Innovative Alphabet-Based Bayesian Compressive Sensing Technique for Imaging Targets with Arbitrary Shape

N. Alselmi, G. Oliveri, M. A. Hannan, M. Salucci, and A. Massa

Abstract

In this work an innovative two-dimensional (*2D*) microwave imaging technique exploiting Bayesian Compressive Sensing (*BCS*) and a wavelet-based *alphabet* for representing the problem unknowns is dealt with. The proposed approach is based on the generalization of the *sparsity* concept, extending the range of applicability of *BCS*-based inverse scattering (*IS*) techniques to objects with arbitrary shape and dimensions. A set of *BCS* reconstructions is performed considering different expansion bases in the alphabet, without the need for a-priori knowledge about the unknown scatterers. Then, the best reconstruction is recognized as that minimizing the number of non-null retrieved coefficients (i.e., the *sparsest* one). In order to verify the effectiveness of the proposed imaging technique, a set of representative numerical benchmarks is presented. Some comparisons with state-of-the-art IS techniques are presented, as well.

1 Numerical Results

1.1 Object Haar #0

Goal: To prove the effectiveness of the alphabet based approach using an "ad-hoc" scatterer for Haar wavelets.

Test Case Description

Object:

- $\varepsilon_{r,max} = 1.01$
- $\sigma = 0$ [S/m]
- Number of Haar coefficients: $Nc = 2$

Sources:

- Plane waves
- Amplitude: $A = 1$
- Frequency: 300 MHz ($\lambda = 1$m)
- Number of views: $V = 36$

Direct solver:

- Square domain divided in $\sqrt{D} \times \sqrt{D}$ cells
- $D = 4096$ (64×64) $(\frac{L_D}{\sqrt{D}} = \frac{\lambda}{16})$

Investigation domain:

- Square domain divided in $\sqrt{N} \times \sqrt{N}$ cells
- $N = 1024$ (32×32) $(\frac{L_D}{\sqrt{N}} = \frac{\lambda}{8})$
- $L_D = 4\lambda$

Measurement domain:

- Measurement points taken on a circle of radius $\rho = 4\lambda$
- $M = 36$

M-BCS parameters:

- $a = 1.0 \times 10^{-2}$
- $b = 1.0 \times 10^{-5}$

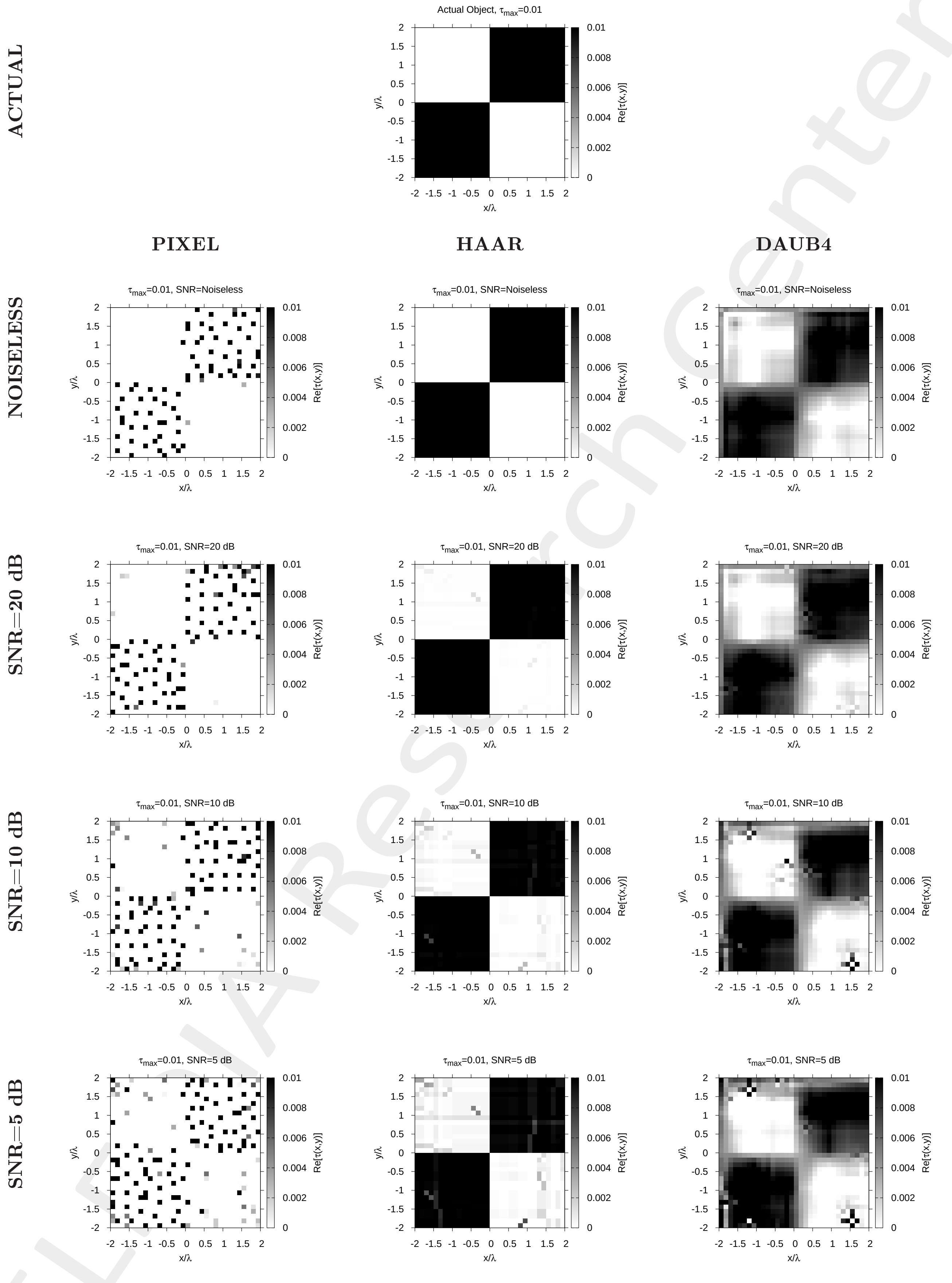

Figure 1: Actual and retrieved object (real part) considering different wavelet expansions.

