



A Fast Iterative Method for Removing Sparse Noise from Sparse Signals

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Introduction

Applications:

- **Sparse Noise Removal From Sparse Signals:**
 - Impulsive Noise Removal from Images/Videos
 - Clicks and Pops Removal from Audios
 - Text/Image Separation
 - Dictionary Learning with Random Missing Samples

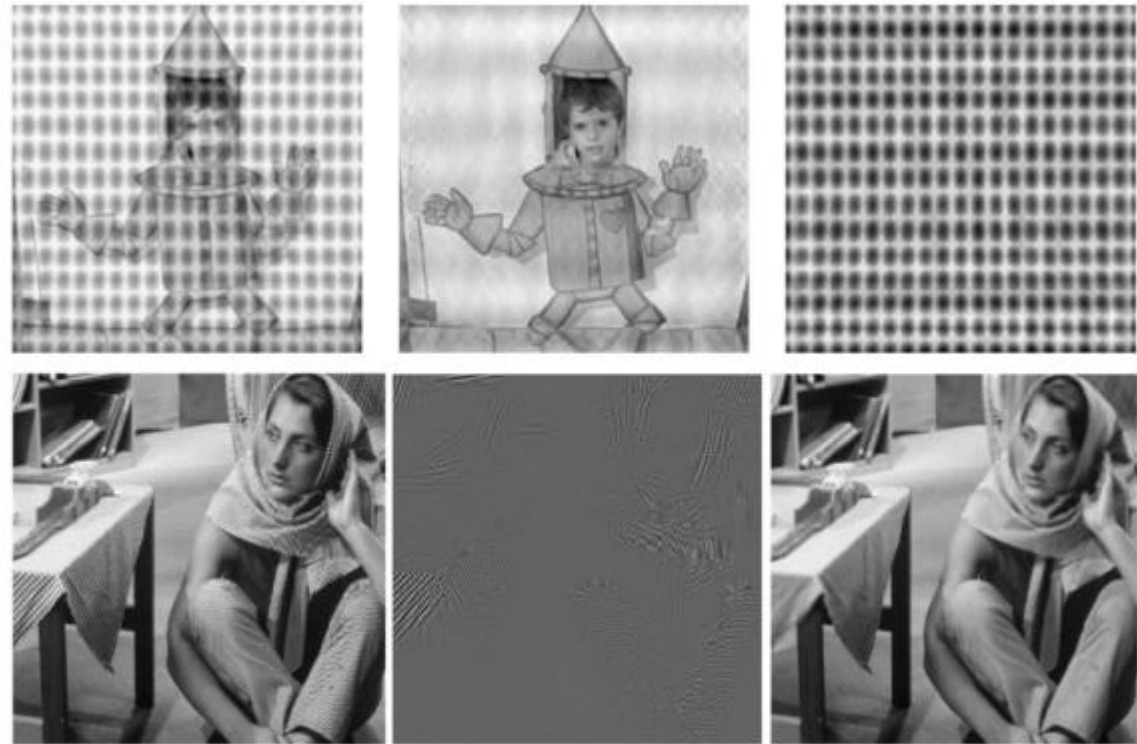
Introduction

Applications:

□ Morphological Component Analysis:

Decomposing Images:

Texture + Cartoon Part (piecewise smooth)



Introduction

Impulsive Noise in Images:

- ❑ Salt-and-Pepper Noise (SPN)
- ❑ Random Valued Impulsive Noise (RVIN)



IDT Method

Problem Formulation:

$$Y = \mathcal{D}^{-1}(\mathbf{X}_0) + \mathbf{N}_0 \quad W \triangleq \{(\mathbf{X}, \mathbf{N}) | Y = \mathcal{D}^{-1}(\mathbf{X}) + \mathbf{N}\}$$

$$\operatorname{argmin}_{(\mathbf{X}, \mathbf{N})} \|\operatorname{vec}(\mathbf{X})\|_0 + \|\operatorname{vec}(\mathbf{N})\|_0, \quad \text{s.t.} \quad (\mathbf{X}, \mathbf{N}) \in W \longrightarrow \text{Np-Hard}$$

$$f_\lambda(\mathbf{X}, \mathbf{N}, \mathbf{T}_1, \mathbf{T}_2) \triangleq \|(\mathbf{1} - \mathbf{T}_1) \odot \mathbf{X}\|_F^2 + \|(\mathbf{1} - \mathbf{T}_2) \odot \mathbf{N}\|_F^2 + \lambda(\|\operatorname{vec}(\mathbf{T}_1)\|_1 + \|\operatorname{vec}(\mathbf{T}_2)\|_1) \longrightarrow \operatorname{argmin}_{(\mathbf{X}, \mathbf{N}), (\mathbf{T}_1, \mathbf{T}_2)} f_\lambda(\mathbf{X}, \mathbf{N}, \mathbf{T}_1, \mathbf{T}_2) \\ \text{s.t.} \quad (\mathbf{X}, \mathbf{N}) \in W$$

