Robust Multi-frame Super-Resolution

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***Abstract*—Image super-resolution(SR) is a popular technique for increasing the resolution of a given image. Its most common application is to provide better visual effect after resizing a digital image for display or printing. [1] In recent years, due to the consumer multimedia products being in vogue, imaging and display device become ubiquitous, and image super-resolution is becoming more and more important. In this paper, we have implemented a basic but very robust multi-frame super resolution technique. Our technique uses L1-Norm minimization to achieve high resolution images making the method immune to outliers.**

***Index Terms*—super resolution, image deblurring, multi-frame, Wiener, median**

I. Introduction

Due to the practical limitation of the resolution of the imaging device, we cannot capture continuous High Resolution(HR) scene before down-sampling. [2] These devices also suffer from issues like relative motion warping, atmospheric interference and artifacts introduced by an imaging device. This leads to an Low Resolution(LR) noise image as an output.

Using this we can formulate a general model:
Y(x,y) = $\{H_{cam} * * F * * H_{atm} * * X(x,y)\} \downarrow\downarrow + N(x,y)$
where Y(x,y) = output of imaging device LR image
X(x,y) = input HR image
H_{atm} = Point-Spread-Function of atmospheric disturbance. H_{cam} = Point-Spread-Function of camera artifacts. F = warp matrix
$\downarrow\downarrow$= Down-sampling
and N(x,y) = Random noise

The idea of the paper is to generate a robust method for estimation HR image with a set of given LR images with few assumptions. This idea is known as Super Resolution(SR).

II. Robust Super Resolution

There are a lot of implementation on the topics of super resolution before the Deep learning Era.

A. Problems with the Pre-Deep-Learning Era

1) Fourier Domain Solutions: Few are present in Fourier domain which are extremely cheap on computation but are extremely sensitive to any model errors. These also give highly degraded output for any deviation from translation motion

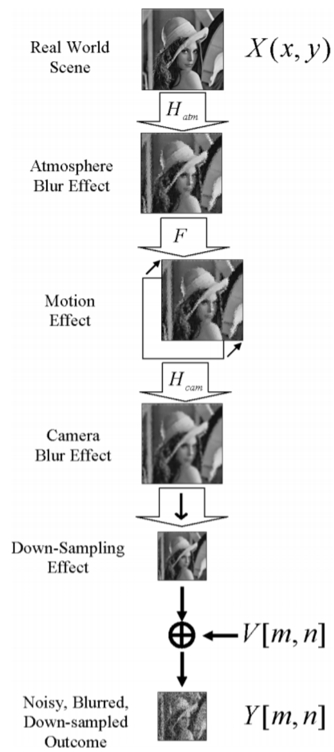

Fig. 1: **HR to LR conversion model [2]**

2) Spatial Domain Solutions: These are computationally expensive in nature. All of the previous work have a good yields but take assumption of white Gaussian noise and use L2 norm for estimator.

B. Solution in Pre-Deep-Learning Era

1) Author's Motivation: When we try to create any HR image we are not only bound to the given LR images. We are free to make assumptions on the noise or motion models which may be mathematically convenient for formulation with general prior information. The models give an approximation of the HR value.

We can use many estimators which can give an optimal solution in a given case but based on certain assumptions. If the data does not fit the model faithfully estimator performance degrades. If there is any outliers in data they also degrade performance of estimators.This limits the usability of the estimators drastically.

Author proposes to implement sub optimal estimator which cater to larger variety of data and provide more stable results.

2) Implementation details: In this paper we tweak the above model since in normal condition H_{cam} is much more important than H_{atm} and we replace them with H so equation reduces to
Y(x,y) = $D_k H_k F_k X(x,y) + N(x,y)$
where D_k = down conversion matrix for kth LR image
Some of the common estimator of We also take some assumption that all the LR images have common decimation factor and common space-invariant PSF under translation motion we get
$D_k = D$ for every k
$F_k = F$ for every k
Y(x,y) = $DH_k FX(x,y)$+N(x,y)
We can use L_p norm where 1¡=p¡=2 to estimate the value X(x,y) which will result in the following equation
$\arg\max(x) \sum_{k=1}^{z} |($ $DH_k FX(x,y)$ - Y $)|_p^p$

Solving this equation for p=1 (equating derivative =0) we get

G1 = $\sum_{k=1}^{z} F_k^T D^T sign(DF_k Z^/hat$ = 0
where Z = FX(x,y)
This equation closely resembles Median filter which can have decent output even if until the outliers are less than 50% of the whole data points. This give our estimator higher tolerance towards outlier /corrupted data.
We have implemented the code in python using the scikit-image [3] and pytackreg [4] libraries.

III. Test results

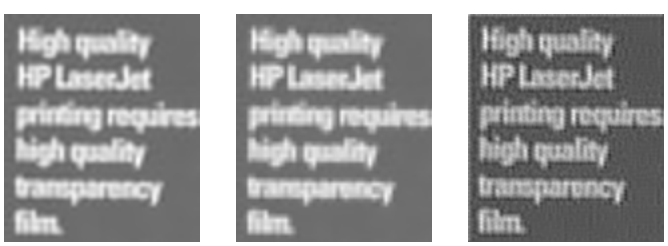

Fig. 2: Interpolated (a) Mean and (b) Median of LR Images (c) Final HR Image with Guassian Blur

We see a huge difference between first set of images as we used a ml estimator was able to extract more data rather than mean and median.
We also see little to no difference in the second set of images since our ml estimator does not exhibit median filter like behaviour. We see differences in different transformation as

Fig. 3: (a) Box Filter (b) Guassian Filter (c) Wiener Filter

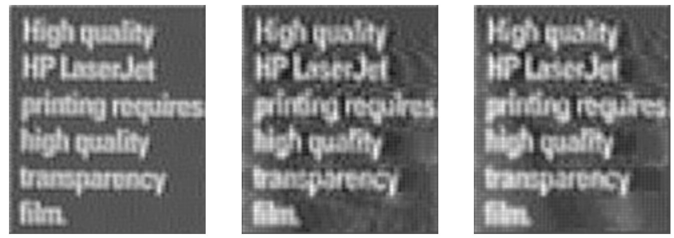

Fig. 4: Image Registration by (a) Translation (b) Translation and Rotation (c) Affine Transformation

the model had assumption for translation motion only but the output of the following are still respectable. [5]

IV. Conclusion

We were able to use noisy LR images to create a HR image. The test result show this implementation of SR is robust since the results do not degraded rapidly over different noise and transform models. We saw L1 norm to better than L2 norm in theory cases with outliers. We also confirmed that L1 norm was more optimal than mean and median interpolation of all the LR images. [6]

V. Future Work

The idea creating a robust model can be enhanced by adding appropriate regularization. This idea was implemented in the paper but out of our scope to implement. The idea of the regularization was to create additional penalty in the cost function. This penalty is high when there are drastic changes in the image. This regularization should also be capable to keep the edges in the HR image.
The algorithm we have implemented fast but it is also to make the algorithm faster using some optimisation namely using non iterative data fusion.

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