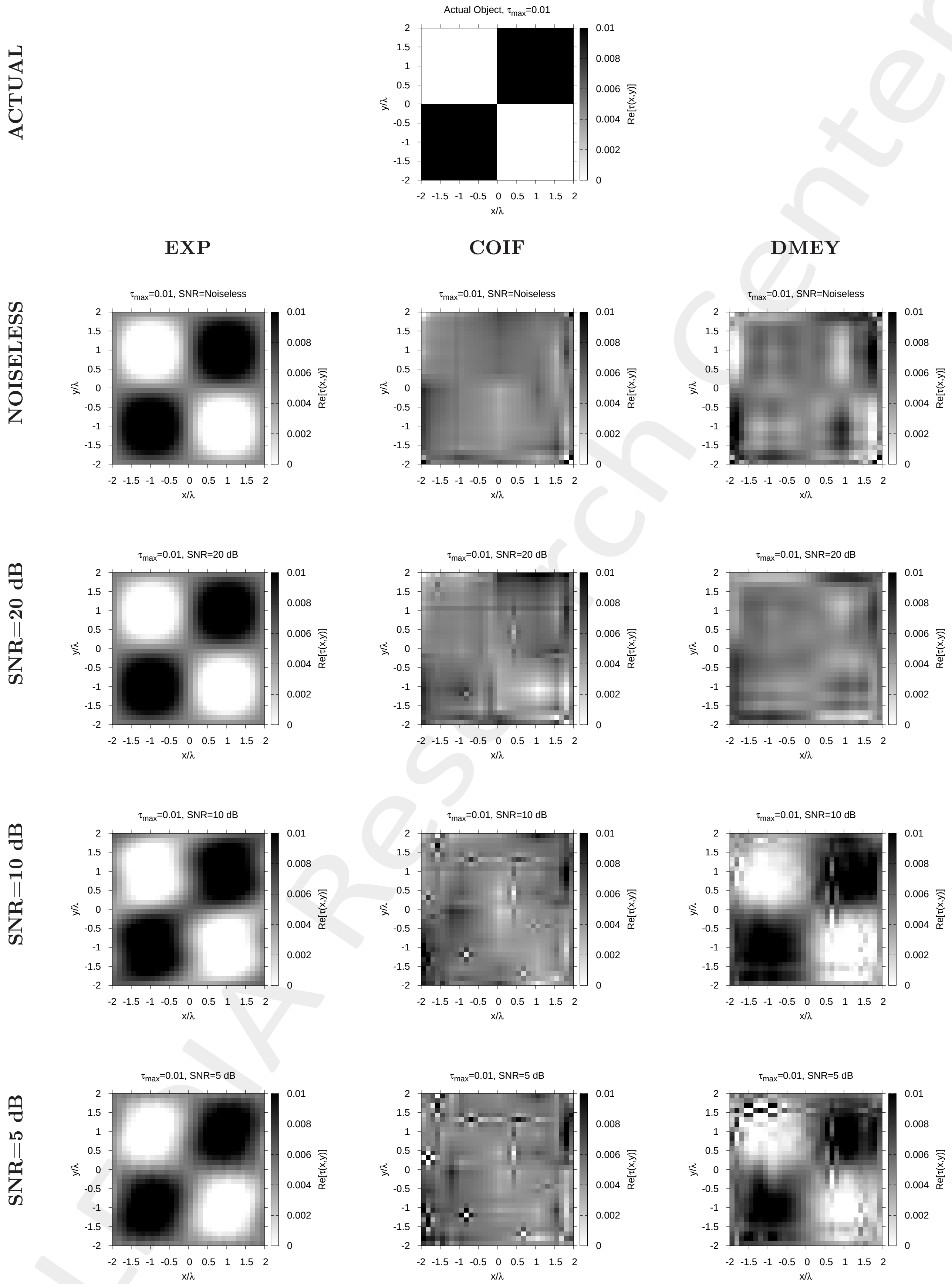

Figure 2: Actual and retrieved object considering different wavelet expansions.

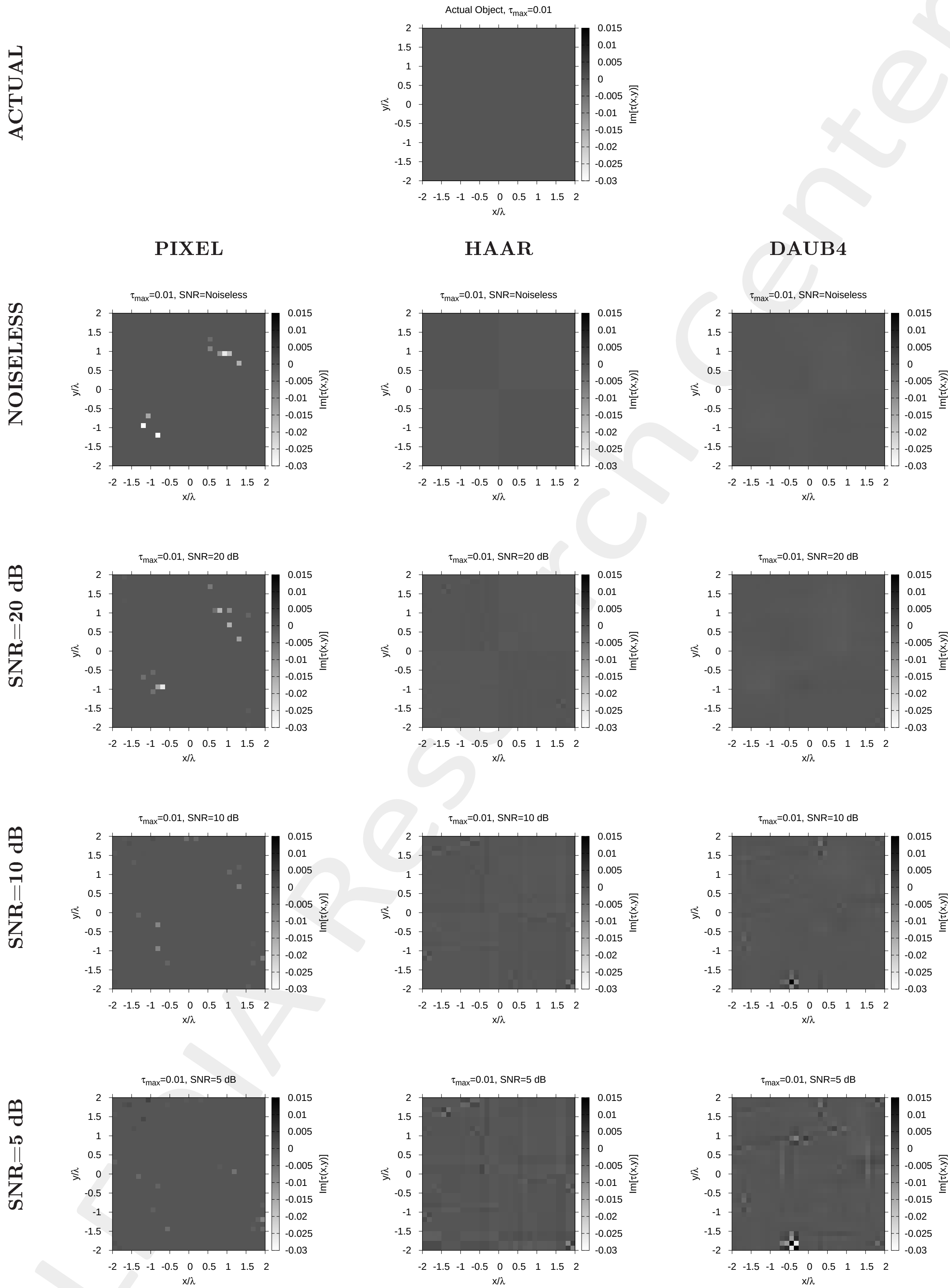

Figure 3: Actual and retrieved object (imaginary part) considering different wavelet expansions.

