

The Lectures and Laboratories

There is no a dramatic difference between lectures and laboratory

Most often, in both cases there will be:

- Some recap on background notions
- Something new: an algorithm, a method, the solution for a specific application.
- Lab sessions typically address some specific notion left from the lectures to be solved in guided practical session

All the materials can be found on the course website:
https://boracchi.faculty.polimi.it/teaching/MMMIP.htm

The Exam

The exam

The exam consists in:

- Solving the **assignment** provided during lectures (to be delivered by 23.59 CET of the exam day).
- An **oral exam** about the course materials (schedule to be defined in 10-15 days after submitting homeworks).

The assignments are given during lectures with the purpose of:

- Let you familiarize and put in practice the presented models and methods
- Make sure you understood the algorithms

Grades

[0- 10] Points from homework marking

- Homework cannot be submitted twice and the grade remains for all the sessions of this academic year.

[0 – 20] points from oral discussion

Assessment Criteria:

- Ability to illustrate algorithms and theory behind them
- Understanding of models and their use in applications

Active participation during lectures and laboratories is encouraged and rewarded at the exam.

Laude is assigned to outstanding students only.

Frequently Asked Questions

Q: Any specific background?

A: linear algebra, statistics and calculus

Q: Any programming skill required?

A: Basic programming in Python using numPy

Q: Plenty of neural networks then?

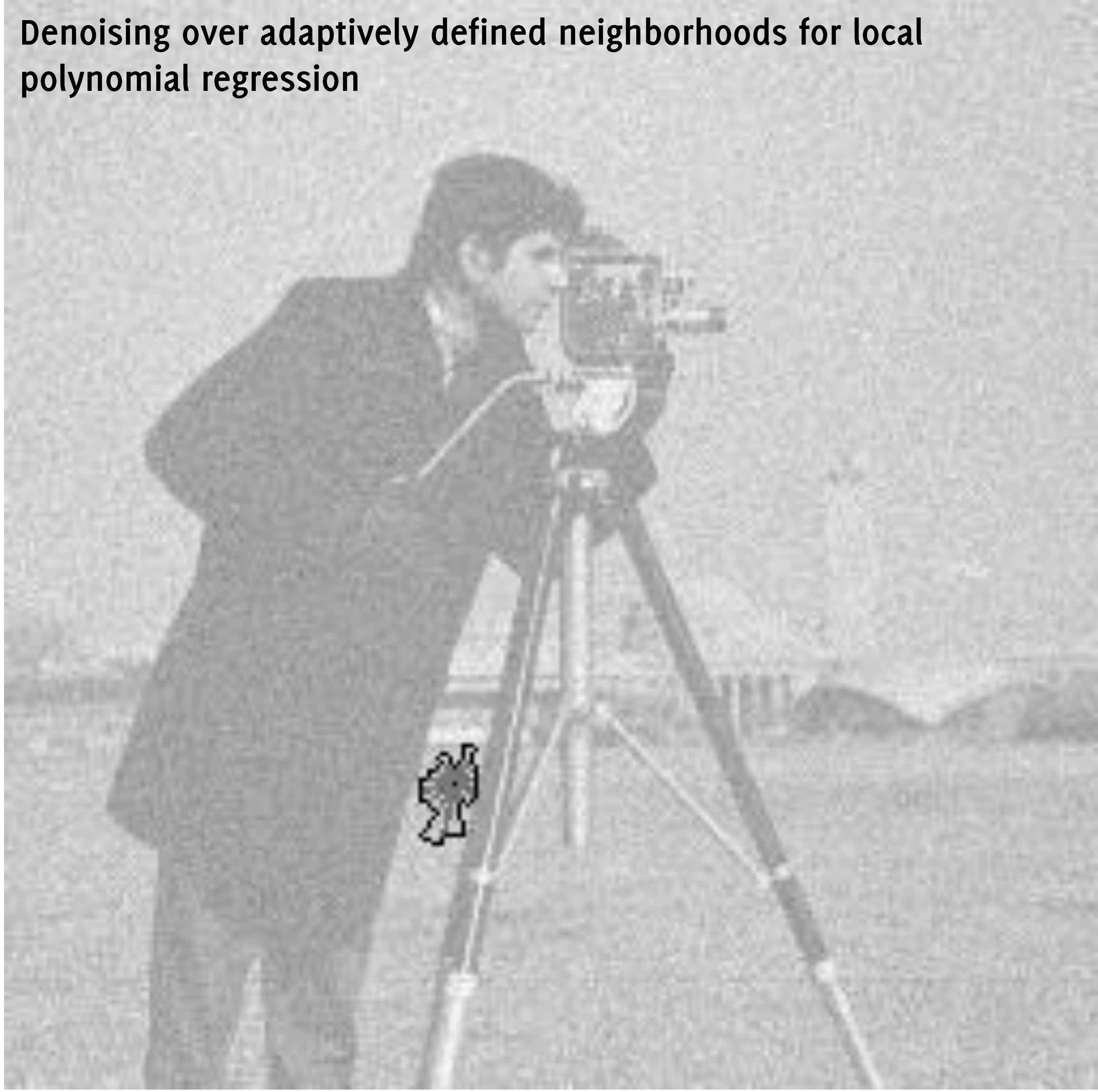
*A: No way. No neural networks allowed here** ☺*
Only expert-driven algorithms designed upon a clear mathematical modeling that admits closed-form solutions / sound optimization schemes.

* Interested in neural networks? Refer to «Artificial Neural Network and Deep Learning» in the first semester

Questions?

This is the fourth edition of the course… but we are always open to changes and improvements.

We might need to adjust quite a few things …. your feedback in this regard is very precious!


Denoising over adaptively defined neighborhoods for local polynomial regression

First Assignment

Today's Assignment: Generate the Basis

- Generate the DCT basis according to the following formula (DCT type II) the k-th atom of the DCT basis in dimension M is defined as

