Department of Computer Science and Engineering, IIT Bombay
CS 754 - Advanced Image Processing

# Course Project

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# Contents

# 1 Project Details

## 1.1 Title of the Project:

Robust video denoising using Low rank matrix completion and comparing it with other algorithms

## 1.2 Reference Paper to be used:

The reference paper used is 'Robust video denoising using Low rank matrix completion' which is given **here**

## 1.3 Data Set to be used:

The link to data set to be used as given in the paper is **here**

## 1.4 The evaluation strategy to test the implementation:

We will evaluate our project using PSNR (Peak Signal to Noise Ratio) values as our metric. The results of the implementation of this paper will be evaluated against methods like PCA and VBM3D which are also used for pre-processing of images with impulsive noise.

## 1.5 Link to the data

The google drive link to the data is **here**

# 2 Abstract

It is seen that many of the video de-noising algorithms assume a single Gaussian noise based statistical model. But in practice, this is not true. That is, there are five different sources of image noise with different statistical distributions: fixed pattern noise, amplifier noise, photon shot noise, dark current noise and quantization noise. Hence, the performance of many of the already existing de-noising techniques will severely degrade when used in real noisy images where there are noises from multiple sources.

The paper that we have used has presented a new patch based video de-noising algorithm capable of removing mixed noise from video data. A low rank matrix completion problem can be formulated by grouping similar patches in both spatial and temporal domain. This frames a denoising scheme which is robust and does not have any strong assumptions on the statistical properties of the noise.

This denoising algorithm is capable of removing Gaussian noise along with mixed impulsive noise which shows the effectiveness of the algorithm.

# 3 Algorithms Implemented

Say we have a input noisy image sequence consisting of K images: $\{f_i\}_{i=1}^{K}$.

In the first step Adaptive Median filter is applied to the images. It mainly identifies the pixels corrupted by impulsive noise. These pixels can then be replaced by some median pixel from a patch around the corrupted pixel.

In the second step, a Patch-Array is formed. The size of each patch is 8 by 8. These are then sampled with sampling rate of 4 by 4 pixels to form reference patches per frame.

In the third step, we perform de-noising of each patch. Using the patch array that we have already formed, we find 5K most similar patches by performing Patch Making. Once these patches are formed, we then perform patch de-noising. Patch de-noising can be done using any of the de-noising techniques: Low Rank Matrix Completion (LMRC) or Principal Component Analysis (PCA). This de-noising is done patch wise.

In the last step we generate de-noised images from the de-noised patches. It should be noted that in the method that has been presented, each pixel is common in multiple de-noised patches. This is due to the fact that we sample image patches such that they have overlapping regions. We then take the mean value of all de-noised patches at the pixel that is required. We now obtain the required de-noised images.

## LRMC based de-noising

Once we find matrix $\mathbf{P}_{j,k}$ similar patches in both spatial and temporal domain using patch making algorithm, we note that the set of missing elements of $\mathbf{P}_{j,k}$ has a subset consisting pixels corrupted by impulsive noise using adaptive median filter based impulsive noise detector. It has another subset that includes pixels whose values differ from mean of the corresponding row vector by an amount greater than pre-defined threshold. We then form a $\Omega$ that contains index of all the remaining pixels.

We then solve the following problem:

$$min_Q(\frac{1}{2}||Q|_\Omega \ - \ P_\Omega||_F \ + \ \mu \ ||Q||_*)$$

where, $||Q||_*$ is the nuclear norm of Q, and $\mu$ is the lagrangian parameter, which is set according to:

$$\mu = (\sqrt{n_1} + \sqrt{n_2})\sqrt{p}\hat{\sigma}.$$

It should be noted that there are many different efficient algorithms that can solve this problem. We have used Fixed point iteration algorithm (svt - Singular Value Thresholding) to solve Low Rank Matrix Completion (LRMC) problem as mentioned below:

1. Set $Q^{(0)} := 0$.
2. Iterating on $k$ till $\|Q^{(k)} - Q^{(k-1)}\|_F \leq \epsilon$,

$$\begin{cases} R^{(k)} = Q^{(k)} - \tau \mathcal{P}_\Omega(Q^{(k)} - P), \\ Q^{k+1} = D_{\tau\mu}(R^{(k)}), \end{cases}$$

where $\mu$ and $1 \leq \tau \leq 2$ are pre-defined parameters, $D$ is the shrinkage operator defined below and $\mathcal{P}_\Omega$ is the projection operator of $\Omega$ defined by

$$\mathcal{P}_\Omega(Q)(i,j) = \begin{cases} Q(i,j), & \text{if } (i,j) \in \Omega; \\ 0, & \text{otherwise.} \end{cases}$$

3. Output $Q := Q^{(k)}$.

Now, the shrinkage operator $D_r(X)$ is defined with respect to the Singular Value Decomposition X = $U\Sigma V^T$ as $D_r(X) = U\Sigma_r V^T$.

# 4 Results

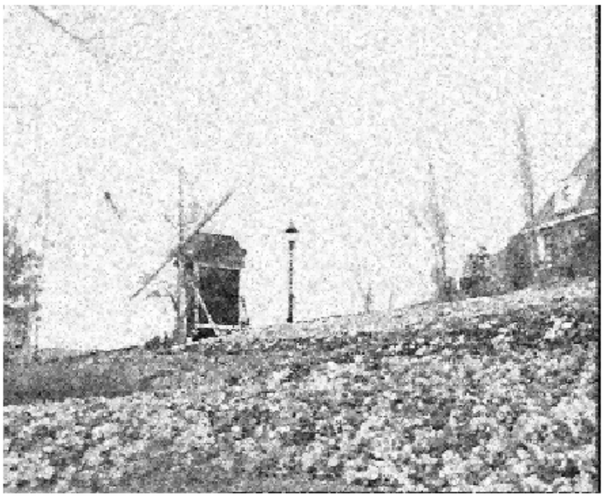
nummatch is the number of matching patches per frame.
nframes is the total number of frames considered.
flag is 1 if second set of missing pixels are to be considered.
Salt and Pepper noise has density of 0.05.