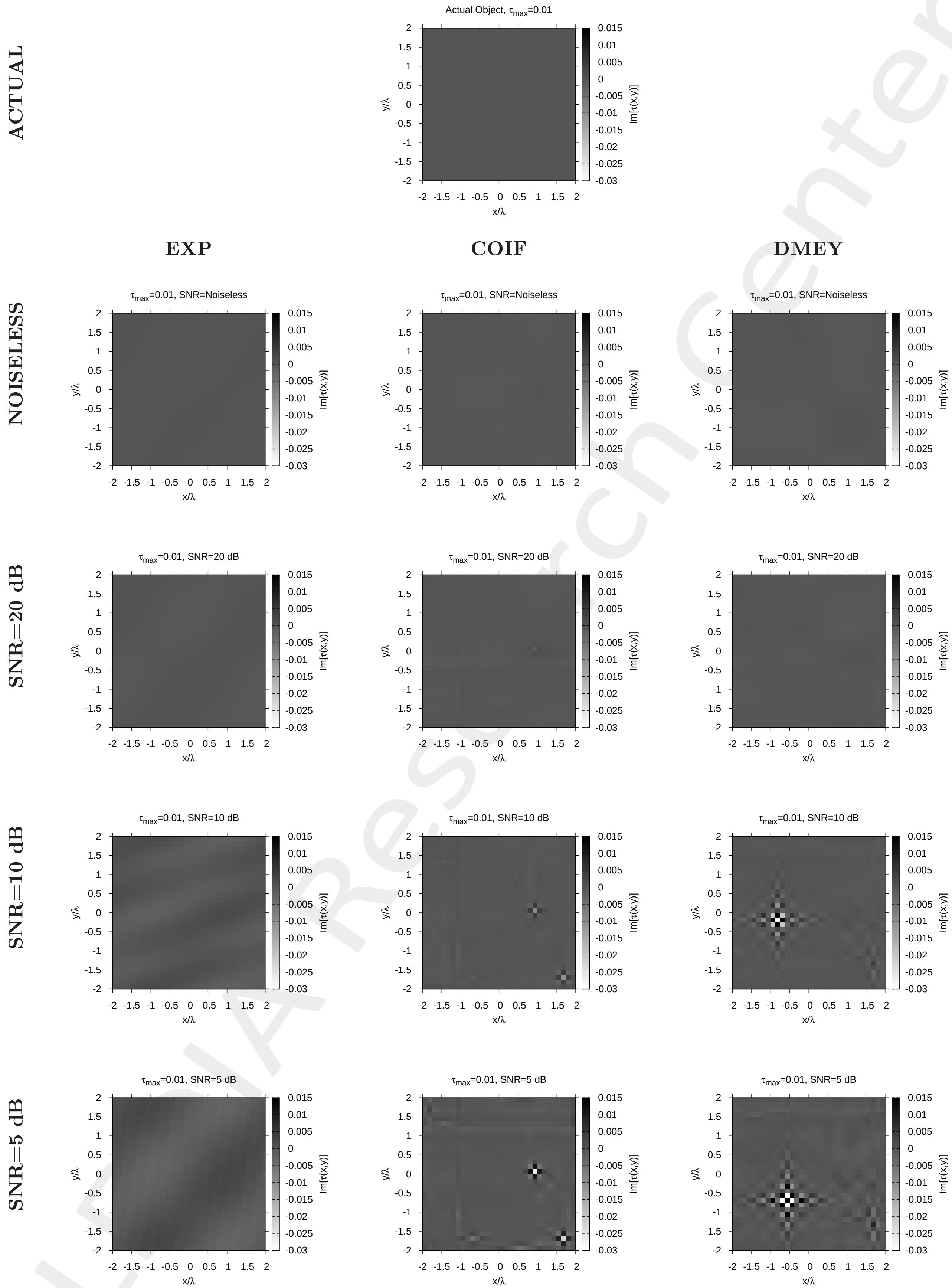

Figure 4: Actual and retrieved object considering different wavelet expansions.

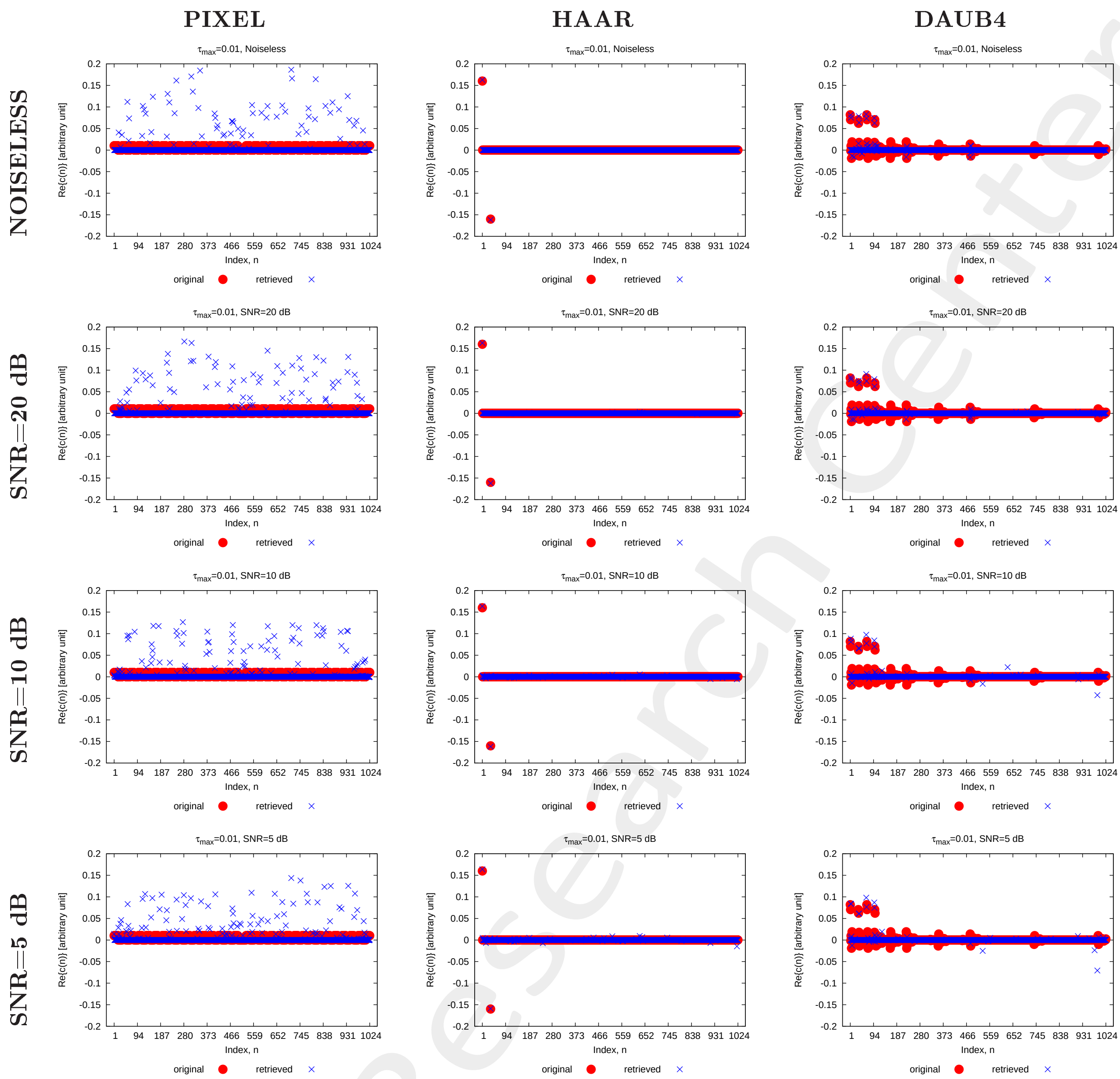

Figure 5: Real part of the actual and retrieved coefficients considering different wavelet expansions.