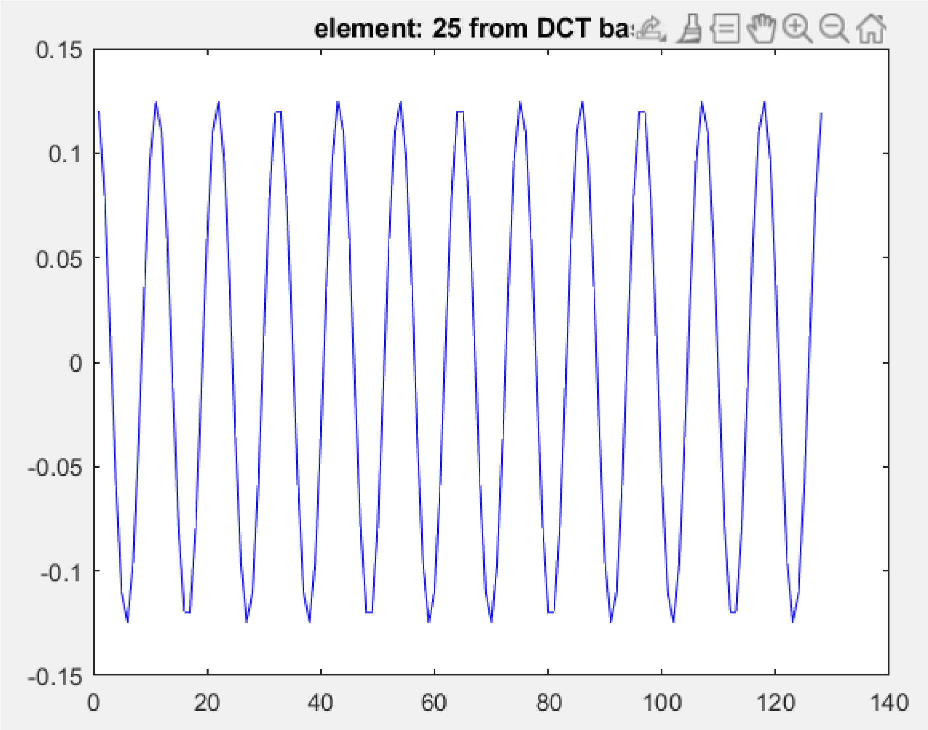
$$DCT_k(n) = c_k \cos\left(k\pi \frac{2n+1}{2M}\right) \; n, k = 0, \dots, M-1$$

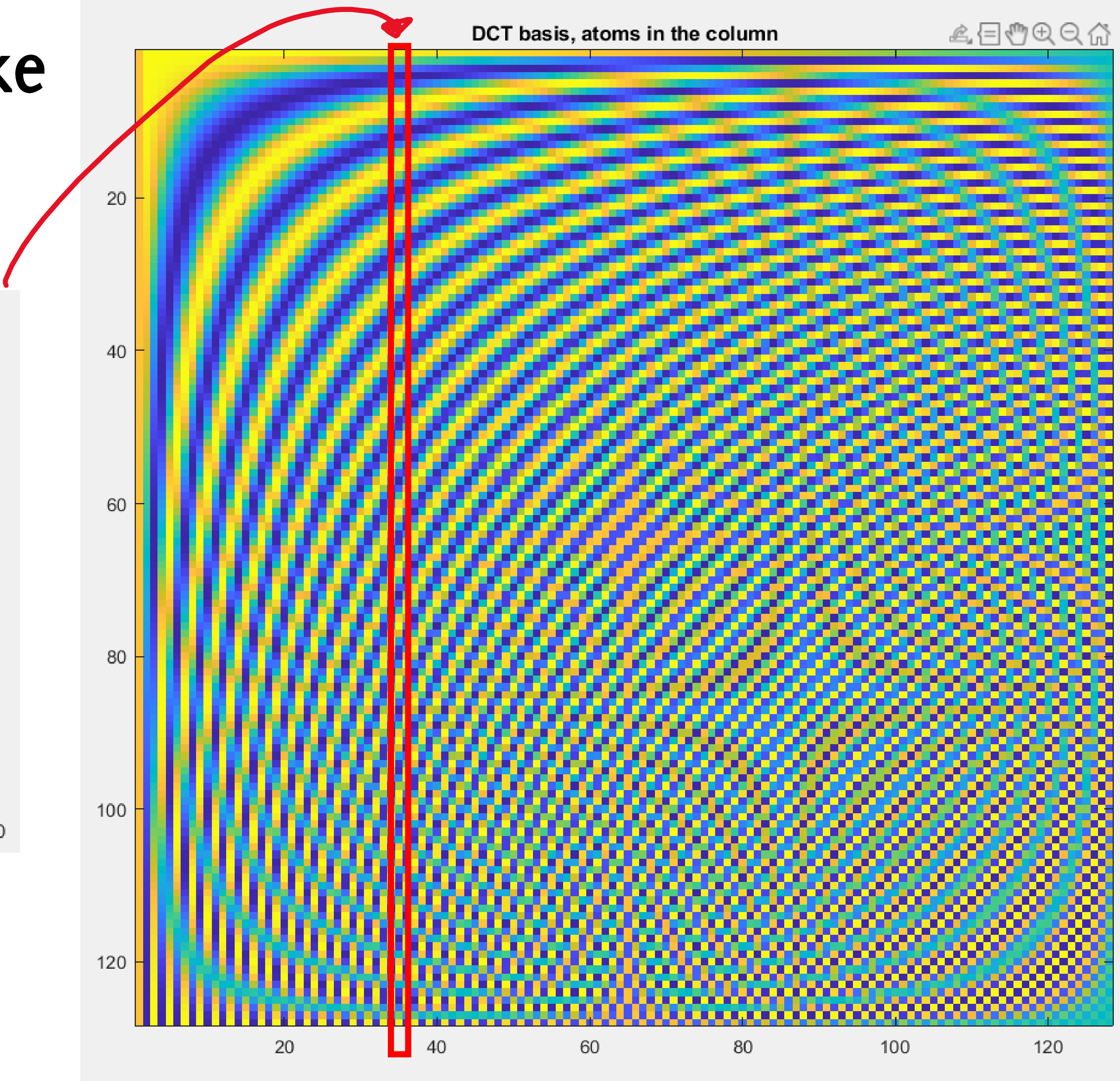
where $c_0 = \sqrt{1/M}$ and $c_k = \sqrt{2/M}$ for $k \neq 0$.

- For each $k = 0, \dots, M-1$, just sample each function $\cos\left(k\pi \frac{2n+1}{2M}\right)$ at $n = 0, \dots, M-1$, obtain a vector. Ignore the normalization coefficient. Divide each vector by its ℓ_2 norm.

- How can you use the function dct and it's inverse idct to define the DCT matrix?