## 4.1 Results for Video2, nummatch=5, nframes=10, flag=1, Gaussian noise variance=0.01

RMSE = 2.7964e-05

Noisy Frame

Median-Filtered Frame



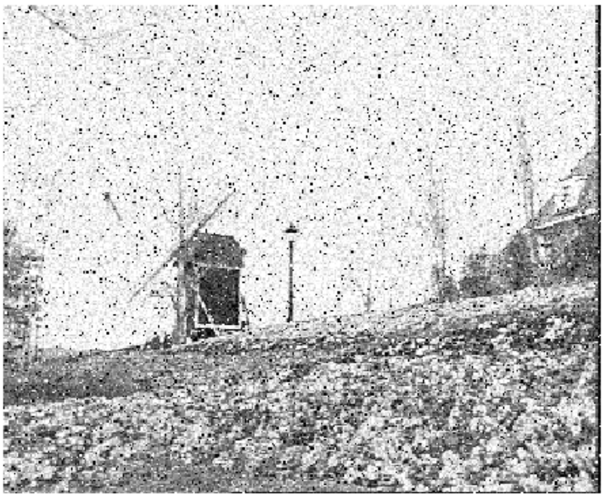
Reconstructed Frame

## 4.2 Results for Video2, nummatch=5, nframes=10, flag=0, Gaussian noise variance=0.01

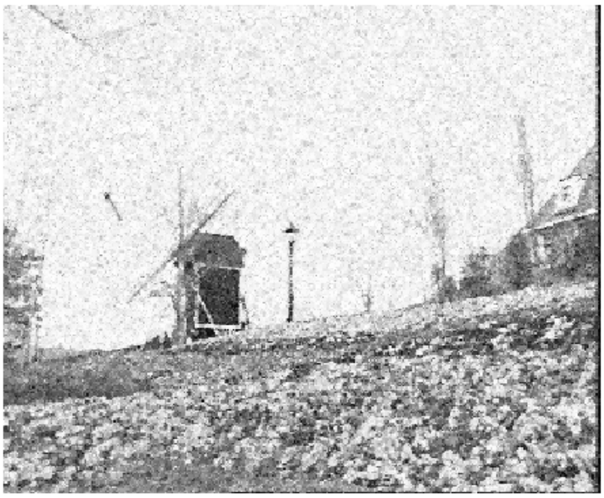
RMSE = 2.8854e-05

Original Frame

Noisy Frame



Median-Filtered Frame



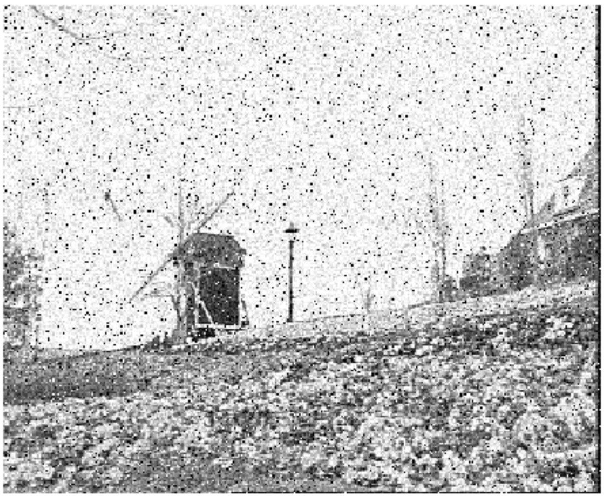
Reconstructed Frame

### 4.3 Results for Video2, nummatch=5, nframes=50, flag=1, Gaussian noise variance=0.01

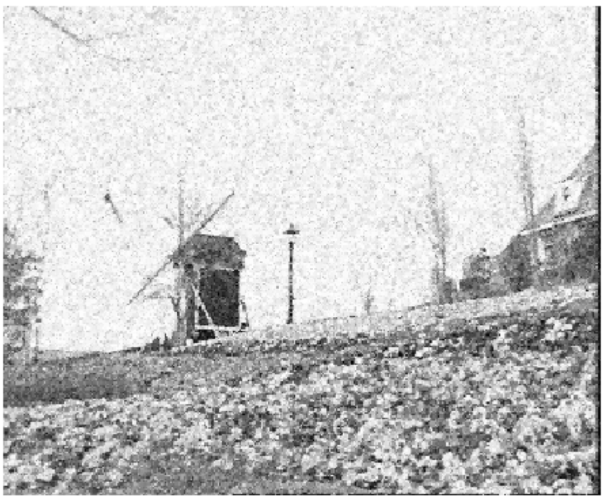