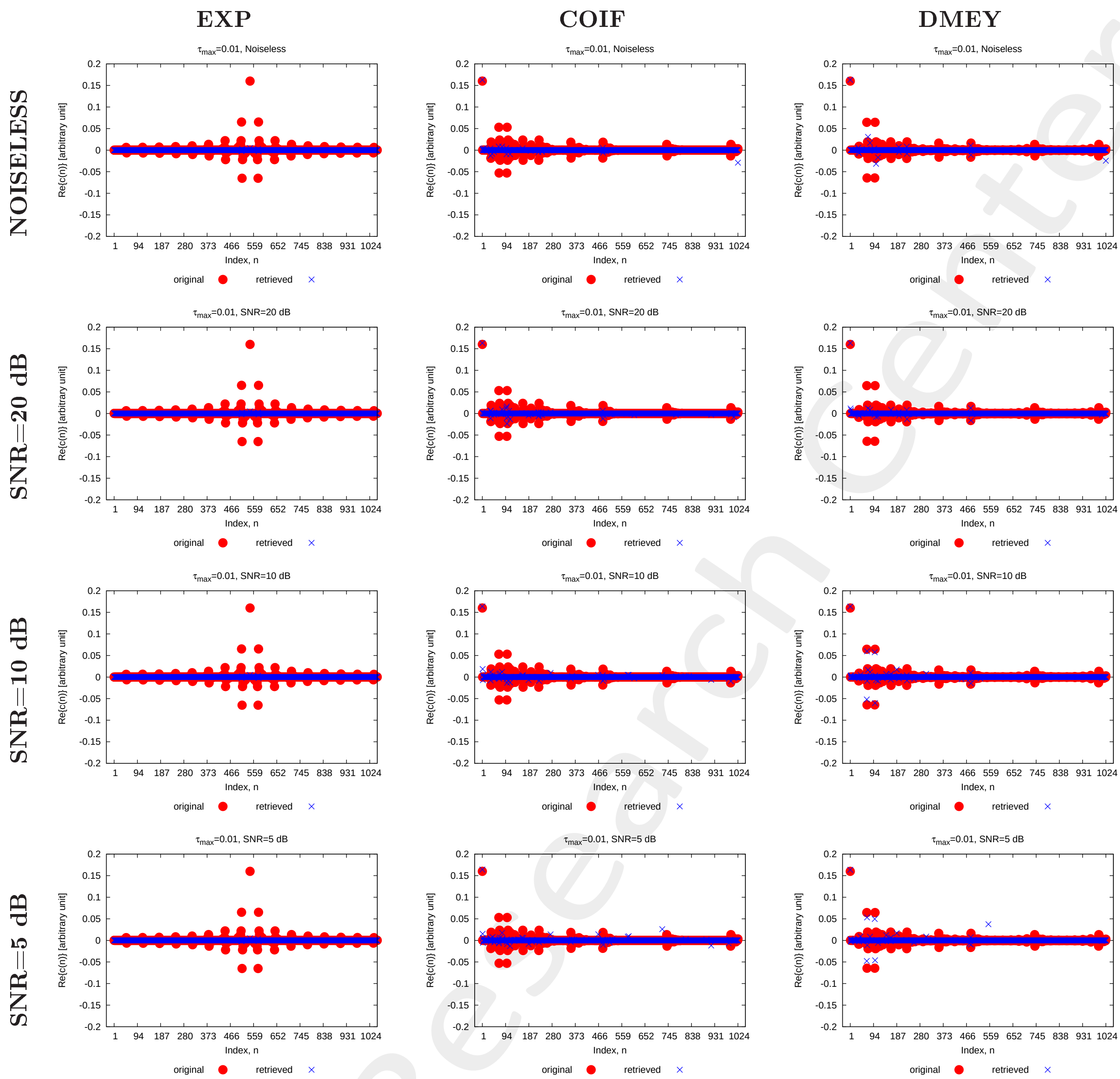

Figure 6: Real part of the actual and retrieved coefficients considering different wavelet expansions.

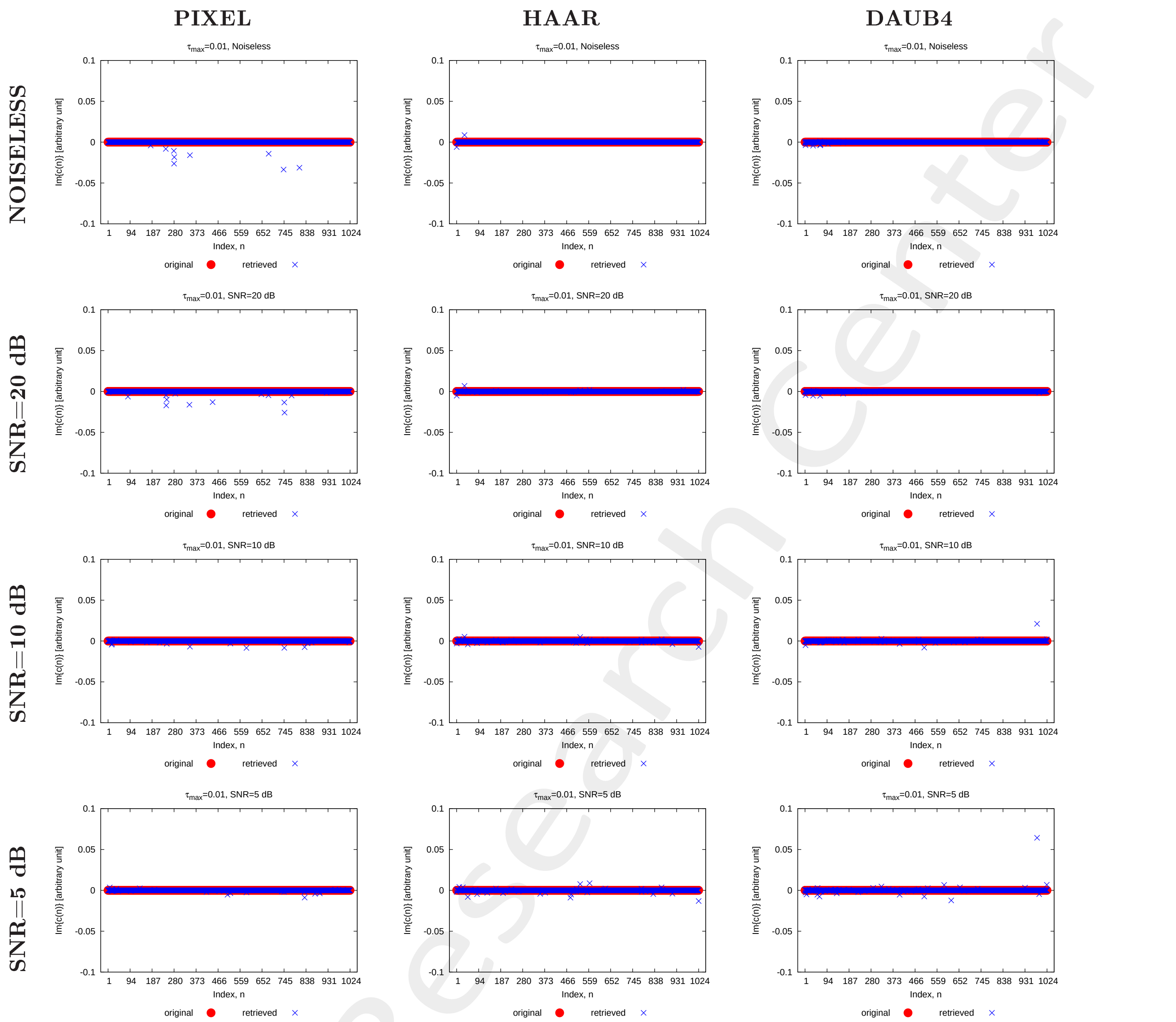

Figure 7: Imaginary part of the actual and retrieved coefficients considering different wavelet expansions.