The Matrix Should Look Like





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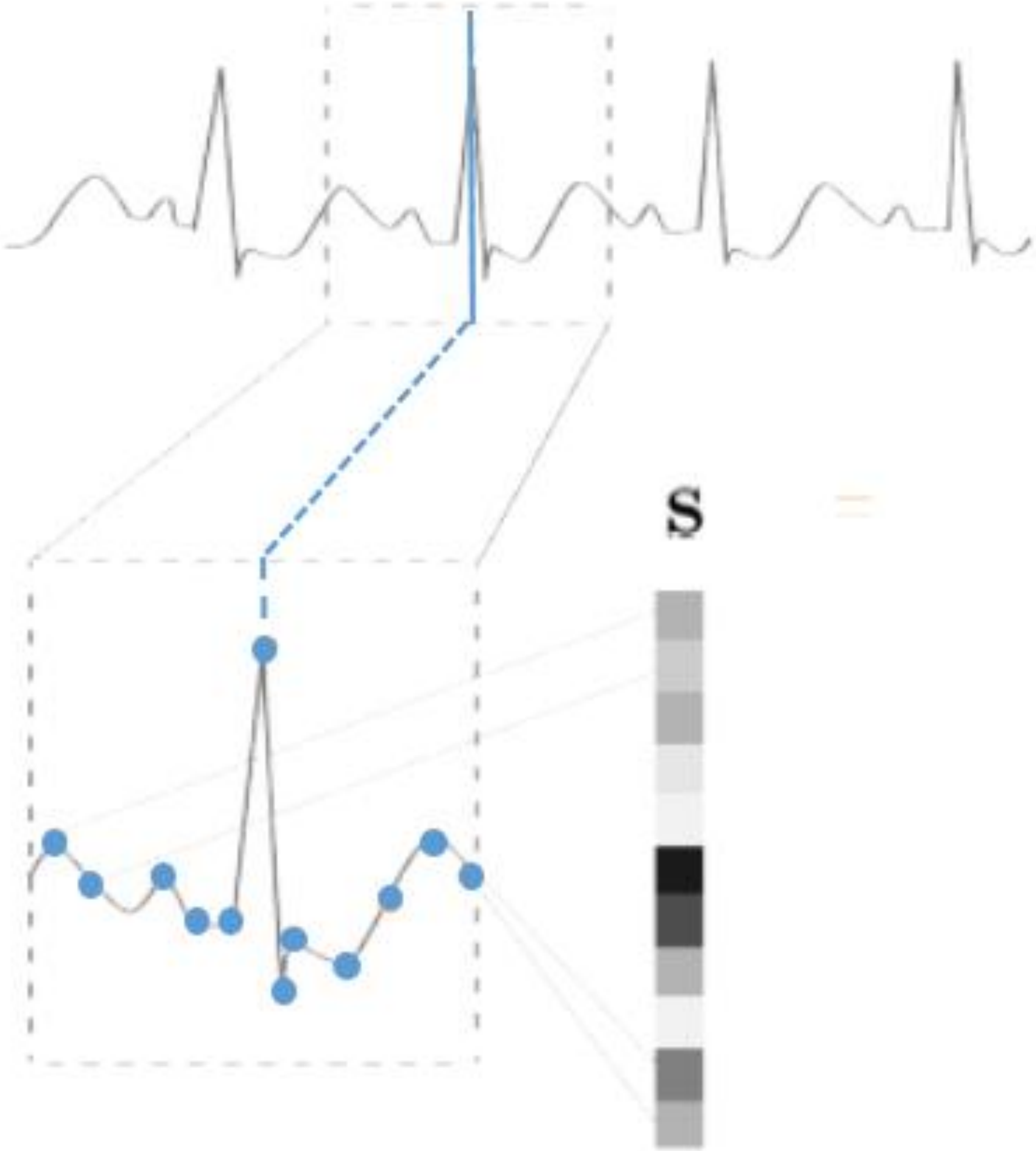
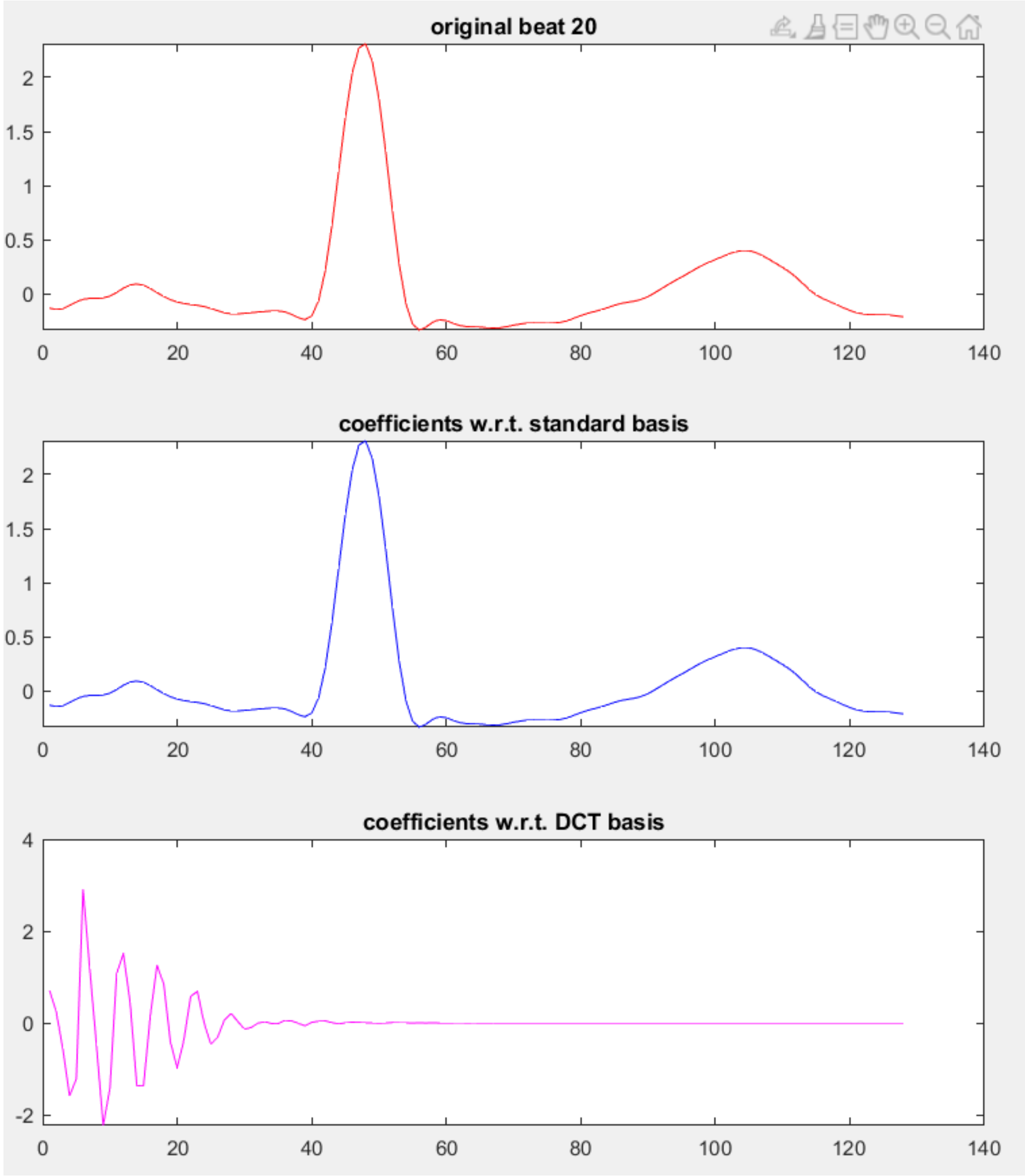
Today's Assignment: Analysis and Synthesis

