

Dictionary Based Filtering

Group - 8

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Abstract—Digital image processing refers to the process of digital images by means of digital computer. The main application area in digital image processing is to enhance the pictorial data for human interpretation. In image some of the unwanted information is present that will be removed by several preprocessing techniques. Filtering helps to enhance the image by removing noise. Initially By creating Dictionary we will store two form of matrix. now when We add new image in dictionary we don't need to pass image from filter instead we will just Dictionary Learn form the Previous Dictionary and just map into.

Index Terms—Dictionary Learning, Low-pass filter, Salt-Pepper Noise, Median filter

I. INTRODUCTION

Basically the idea of Dictionary based filtering is instead of doing classical convolution every time, we directly take de-noise image from the dictionary using searching algorithm and time after time Learning of dictionary is also done by the same algorithm. We are planning to do low pass or high pass filtering to de-noise the noisy image. Low pass filter is used to remove salt and paper noise while high pass filter is used to separate of edges. We use OpenCV libraries and Python libraries to implement the low pass filter and to create blocks of image.

Initially we take some training and filter them by using classical convolution. Both filtered and non-filtered images are divided into blocks which are stored in a dictionary. In the dictionary the key is noisy part of the image and the value is filtered part of the image.

II. LITERATURE REVIEW

A. Sparse Dictionary Learning^[2]

Sparse dictionary learning is a representation learning method which aims at finding a sparse representation of the input data (also known as sparse coding) in the form of a linear combination of basic elements as well as those basic elements themselves. These elements are called atoms and they compose a dictionary. Atoms in the dictionary are not required to be orthogonal, and they may be an over-complete spanning set. This problem setup also allows the dimensionality of the signals being represented to be higher than the one of the signals being observed.

One of the key principles of dictionary learning is that the dictionary has to be inferred from the input data. The emergence of sparse dictionary learning methods was stimulated by the fact that in signal processing one typically wants to represent the input data using as few components as possible.

Different Algorithm for Sparse Dictionary Learning are as follow.

- 1) **K-SVD**^[8] Applications that use sparse representation are many and include compression, regularization in inverse problems, feature extraction, and more. Sparsity in over-complete dictionaries is the basis for a wide variety of highly effective signal and image processing techniques. Model: Given a dictionary D and a signal y ,

$$\min_x \|x\|_0 \quad s.t. \quad y = Dx$$
or

$$\min_x \|x\|_0 \quad s.t. \quad \|y - Dx\|_2 \leq \varepsilon$$
where,

$D \in \mathbb{R}^{n \times K}$: an overcomplete dictionary matrix

$y \in \mathbb{R}^n$: a signal can be represented as a sparse linear combination of columns of D

$x \in \mathbb{R}^K$: a vector contains the representation coefficients of the signal y .

Training Approach And Algorithm

Train the dictionary directly based on the given examples, optimizing w.r.t. sparsity and other desired properties.

Output:

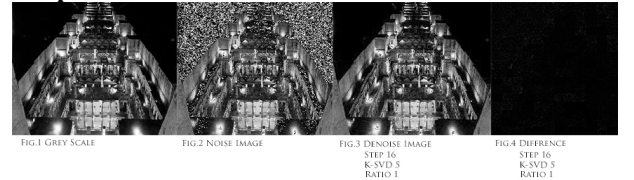


Fig. 1: K-SVD - Step 16 - kSVD 5 - Ratio 1^[12]

- 2) **Online dictionary learning**^[3]: Many common approaches to sparse dictionary learning rely on the fact that the whole input data X (or at least a large enough training dataset) is available for the algorithm. However, this might not be the case in the real-world scenario as the size of the input data might be too big to fit it into memory. The other case where this assumption can not be made is when the input data comes in a form of a stream. Such cases lie in the field of study of online learning which essentially suggests iteratively updating the model upon the new data points x becoming available.

A dictionary can be learned in an online manner the following way

- a) for $t = 1, 2, 3 \dots T$
- b) Draw a new sample x_t

- c) Find a sparse coding using LARS
- d) Update dictionary using block-coordinate approach

Output:



Fig. 2: On-line Dictionary Learning for $m=2,4,8,12,16$ ^[7]

III. OUR OWN APPROACH FOR DICTIONARY BASED FILTERING

A. Input

Salt-and-pepper noise is a form of noise sometimes seen on images. It presents itself as sparsely occurring white and black pixels. An effective noise reduction method for this type of noise is a median filter. We take a set of images with salt and pepper noise present at random positions.