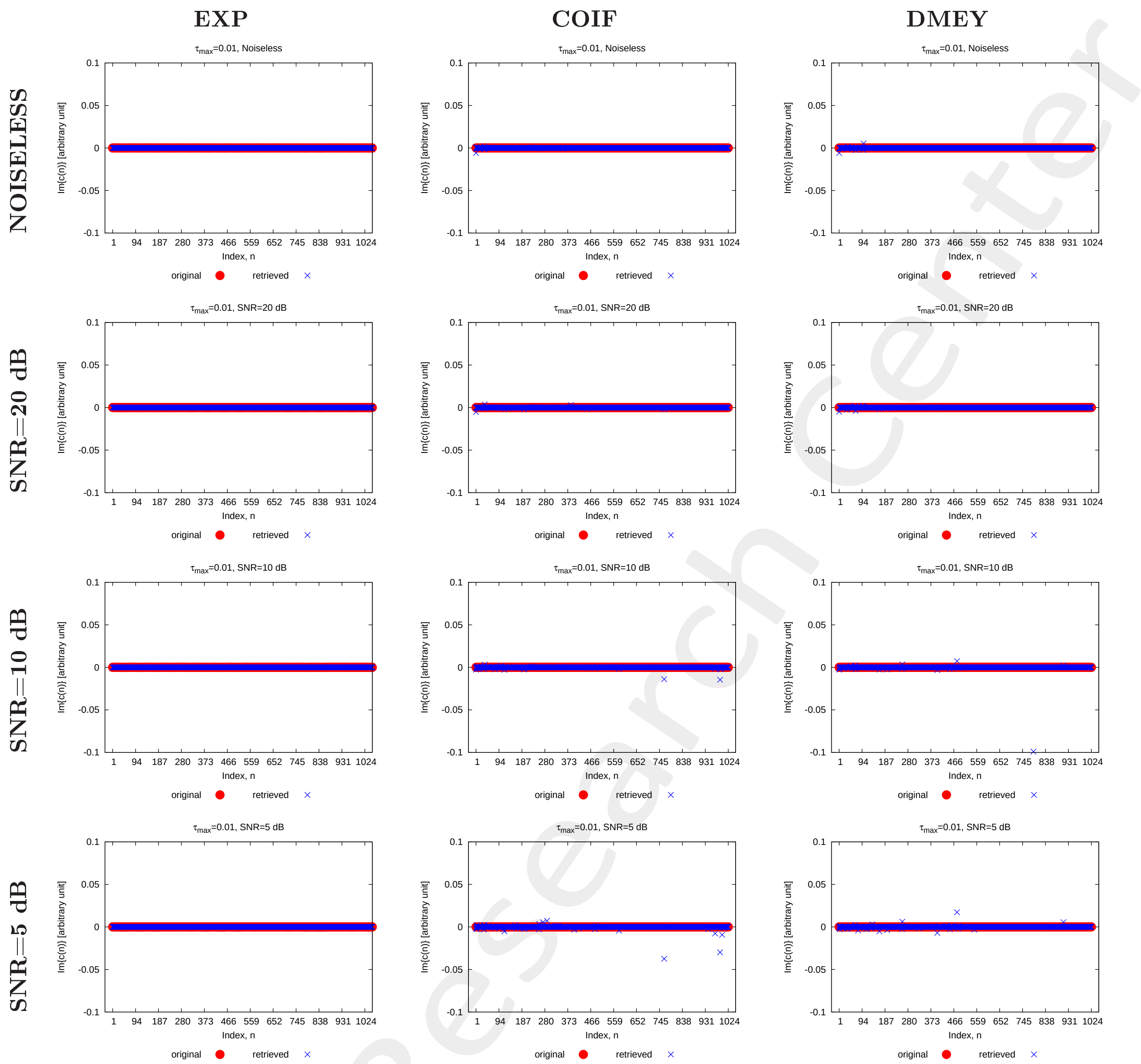

Figure 8: Imaginary part of the actual and retrieved coefficients considering different wavelet expansions.

Coefficients Analysis $T = 100\%$:

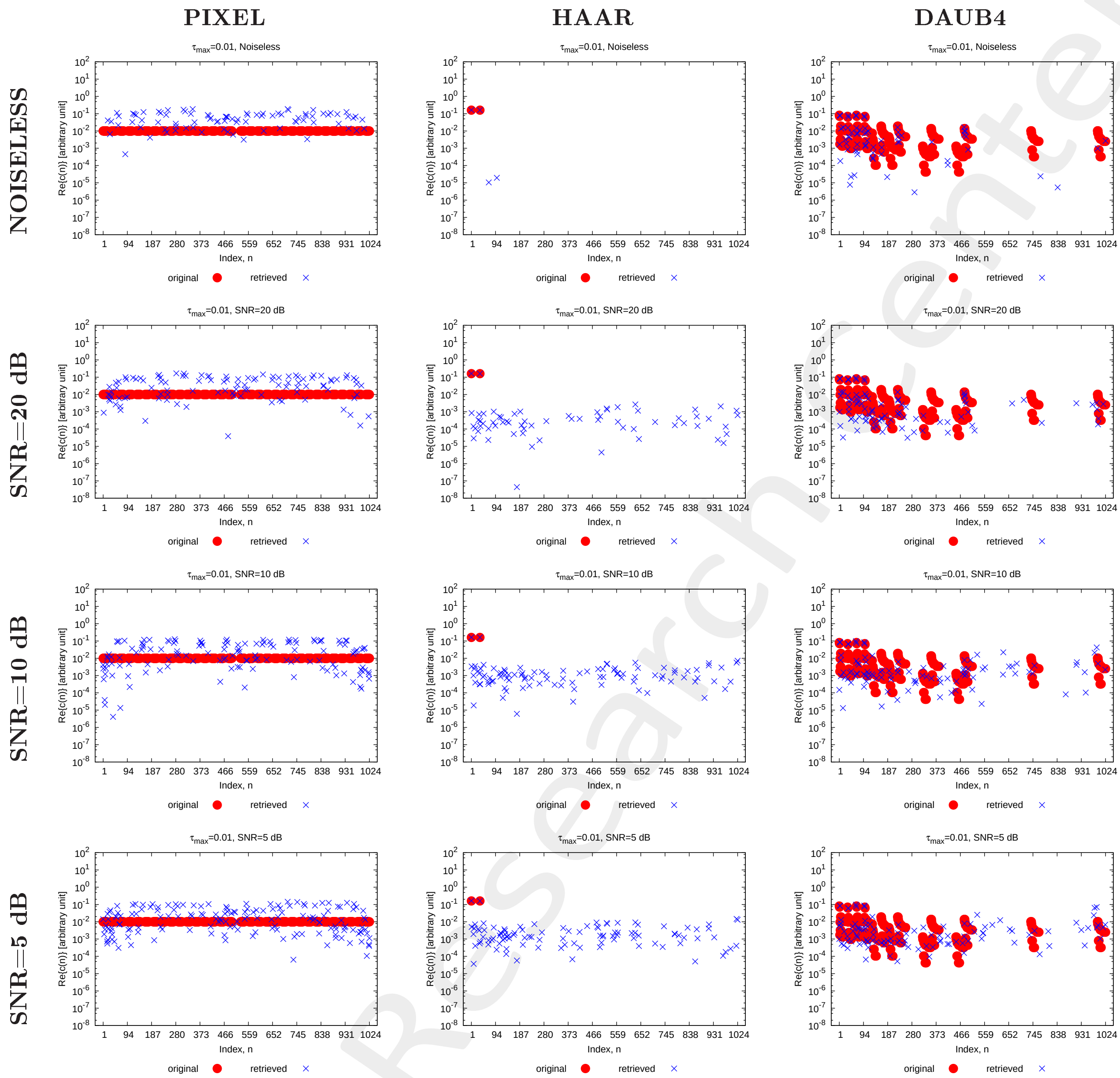

Figure 9: Absolute value (dB) of the actual and retrieved coefficients considering different wavelet expansions.