RMSE = 2.6899e-05

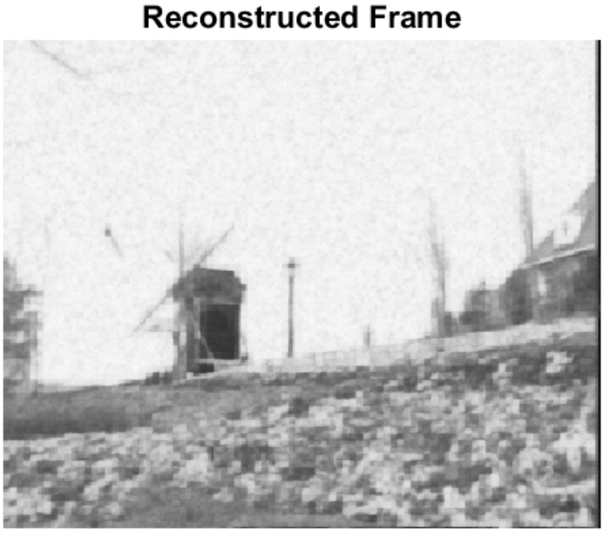
**Original Frame**

**Noisy Frame**



**Median-Filtered Frame**

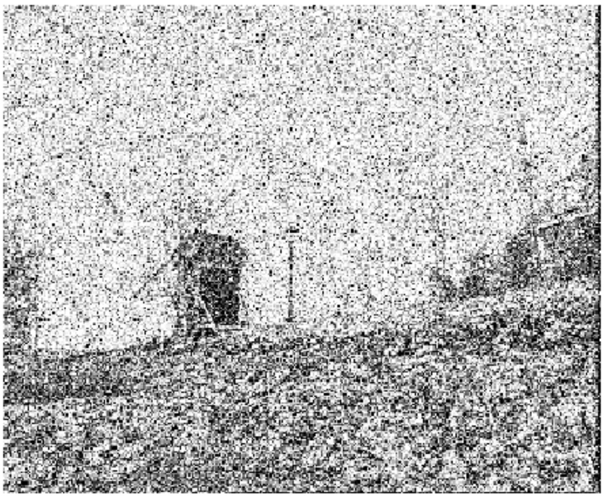




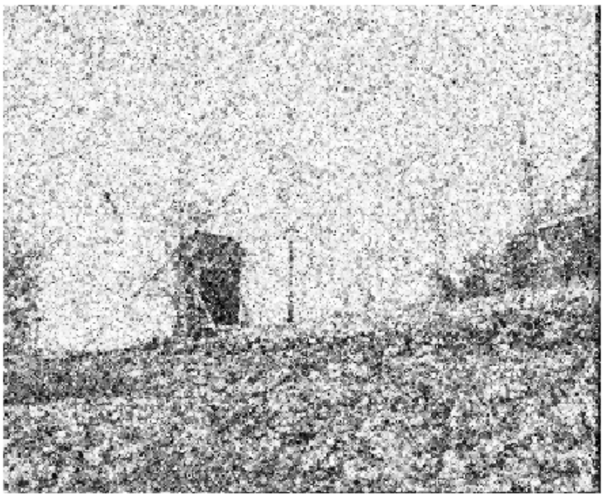

### 4.4 Results for Video2, nummatch=5, nframes=10, flag=1, Gaussian noise variance=0.1

RMSE = 5.5295e-05

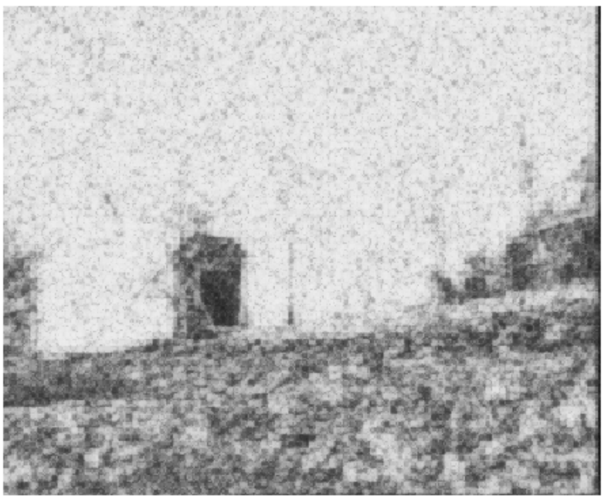
**Noisy Frame**



**Median-Filtered Frame**

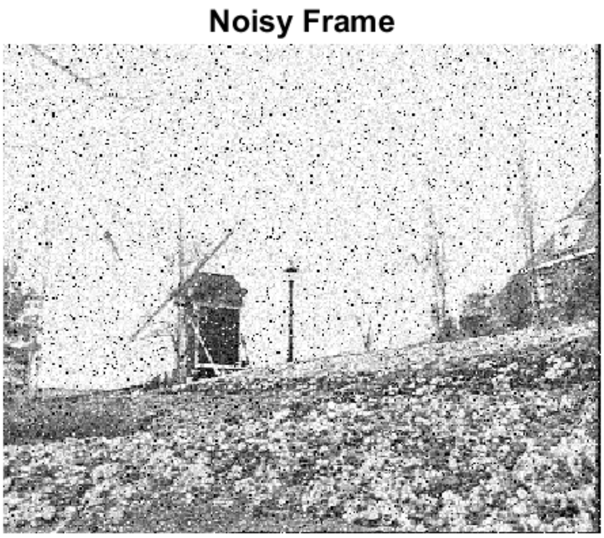


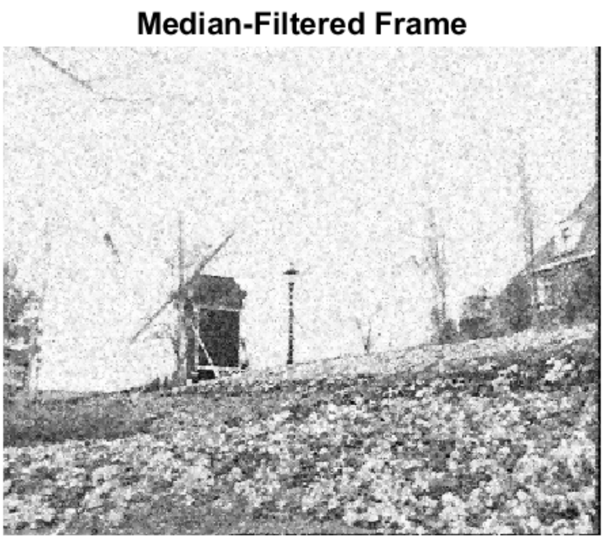