B. Algorithm

An effective noise reduction method for this type of noise is a median filter. Like the mean filter, the median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

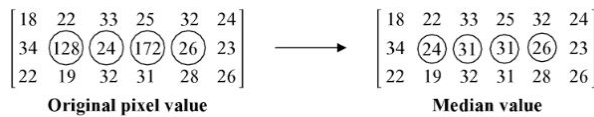


Fig. 3: Median Filter Conversion^[9]

From the above illustration it is clear that the pixel value 128 is replaced by the median value 24 and the pixel value 172 is replaced by the median value 31. here the values 128 and 172 are entirely different from their neighboring pixels. when we take the median value, the pixel values which are totally different from their neighboring pixels are replaced by

a value equal to the neighboring pixel value. We are using a Cross-correlation. It is a simple metrics which you can use for comparison of image areas. It is much more faster and robust than simple euclidean distances. We will need threshold to compare two image. It is very efficient while searching in a dictionary. First step of our algorithm is to take a set noisy images. Now, we divide the image in $m \times m$ chunks and store them. These chunks are now compare with our dictionary. If no image is present with normalize distance less than delta then we add present image in out dictionary. If image is present then replace with corresponding filtered image. We will repeat the above steps till we get chunks of filtered images. At the end we will merge all the chunks.

C. Flow Algorithm

First of all we have to take $n \times k$ training image.
Create $m \times m$ blocks.

Create dictionary using blocks.

Dictionary:

Key - Noisy image

value - filtered image

Search algorithm

if *Nearest Possible Match* **then**

 | Noisy Patch Replaced with this Image

else

 | Add to Dictionary

end

return **Final Filtered Image**

IV. RESULTS

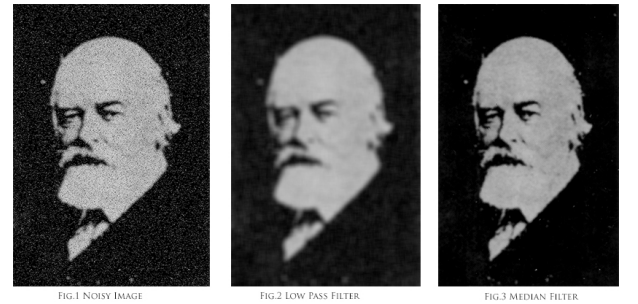


Fig. 4: Direct Filter

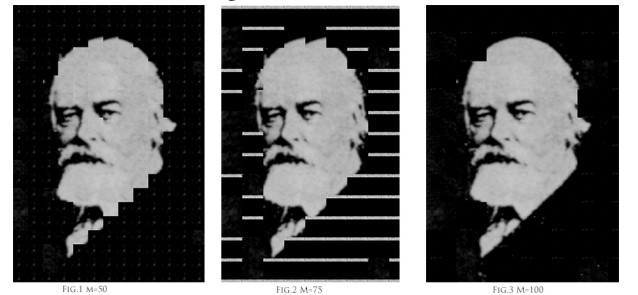


Fig. 5: Dictionary Based Filter for $m=50,75,100$

We can infer from the output that median filters are much more accurate than low pass filter for image with salt and pepper noise.

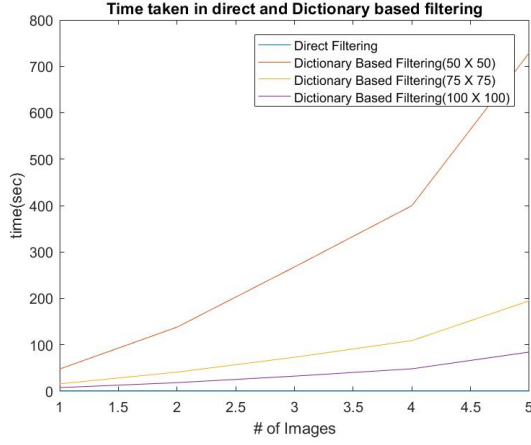


Fig. 6: Time Analysis

Above analysis states that less the value of m more is the time taken to filter images. This is mainly due to size of dictionary. Less is the value of m , less is value of threshold and more is value of dictionary. It would take more time to search in a big dictionary. Here, time is exponentially varying with no. of images.

Dimension(m)	Threshold	Percentage Error
50 x 50	175	9.89 %
75 x 75	140	9.19 %
100 x 100	90	3.5 %

Table-1 Error Analysis

Here, more is the value of m , less is the percentage error.

V. CONCLUSION

While using dictionary based filtering for median filter we can conclude that more is the value of m , better is the performance. Direct approach is much more efficient than dictionary based approach for median filter for lower no. of images. Dictionary based approach can be used with filters with higher polynomial terms.

VI. FUTURE WORK

We would try to implement more efficient searching algorithm to search image from the dictionary and try the whole approach of dictionary based filtering for filters with higher polynomial terms.

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