- Load the ECG traces
- Analysis: Use the DCT basis you have defined to compute the representation of each signal $\boldsymbol{s}$ w.r.t the basis
- Display the coefficients and check whether they are sparse
- Synthesis: Reconstruct the signal from the coefficients. Check whether the reconstruction is perfect
- Add noise

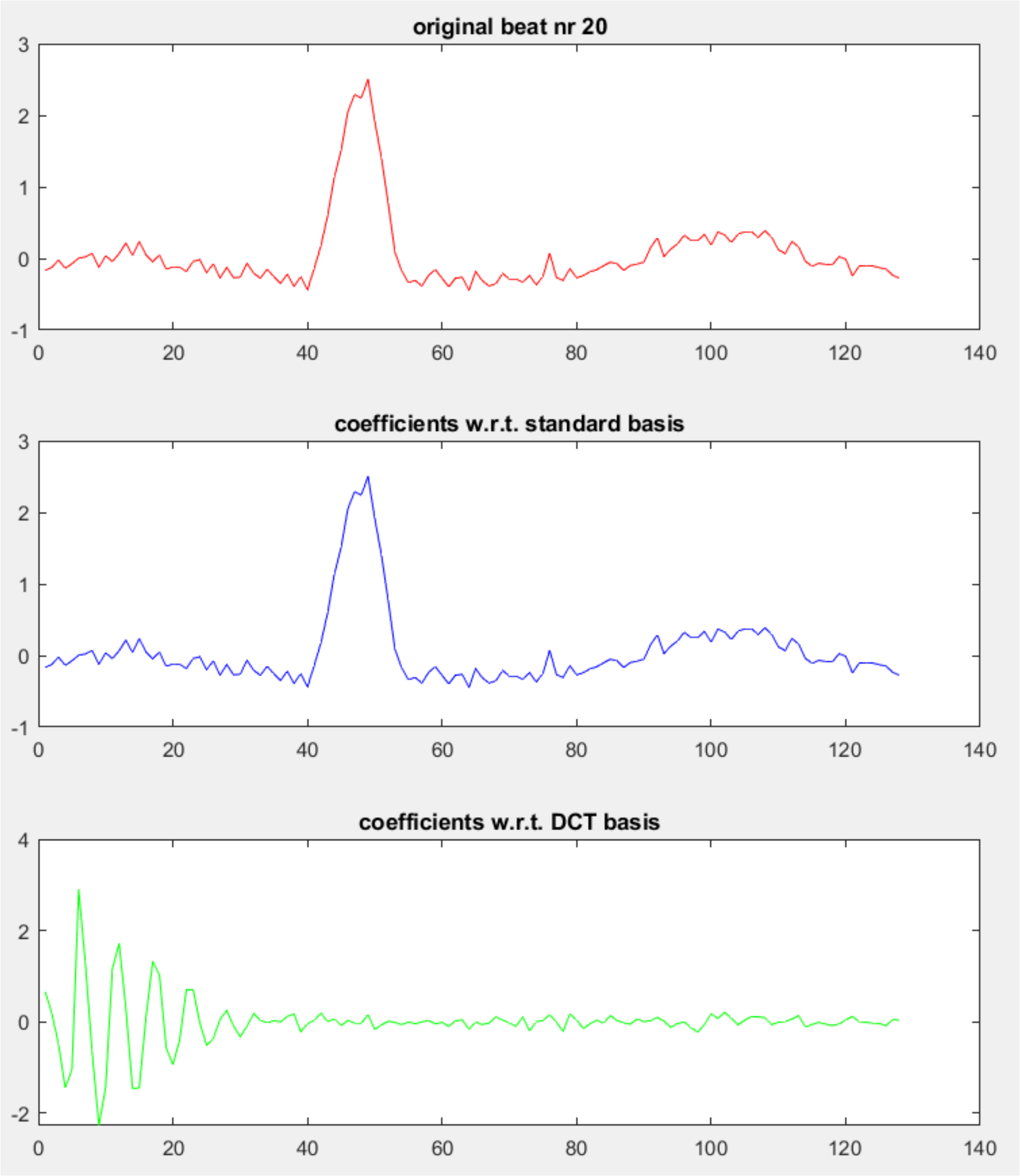
Modeling Scheme



w/o noise

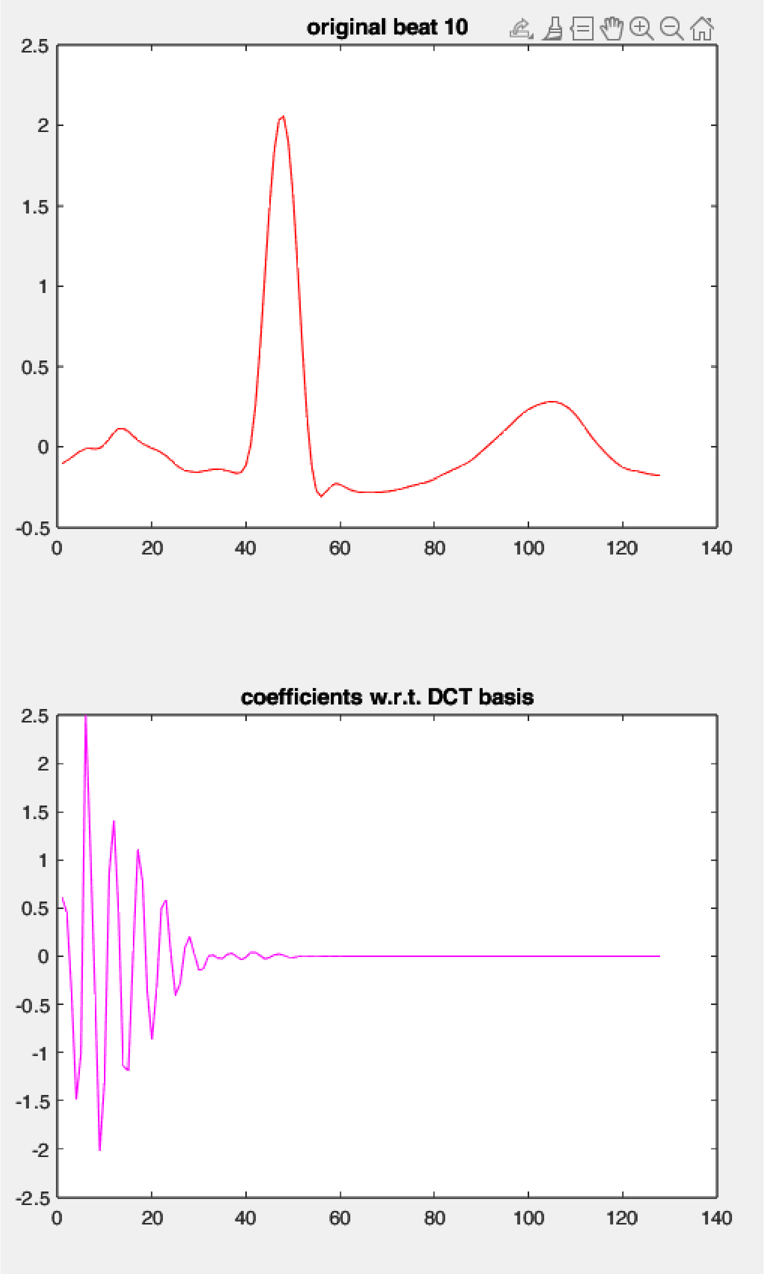


w/ noise



w/o noise

w/ noise

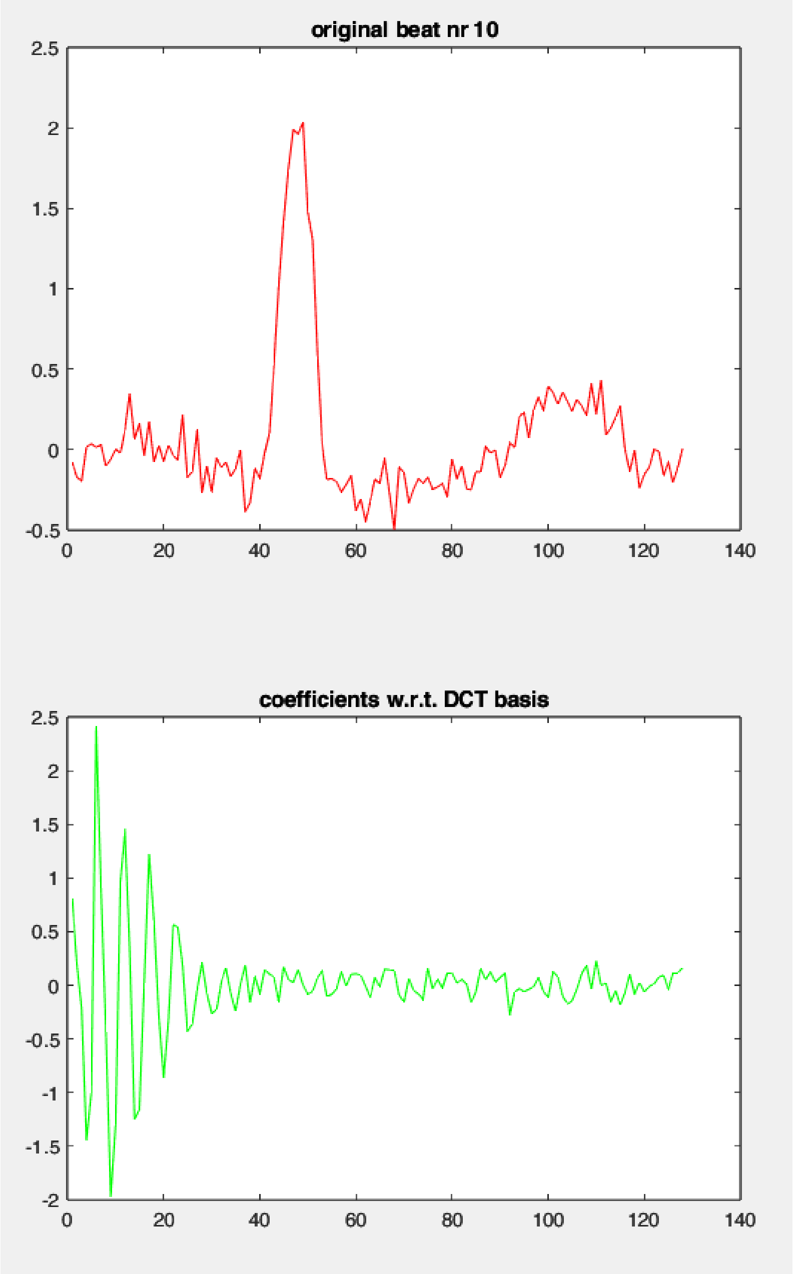


The sparsity prior seems to be effective on this type of signals. There are **only few nonzero coefficients** in here.