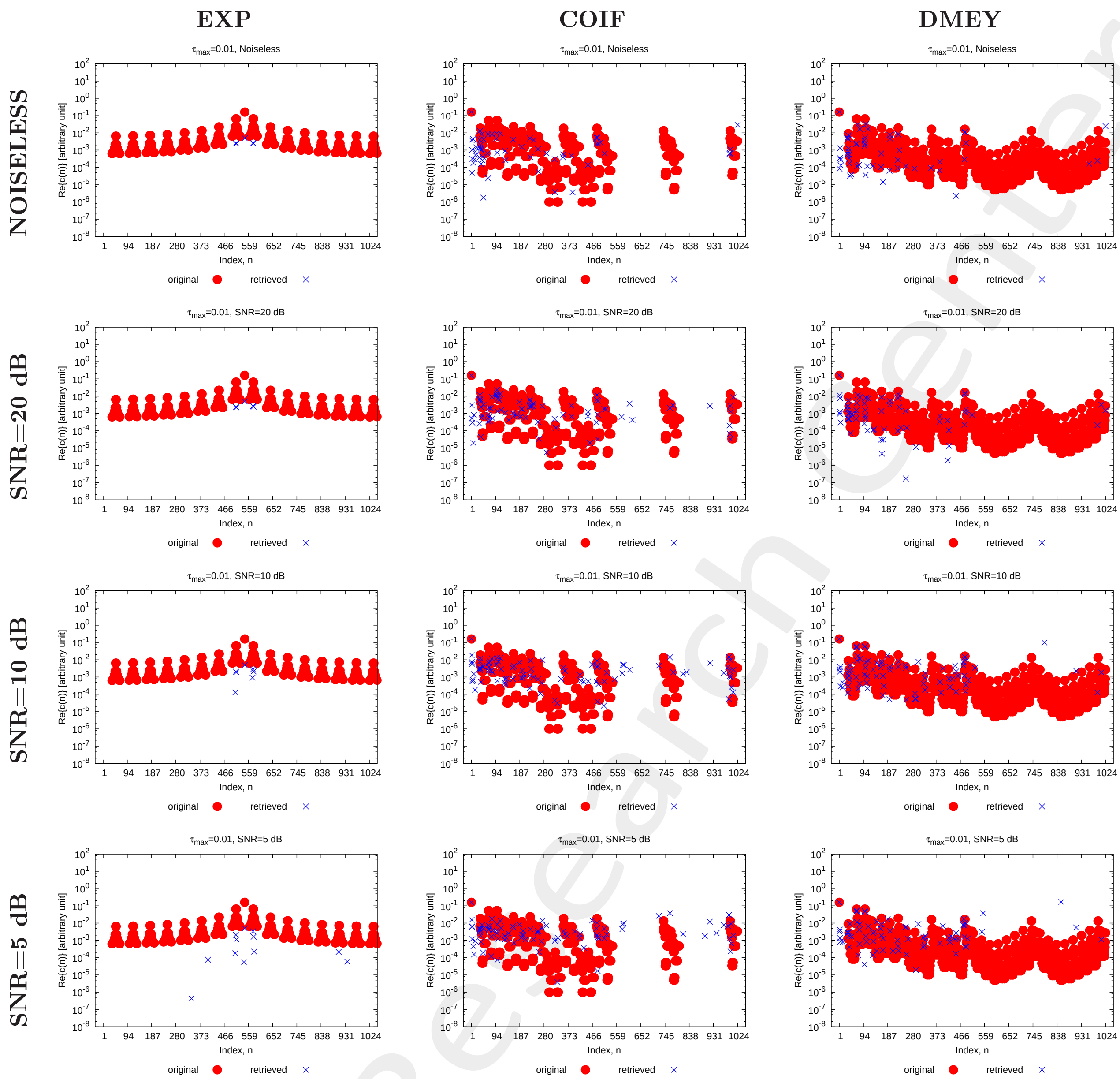

Figure 10: Absolute value (dB) of the actual and retrieved coefficients considering different wavelet expansions.

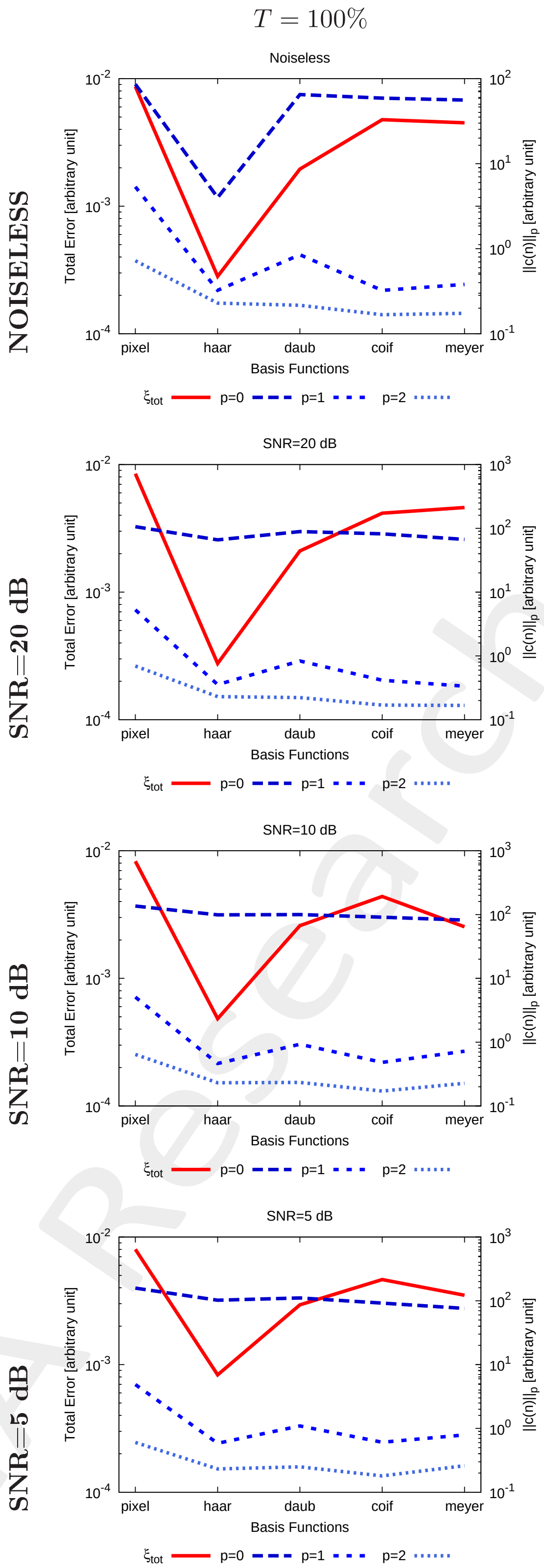

Figure 11: $[T = 100\%]$ - Comparison of ξ_{tot}, and L_0, L_1, L_2 Norms of the retrieved basis expansion coefficients, for each alphabet basis.

	$L_0 - norm$					
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$	Exp
$Actual$	512	2	196	358	962	241
$Noiseless$	86	**4**	65	49	56	5
20	106	**66**	89	89	82	5
10	136	99	100	91	**82**	7
5	158	102	111	92	**76**	12
	$L_1 - norm$					
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$	Exp
$Actual$	163.8	0.32	1.53	1.60	1.50	1.32
$Noiseless$	5.34	0.32	0.85	0.32	0.38	1.5×10^{-2}
20	5.28	0.35	0.83	0.42	0.33	1.5×10^{-2}
10	5.09	0.46	0.93	0.48	0.72	1.5×10^{-2}
5	4.87	0.58	1.09	0.61	0.79	1.4×10^{-2}
	$L_2 - norm$					
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$	Exp
$Actual$	7.24	0.23	0.23	0.23	0.23	0.23
$Noiseless$	0.72	0.23	0.22	0.20	0.17	7.0×10^{-3}
20	0.69	0.23	0.22	0.17	0.16	6.9×10^{-3}
10	0.64	0.23	0.23	0.17	0.22	6.8×10^{-3}
5	0.60	0.23	0.24	0.18	0.26	6.7×10^{-3}

Table 1: $[T = 100\%]$ - Number of the retrieved non-zero coefficients ($L_0 - norm$), $L_1 - norm$, and $L_2 - norm$ using different wavelet functions.

Thresholded Analysis:

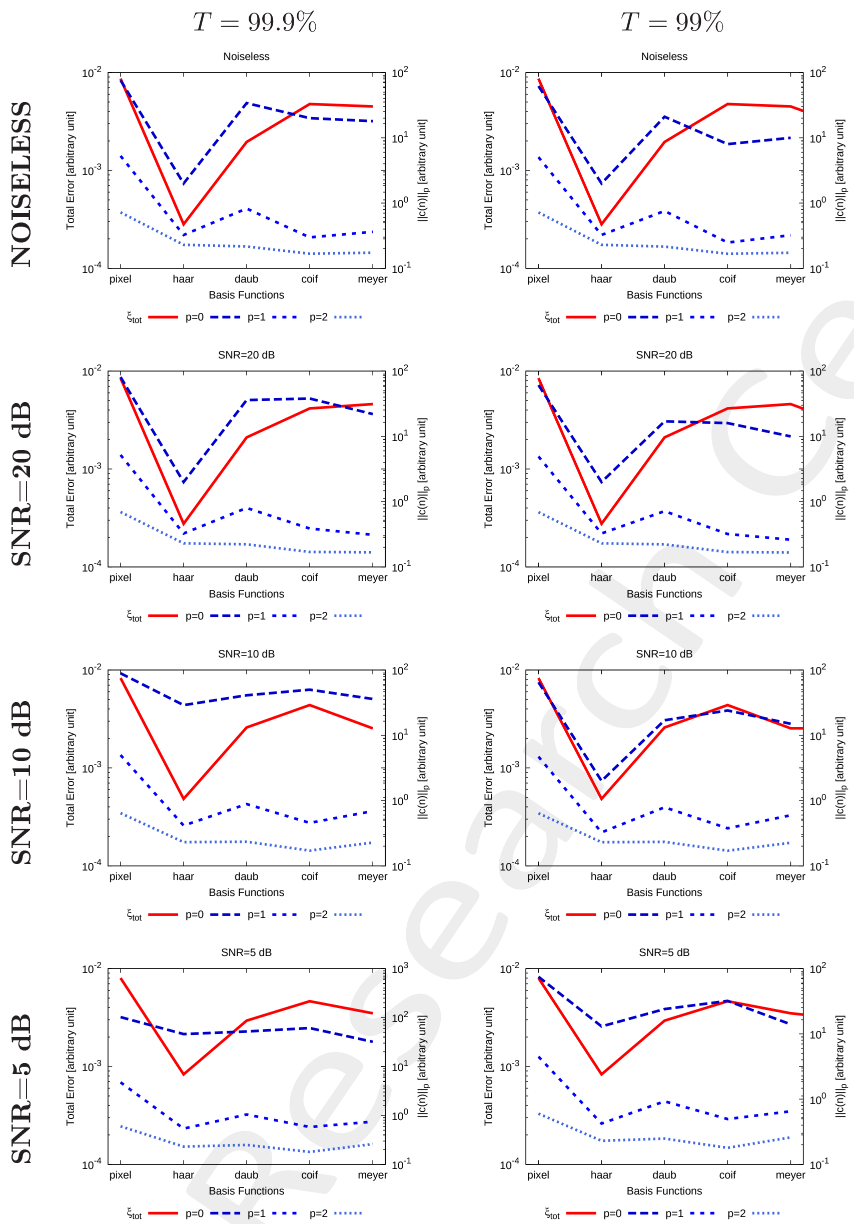

Figure 12: Comparison of ξ_{tot}, and L_0, L_1, L_2 Norms of the retrieved basis expansion coefficients, for each alphabet basis.