IDT Method

Algorithm:

Algorithm 1 IDT

```
1: Input:  
2:   Observed matrix:  $\mathbf{Y} \in \mathbb{R}^{m \times n}$   
3:   Four constants:  $\alpha_1, \beta_1, \alpha_2, \beta_2$   
4:   Standard deviation of the gaussian filter:  $\sigma$  (*)  
5:   Maximum number of iterations:  $K$   
6:   Stopping threshold:  $\delta$   
7: Output:  
8:   Recovered estimate of the signal:  $\hat{\mathbf{X}} \in \mathbb{R}^{m \times n}$   
9:   Recovered estimate of the noise:  $\hat{\mathbf{N}} \in \mathbb{R}^{m \times n}$   
10: procedure  
11:    $\mathbf{X}^0 \leftarrow \mathcal{D}(\mathbf{Y}), \quad \mathbf{N}^0 \leftarrow 0, \quad k \leftarrow 0$   
12:   while  $e > \delta$  &  $k \leq K$  do  
13:      $\mathbf{X}^k \leftarrow \text{threshold}(|\mathbf{X}_{i,j}^k|_{i=1,j=1}^{m,n}, \beta_1 e^{-\alpha_1 k})$   
14:      $\mathbf{X}^k \leftarrow \text{clip}(\mathcal{D}^{-1}(\mathbf{X}^k))$  (*)  
15:      $\mathbf{X}^k \leftarrow \text{gaussian-filter}(\mathbf{X}^k, \sigma)$  (*)  
16:      $\mathbf{N}^{k+1} \leftarrow \mathbf{Y} - \mathbf{X}^k$   
17:      $\mathbf{N}^{k+1} \leftarrow \text{threshold}(|\mathbf{N}_{i,j}^{k+1}|_{i=1,j=1}^{m,n}, \beta_2 e^{-\alpha_2 k})$   
18:      $\mathbf{X}^{k+1} \leftarrow \mathcal{D}(\mathbf{Y} - \mathbf{N}^{k+1})$   
19:      $e \leftarrow \|\mathbf{N}^{k+1} - \mathbf{N}^k\|_F$   
20:      $k \leftarrow k + 1$   
21:   end while  
22:   return  $\hat{\mathbf{X}} \leftarrow \mathbf{X}^k, \hat{\mathbf{N}} \leftarrow \mathbf{N}^k$   
23: end procedure
```

IDT Method

Theorems:

- ❑ **Theorem 1:** Under sufficient condition, the solution of the proposed optimization problem is the sparsest member of set W .
- ❑ **Theorem 2:** Under sufficient condition, the sparsest member of set W is unique.

IDT Method

Simulation Results:

□ Artificial Sparse Signals

$\rho_x \backslash \rho_n$	10%	20%	30%
10%	316.5 (100%)	313.5 (100%)	311.6 (100%)
20%	315.9 (100%)	312.6 (100%)	310.4 (100%)
30%	314.9 (100%)	311.4 (100%)	224.082 (73%)

SNR (Success Rate)

IDT Method

Simulation Results:

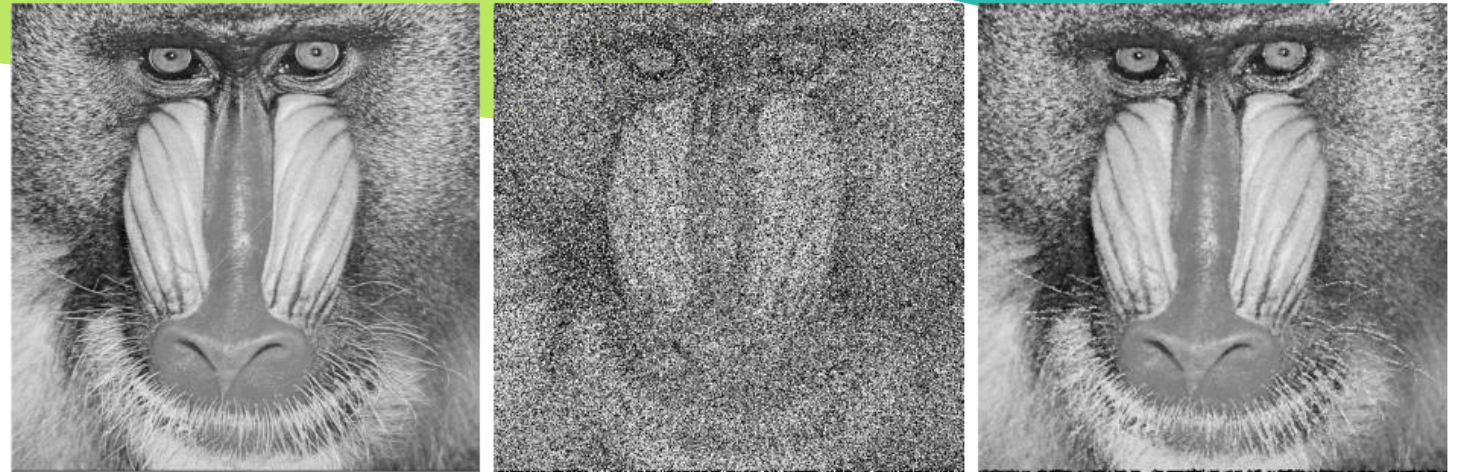
❑ Salt-and-Pepper Noise

Noise Densities		PSNR					SSIM				
		10%	20%	30%	40%	50%	10%	20%	30%	40%	50%
Lena	AMF	38.27	35.9	33.56	31.87	30.39	0.9628	0.9545	0.9389	0.9174	0.8908
	TPFF	35.78	35.06	32.79	30.98	29.71	NOT AVAILABLE				
	WESNR	35.91	35.56	35.11	34.52	33.61	0.9151	0.9134	0.9099	0.9045	0.8963
	IDT	44.54	41.19	38.78	36.85	34.74	0.9939	0.9831	0.9712	0.9572	0.9379
Peppers	AMF	36.06	33.98	32.17	30.67	29.23	0.9482	0.9410	0.9257	0.9021	0.8733
	TPFF	35.80	33.45	31.27	29.21	28.00	NOT AVAILABLE				
	WESNR	35.01	34.59	34.08	33.34	32.49	0.8842	0.8834	0.8818	0.8785	0.8727
	IDT	40.20	37.03	35.26	32.46	31.50	0.9848	0.9669	0.9450	0.9187	0.8920
F-16	AMF	35.87	32.97	31.05	29.43	27.77	0.9780	0.9699	0.9560	0.9377	0.9118
	TPFF	35.78	32.83	30.72	29.18	28.01	NOT AVAILABLE				
	WESNR	35.27	34.64	33.96	32.80	31.85	0.9382	0.9361	0.9322	0.9264	0.9187
	IDT	42.79	38.99	35.96	32.79	31.40	0.9979	0.9911	0.9816	0.9678	0.9504
Baboon	AMF	26.95	25.73	24.53	23.29	22.14	0.8922	0.8717	0.8351	0.7866	0.7264
	TPFF	30.96	27.90	26.34	25.15	23.87	NOT AVAILABLE				
	WESNR	26.44	26.17	25.70	24.93	24.11	0.7982	0.7938	0.7784	0.7529	0.7170
	IDT	33.04	30.05	27.90	26.35	25.06	0.9777	0.9486	0.9117	0.8701	0.8140
Boat	AMF	33.94	32.05	30.25	28.74	27.16	0.9345	0.9215	0.8986	0.8679	0.8274
	TPFF	NOT AVAILABLE									
	WESNR	32.78	32.40	31.84	31.13	30.08	0.8659	0.8635	0.8567	0.8478	0.8317
	IDT	39.03	36.06	34.10	32.06	30.36	0.9832	0.9621	0.9382	0.9120	0.8780

IDT Method

Simulation Results:

❑ Salt-and-Pepper Noise



(a)

(b)

(c)

AMF	TPFF	WESNR	IDT
1.13	1.75	32.26	1.65

Run-Time for *Lena* corrupted
with 30% SPN



(d)

(e)

(f)

50% SPN

IDT Method

Simulation Results:

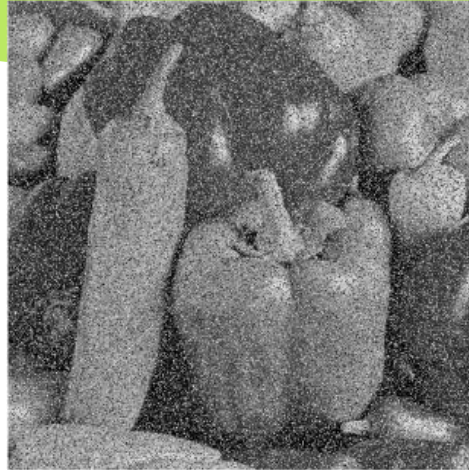
- Random-Valued Impulsive Noise

Noise Densities		PSNR						SSIM					
		5%	10%	20%	30%	40%	50%	5%	10%	20%	30%	40%	50%
Lena	ACWMF	38.53	35.32	31.61	28.76	26.15	23.52	0.9669	0.9325	0.8562	0.7592	0.6459	0.5133
	WESNR	36.83	36.30	35.10	33.00	30.91	28.18	0.9271	0.9245	0.9165	0.8972	0.8619	0.7880
	SAFE	35.92	34.97	34.79	33.33	31.97	30.43	0.9635	0.9587	0.9551	0.9407	0.9208	0.8930
	ALOHA	40.79	38.81	35.32	32.66	30.62	26.69	0.9821	0.9695	0.9403	0.9023	0.8752	0.7729
	IDT	41.32	38.97	36.10	34.19	32.56	30.95	0.9877	0.9770	0.9554	0.9331	0.9061	0.8750
Peppers	ACWMF	36.73	34.30	30.56	27.85	25.06	22.23	0.9659	0.9311	0.8494	0.7469	0.6201	0.4819
	WESNR	35.31	34.68	33.61	31.83	29.13	26.01	0.8955	0.8949	0.8888	0.8752	0.8342	0.7398
	SAFE	30.80	30.56	30.40	29.82	28.97	28.40	0.9537	0.9492	0.9423	0.9151	0.8812	0.8742
	ALOHA	37.55	35.91	33.00	31.16	28.50	25.02	0.9585	0.9310	0.8759	0.8337	0.7767	0.6824
	IDT	38.62	36.42	33.32	32.22	30.75	29.14	0.9808	0.9691	0.9341	0.9189	0.8888	0.8499
F-16	ACWMF	36.78	33.62	29.95	27.28	24.57	21.72	0.9700	0.9351	0.8561	0.7576	0.6220	0.4784
	WESNR	35.75	34.80	32.85	30.72	28.37	25.44	0.9453	0.9420	0.9321	0.9115	0.8601	0.7511
	SAFE	28.81	28.64	28.29	28.02	27.31	26.47	0.9525	0.9447	0.9498	0.9188	0.8898	0.8804
	ALOHA	36.17	34.93	32.26	28.33	27.76	24.68	0.9410	0.9255	0.9072	0.8788	0.8633	0.7503
	IDT	39.50	36.99	33.97	31.87	30.03	28.27	0.9891	0.9809	0.9633	0.9420	0.9151	0.8779
Baboon	ACWMF	27.63	26.31	24.37	22.64	21.28	19.83	0.9311	0.8955	0.8214	0.7299	0.6329	0.5171
	WESNR	26.90	26.12	24.86	23.76	22.62	21.42	0.8420	0.8251	0.7852	0.7402	0.6761	0.5931
	SAFE	24.57	24.26	24.02	23.35	22.24	21.19	0.8558	0.8382	0.8217	0.7827	0.7126	0.6305
	ALOHA	29.37	28.59	25.56	22.66	22.33	20.56	0.7721	0.7716	0.7015	0.6495	0.6433	0.5792
	IDT	31.58	28.98	26.22	24.55	23.22	22.15	0.9474	0.9089	0.8368	0.7632	0.6828	0.6097
Boat	ACWMF	34.65	32.29	29.15	26.86	24.64	22.31	0.9633	0.9274	0.8476	0.7545	0.6451	0.5193
	WESNR	33.13	32.55	31.24	29.58	27.85	25.72	0.8892	0.8835	0.8675	0.8387	0.7945	0.7161
	SAFE	31.33	30.65	30.19	29.26	28.04	26.62	0.9377	0.9187	0.9171	0.8922	0.8560	0.8051
	ALOHA	35.88	34.53	31.11	29.47	26.99	24.29	0.9574	0.9536	0.8869	0.8571	0.7594	0.6818
	IDT	36.24	34.23	31.8	30.13	28.87	27.10	0.9726	0.9543	0.9186	0.8819	0.8409	0.7914

IDT Method

Simulation Results:

- ❑ Random-Valued Impulsive Noise



(a)



(b)



(c)



(d)



(e)



(f)

40% RVIN

ACWMF	WESNR	SAFE (on GPU)	ALOHA on GPU	IDT
1.94	34.32	763.48 (21.07)	1368.2	1.71

Run-Time for *Lena* corrupted
with 30% RVIN

Contributions

- ❑ **A General Framework for Separating Two Sparse Signal**
- ❑ **Fast Algorithm with Low Complexity**
- ❑ **Comparable Reconstruction Quality**

Future Works

- ❑ **Impulsive Noise Removal from Videos**
- ❑ **Block Sparse Noise Removal**
- ❑ **Mixed Noise (Gaussian + Impulsive) Removal**

Thank You

For Your Attention 😊