DCT bases yields a **sparse representation** of heartbeats

w/o noise

w/ noise

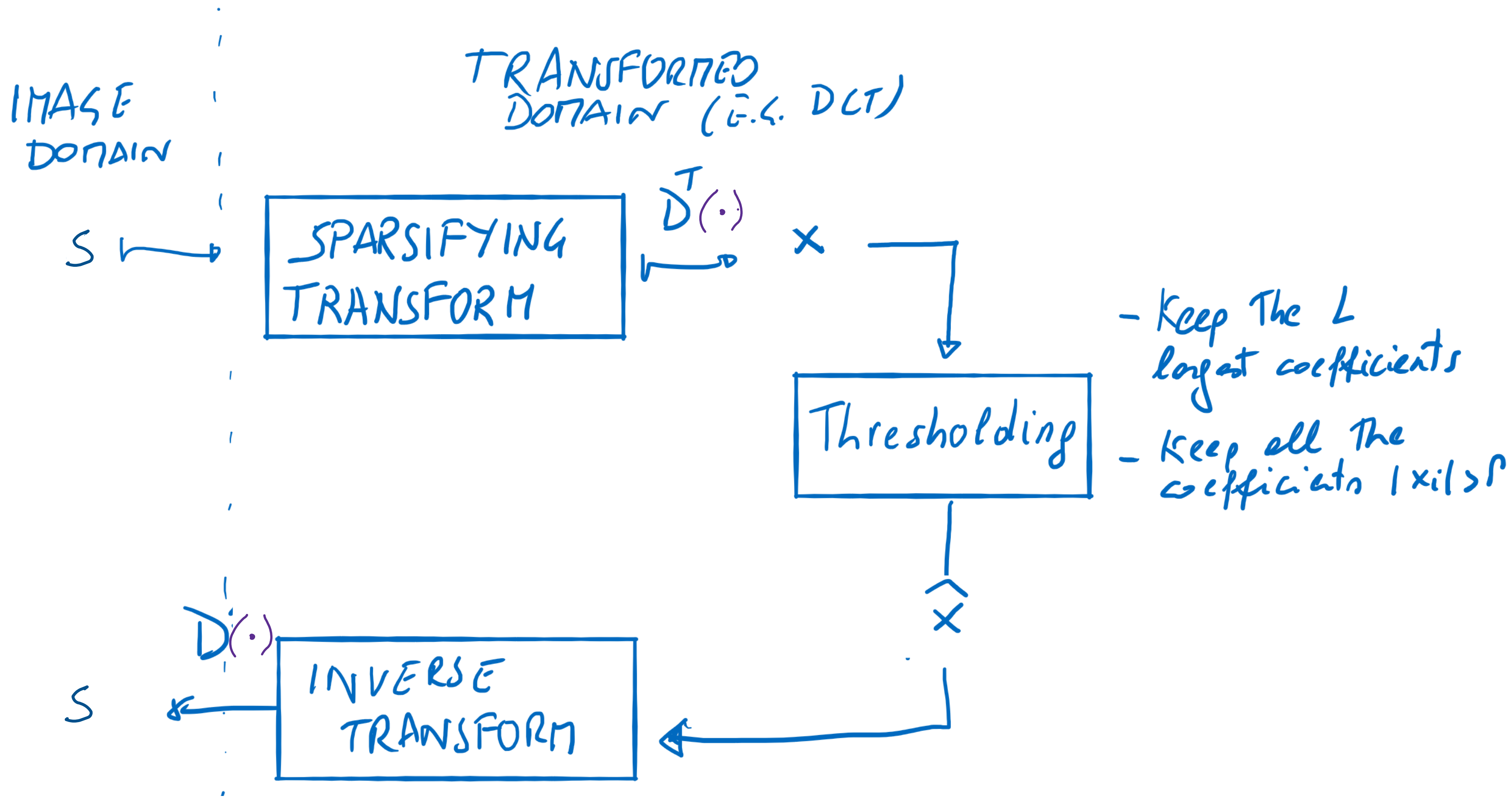


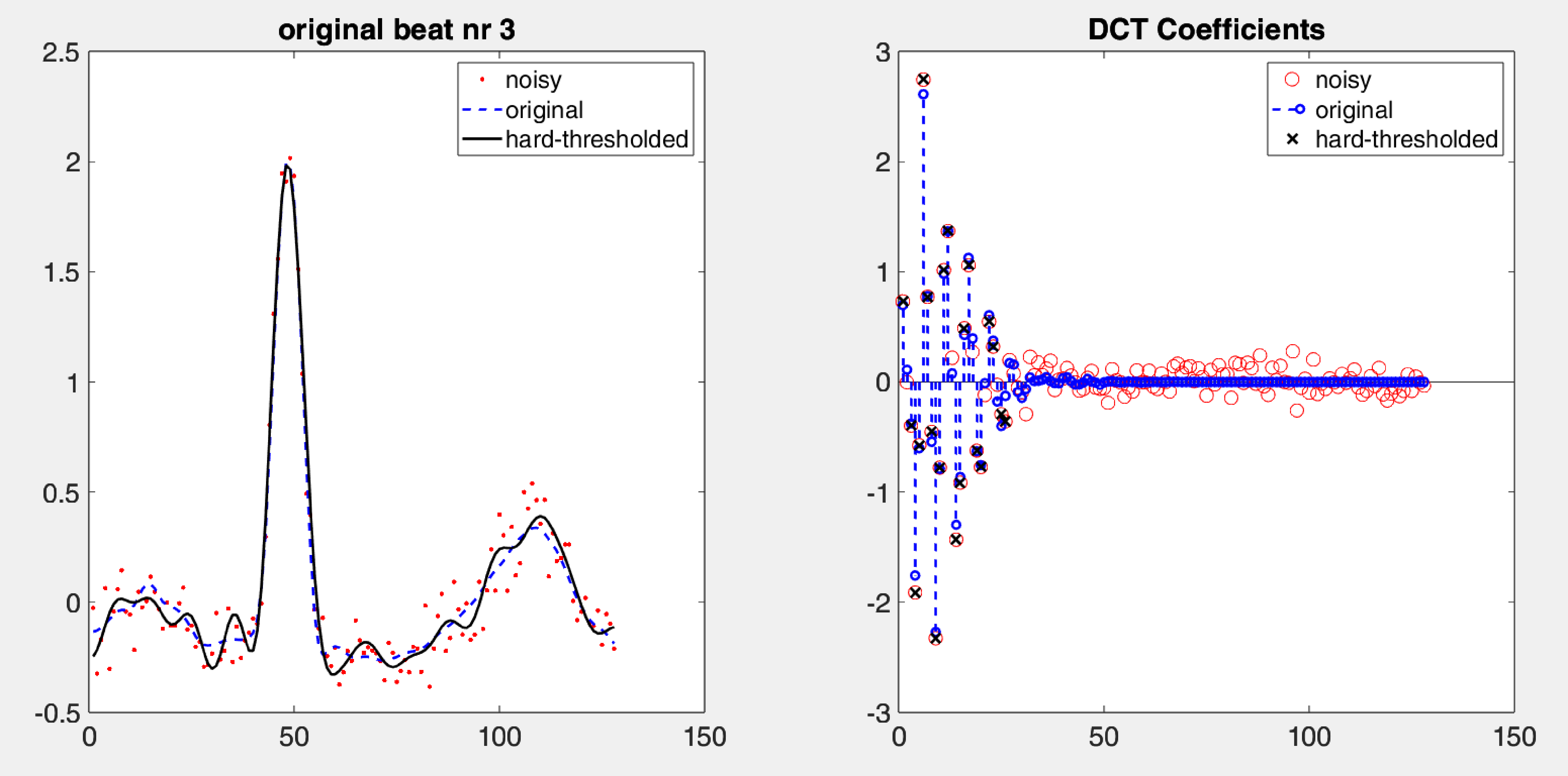
Still, the **coefficients referring to the noise-free** signal have a **magnitude** that is **larger** than those coefficients that are only affected by noise

However, the **large coefficients are also affected by noise** (therefore getting rid of the smallest coefficients won't return the noise-free signal)