	$L_0 - norm$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Actual$	512	2	196	358	962
$Noiseless$	76	2	34	20	18
20	81	2	36	38	22
10	89	29	41	50	36
5	102	46	52	61	32
	$L_1 - norm$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Actual$	163.8	0.32	1.53	1.60	1.50
$Noiseless$	5.28	0.32	0.82	0.30	0.36
20	5.20	0.33	0.80	0.39	0.31
10	4.98	0.41	0.88	0.45	0.69
5	4.75	0.54	1.04	0.58	0.75
	$L_2 - norm$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Actual$	7.24	0.23	0.23	0.23	0.23
$Noiseless$	0.72	0.23	0.22	0.17	0.17
20	0.69	0.23	0.22	0.17	0.17
10	0.64	0.23	0.23	0.17	0.23
5	0.60	0.23	0.25	0.18	0.26

Table 2: [$T = 99.9\%$] - Number of the retrieved non-zero coefficients ($L_0 - norm$), $L_1 - norm$, and $L_2 - norm$ using different wavelet functions.

	$L_0 - norm$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Actual$	512	2	196	358	962
$Noiseless$	62	2	21	8	10
20	61	2	17	16	10
10	65	2	17	24	15
5	75	13	24	32	14
	$L_1 - norm$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Actual$	163.8	0.32	1.53	1.60	1.50
$Noiseless$	5.06	0.32	0.76	0.25	0.32
20	4.92	0.33	0.72	0.32	0.26
10	4.71	0.33	0.79	0.38	0.60
5	4.48	0.42	0.93	0.50	0.65
	$L_2 - norm$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Actual$	7.24	0.23	0.23	0.23	0.23
$Noiseless$	0.72	0.23	0.22	0.17	0.17
20	0.69	0.23	0.22	0.17	0.17
10	0.64	0.23	0.23	0.17	0.23
5	0.60	0.23	0.25	0.18	0.26

Table 3: [$T = 99\%$] - Number of the retrieved non-zero coefficients ($L_0 - norm$), $L_1 - norm$, and $L_2 - norm$ using different wavelet functions.

Resume:

	$T = 100\%$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Noiseless$	86	**4**	65	49	56
20	106	**66**	89	89	82
10	136	99	100	91	**82**
5	158	102	111	92	**76**
	$T = 99.9\%$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Noiseless$	76	**2**	34	20	18
20	81	**2**	36	38	22
10	89	**29**	41	50	36
5	102	46	52	61	**32**
	$T = 99\%$				
SNR [dB]	$Pixel$	$Haar$	$Daub4$	$Coiflet$	$DMeyer$
$Noiseless$	62	**2**	21	8	10
20	61	**2**	17	16	10
10	65	**2**	17	24	15
5	75	**13**	24	32	14

Table 4: $L_0 - norm$.

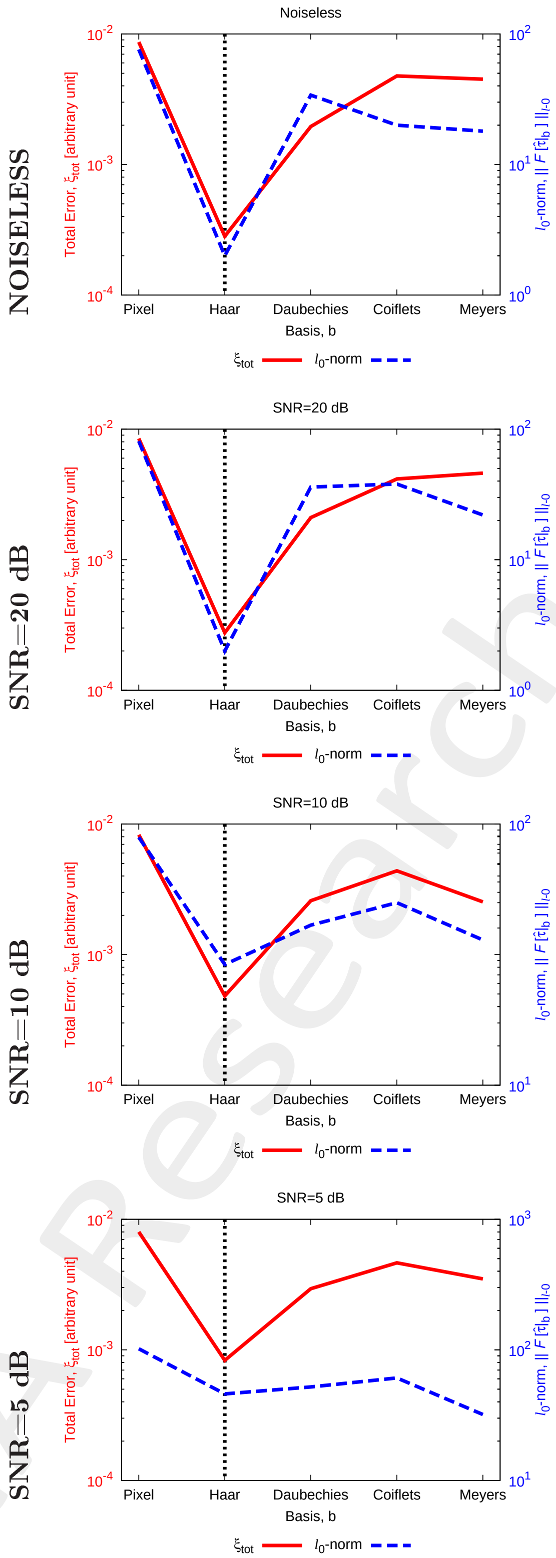

Figure 13: $L_0 - norm$ vs Total Error, considering $T = 99.9\%$.