**Reconstructed Frame**



## 4.5 Results using PCA with C=2

RMSE = 2.4536e-05

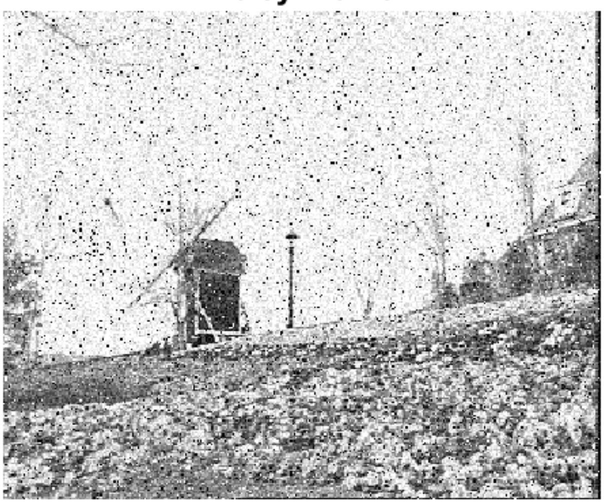
Reconstructed Frame

## 4.6 Results using PCA with C=6

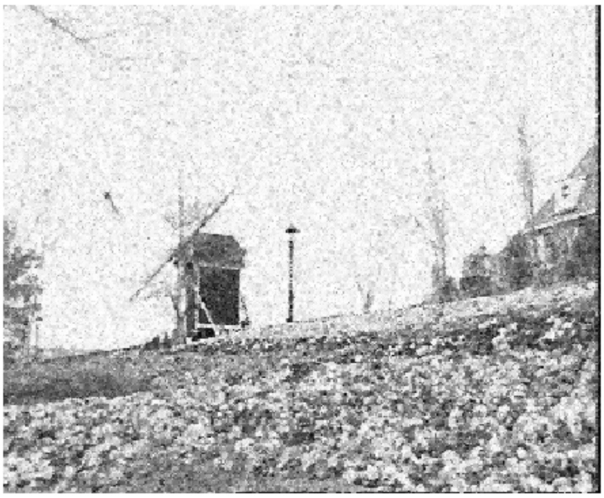
RMSE = 2.4430e-05

Original Frame

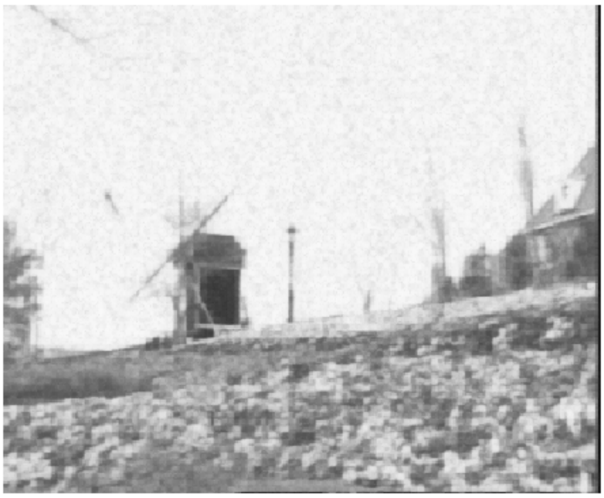
Noisy Frame



Median-Filtered Frame



Reconstructed Frame



# 5 Other References

- Adaptive median filter was designed with the help of this **paper** (given in original ref paper)
- PCA was implemented with the help of this **paper** (given in original ref paper)