Today's Assignment: Enforce Sparsity

- Enforce Sparsity to get rid of noise




original beat nr 3
noisy
original
hard-thresholded
2.5
2
1.5
1
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DCT Coefficients
noisy
original
hard-thresholded
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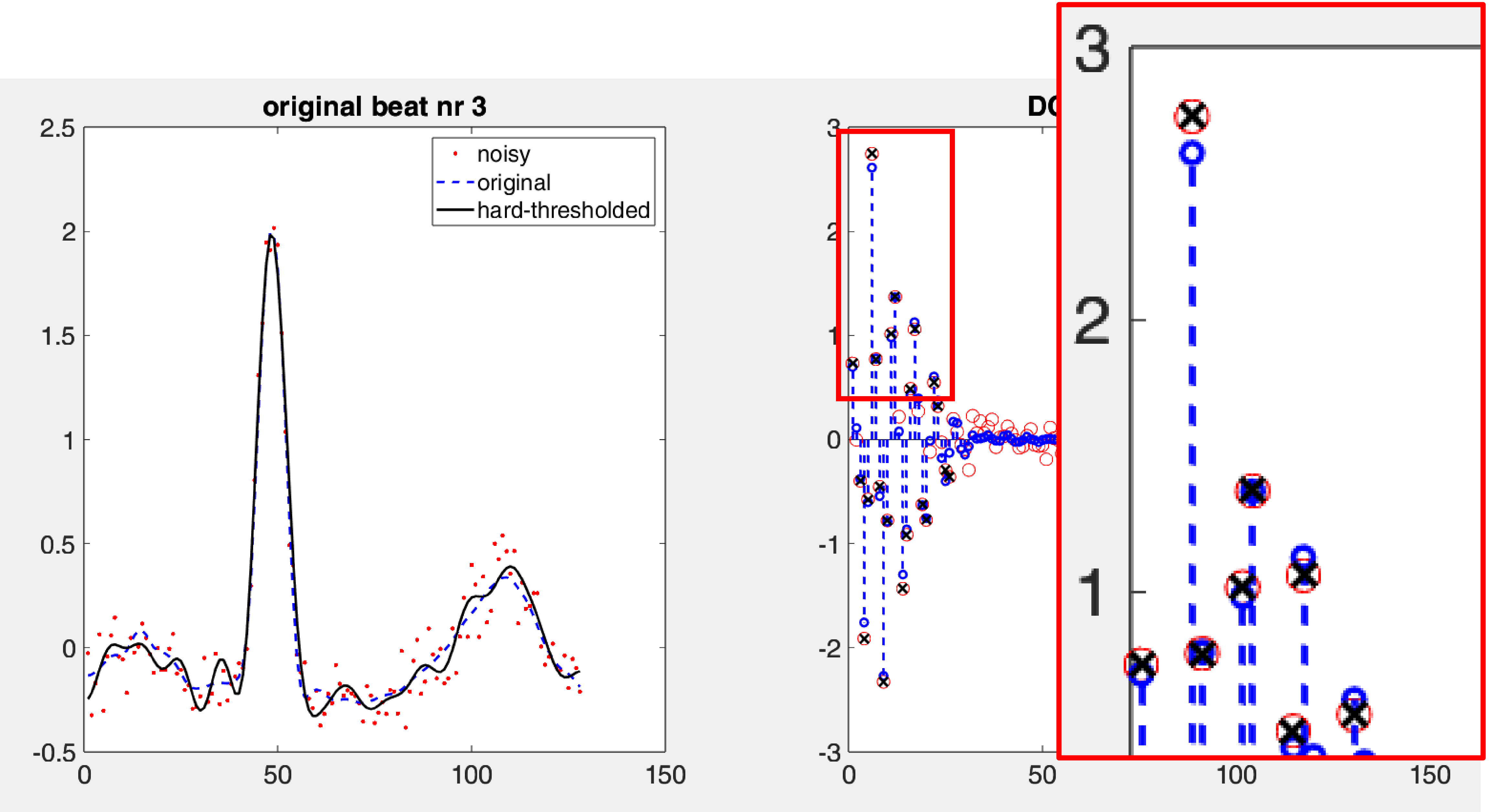