Comparison SoA

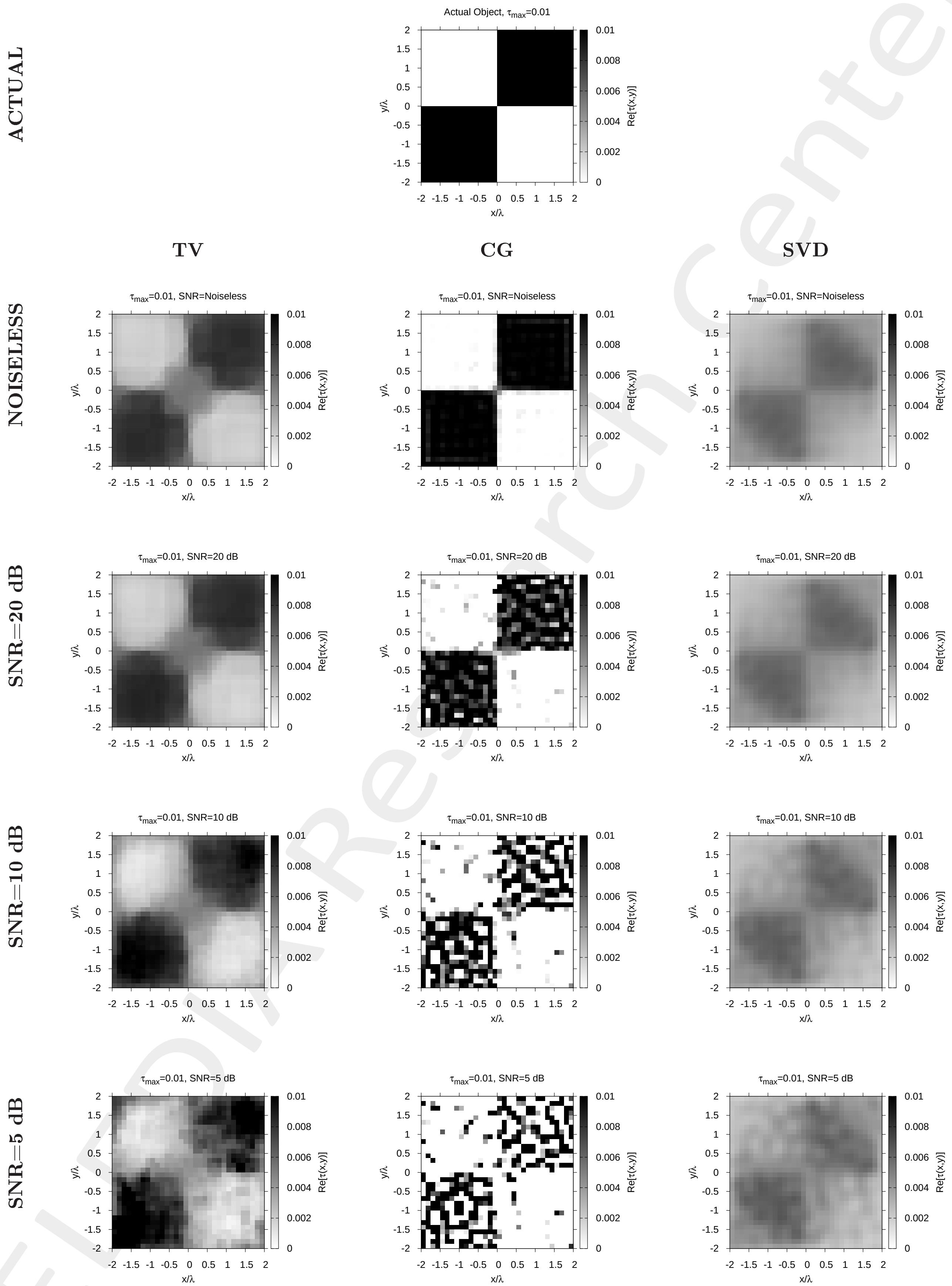

Figure 14: Actual and retrieved object considering different wavelet expansions.

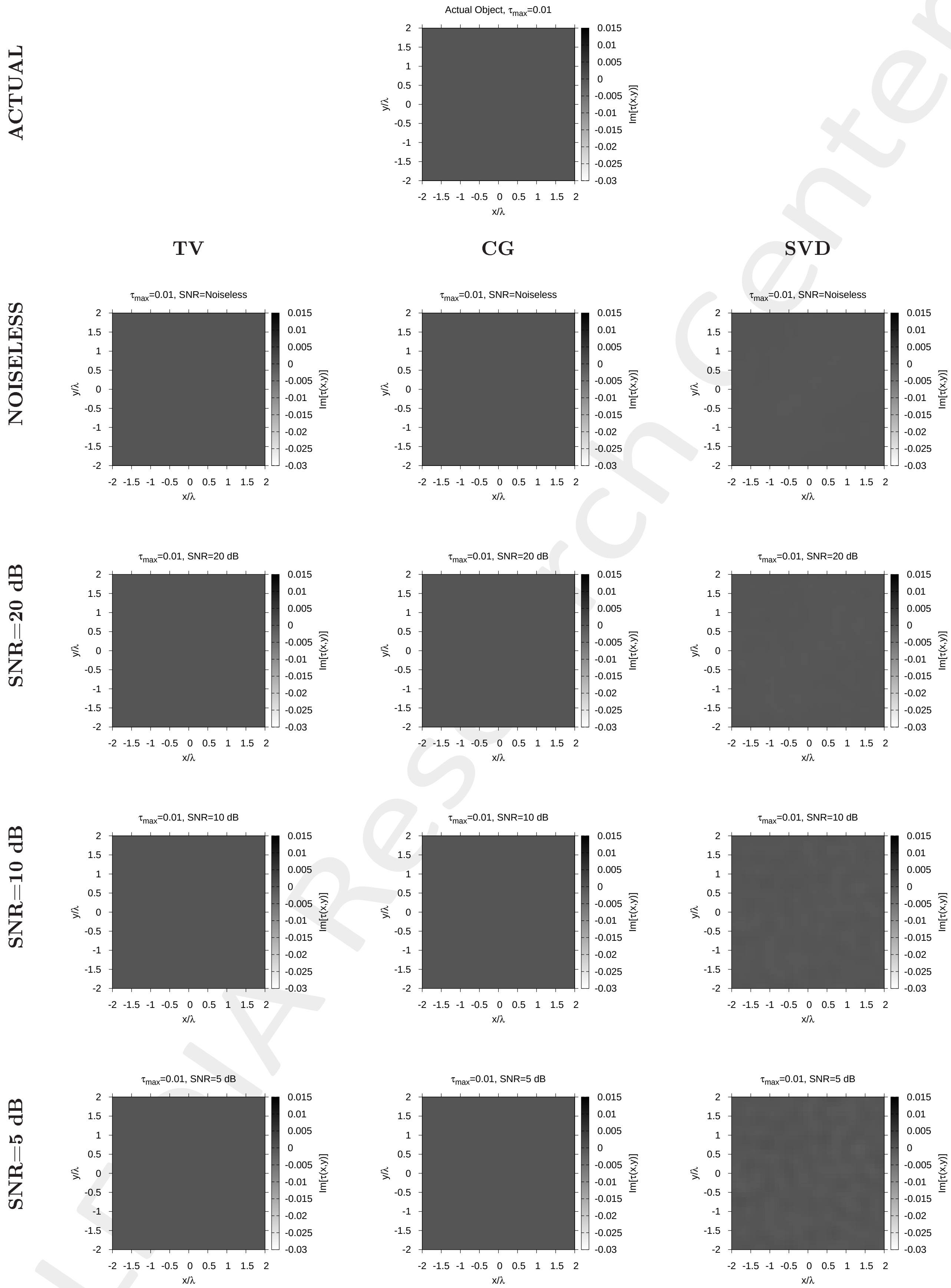

Figure 15: Actual and retrieved object considering different wavelet expansions.

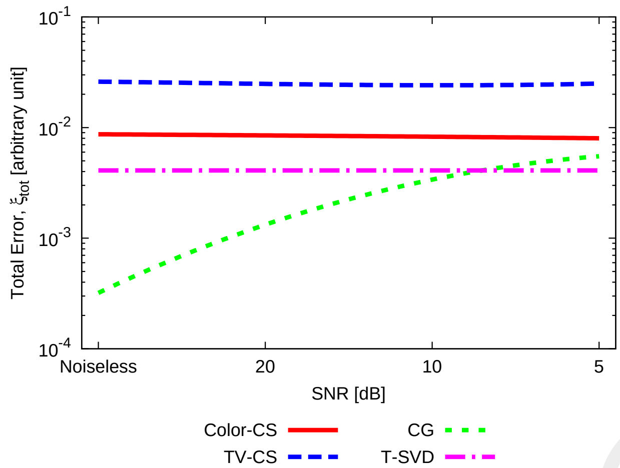

Figure 16: Comparison with SoA - Total Error vs SNR, considering $T = 99.9\%$.

SNR [dB]	**TV [s]**	**CG [s]**	**SVD [s]**	**ALPHABET [s]**
Noiseless	3.9×10^2	6.9×10^3	3.3×10^1	9.5×10^2
20	3.7×10^2	5.8×10^3	3.4×10^1	1.0×10^3
10	3.8×10^2	6.1×10^3	3.5×10^1	8.7×10^2
5	3.9×10^2	5.7×10^3	3.5×10^1	$8.5. \times 10^2$

Table 5: Timings.

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