

Dictionary Based Filtering

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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. METHODOLOGY

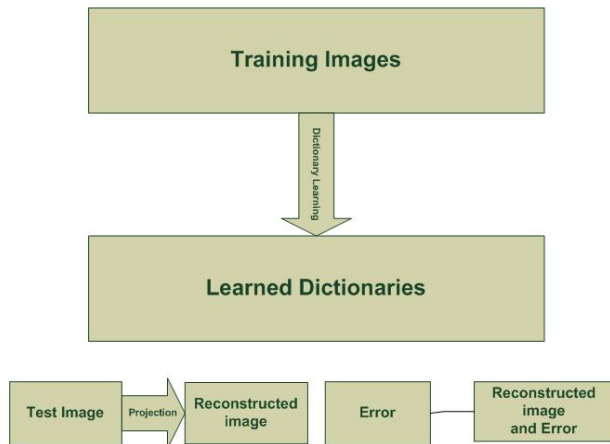


Fig. 1: Methodology[3]

III. LITERATURE REVIEW

A. Salt and Pepper Filtering

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.[2]

In Median Filter, The original pixel values and the values replaced by their median are shown side by side below

18	22	33	25	32	24
34	128	24	172	26	23
22	19	32	31	28	26

Original pixel value

→

18	22	33	25	32	24
34	24	31	31	26	23
22	19	32	31	28	26

Median value

Fig. 2: Median Filter Conversion[1]

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. hence Median Filter will reduce salt-pepper noise of image.

B. Sparse Dictionary Learning

[5] 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) Method of optimal directions (MOD)
- 2) K-SVD[4]
 - a) K-SVD method learns an over-complete dictionary from an input image via solving the following minimization model
 - b) **Limitation:** Choosing an appropriate "dictionary" for a dataset is a non-convex problem, and K-SVD operates by an iterative update which does not guarantee to find the global optimum.

- 3) Stochastic gradient descent
- 4) Parametric training methods
- 5) Online dictionary learning

C. Flow of Implementation

First of all we have to take $n \times n$ 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**

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IV. OUTPUT

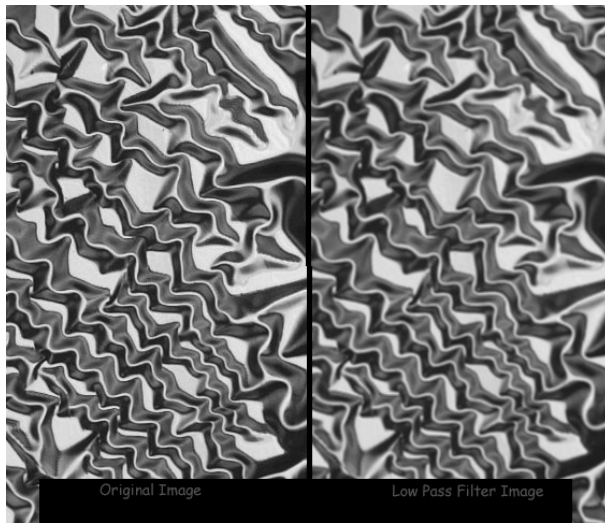


Fig. 3: Output

V. CONCLUSION

We are successfully able to create $m \times m$ blocks from $n \times n$ dimension image where $m \ll n$. We also have implemented low pass filtering. We take $m = 3, 5, 7, 10, 50$ and observe that, when m is very small we get more accurate result. Size of dictionary is inversely proportional to m . Therefore, there is always trade-off between accuracy of result and size of dictionary.

VI. FUTURE WORK

We are planning to implement efficient searching algorithm to search image from the dictionary and trying to compare running time of our algorithm (dictionary based approach) with running time of classical convolution approach.