original beat nr 3
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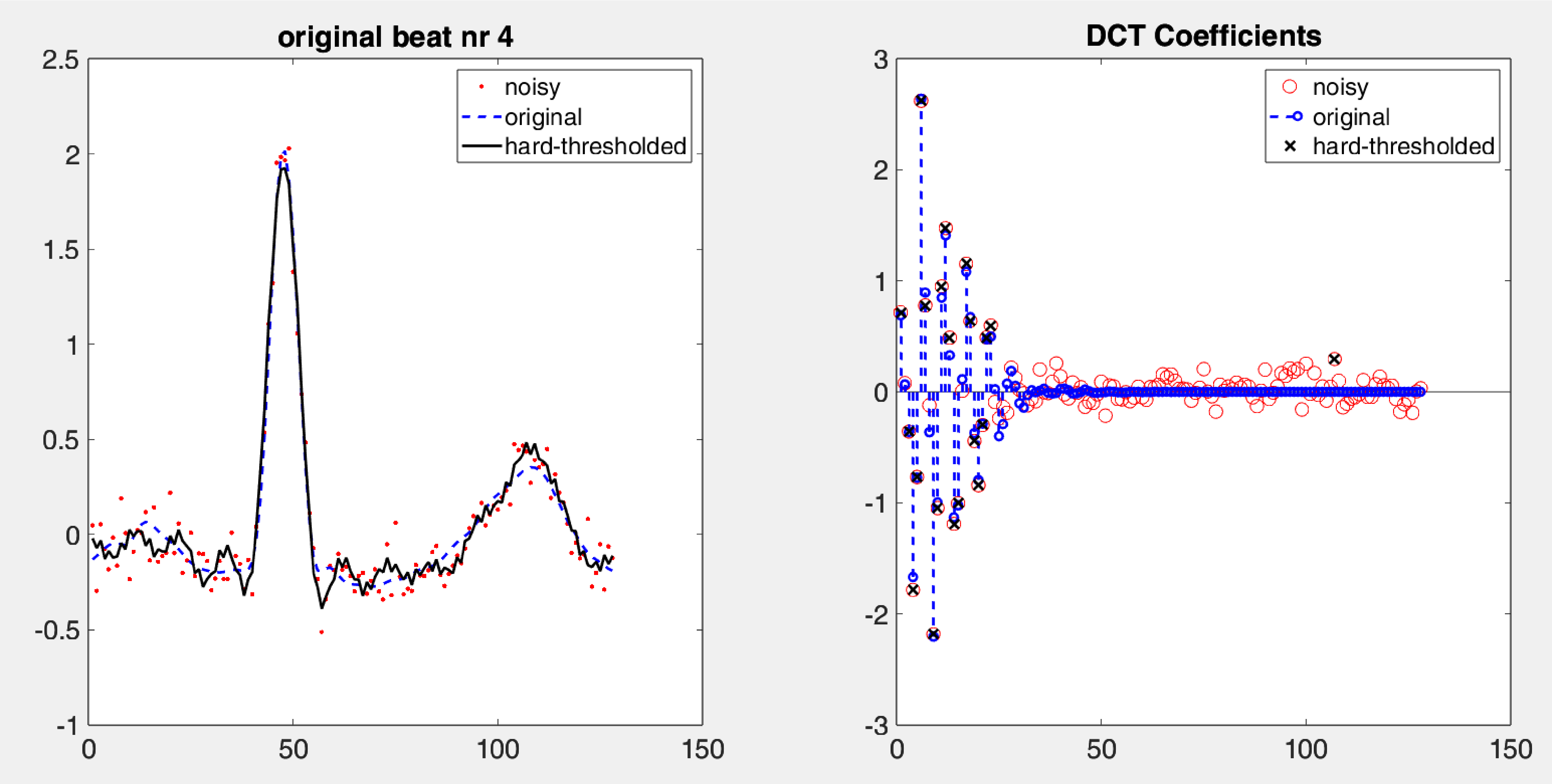
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DCT Coefficients
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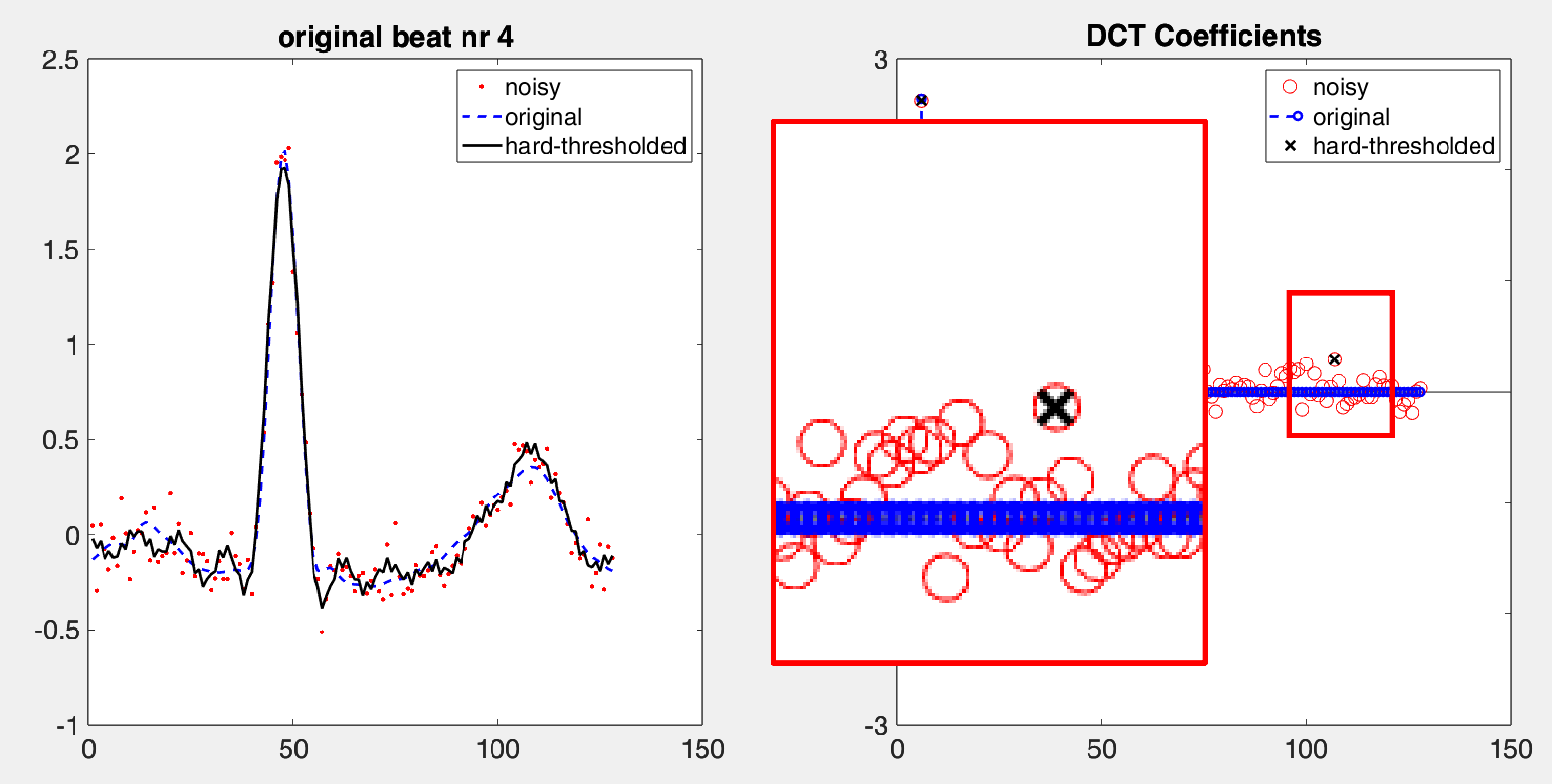
original beat nr 4
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DCT Coefficients
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Sparsity

From “**Sparse Modeling for Image and Vision Processing**”

J. Mairal, F.Bach, J.Ponce

Now Publisher 2012

Sparsity and Parsimony

The principle of sparsity or "parsimony" consists in *representing some phenomenon with as few variable as possible*

Stretch back to philosopher William Ockham in 14^{th} Century

Wrinch and Jeffreys [1921] relate simplicity to parsimony:

> *The **existence of simple laws** is, then, apparently, to be regarded as **a quality of nature**; and accordingly we may infer that it is justifiable to **prefer a simple law to a more complex one that fits our observations slightly better**.*

Simplicity <-> number of learning parameters

Sparsity in Statistics

Statistics: simple models are preferred.

Sparsity is used to **prevent overfitting and improve interpretability of learned models.**

In model fitting, the number of parameters is typically used as a criterion to perform model selection.

See Bayes Information Criterion (BIC), Akaike Information Criterion (AIC), …., Lasso.

Sparsity in Signal Processing

Signal Processing: similar concepts but different terminology. **Vectors corresponds to signals** and **data modeling is crucial** for performing various operations such as **restoration, compression, solving inverse problems**.

Signals are approximated by sparse linear combinations of **prototypes** (basis elements / atoms of a dictionary), resulting in simpler and compact model.

Best subset selection <-> computing the sparse representation of a signal w.r.t. a give basis/dictionary

Neuroscience: Olshausen and Field [1996], learning the from a training set of data dictionaries yielding sparse representations