Fast super-resolution using weighted median filtering*

Appidi Abhinav, Praneetha Moturi and Subha Karnam
CV Project, IIIT Hyderabad

***Abstract*— The paper proposes a fast super resolution method using weighted median filtering. It is a non iterative approach using the Gaussian weights. The approach reduces the errors caused by inaccurate motion vectors.**

I. INTRODUCTION

Resolution of image plays a vital role in image processing. Though there is great increase in the resolution of camera sensors in modern times image re-sampling is one of the important problems because of old resolution images/videos, surveillance camera videos and many more. There are many image re-sampling algorithms like NEDI algorithm which uses the prior information like self-similarity at different resolutions.

(top row) and pixels of high-resolution image (bottom row).

Super Resolution takes several images of a single image with sub pixel shift as input (see Figure 1) and we will construct a single high resolution image. If the object motion and the approximation function is known then we can construct a super-resolution image from the information of all the frames. The issue of this approach is we need to know the accurate motion estimation. Here we propose a super-resolution method stable enough to the errors of motion vector estimation.

II. MATHEMATICAL MODEL

The approach includes a set of down sampling steps. First we produce a set of low-resolution images after motion transformation and down scaling the high resolution image z using the operator A_k.

$$A_k z = u_k \qquad k = 1, 2, ...N.$$

The operation A_k depends on the atmosphere blur H_{atm}, motion operator F_k, camera lens blur H_{cam}, noise n and the downscaling operator D. The H_{cam} and H_{atm} are modeled using a single Gaussian filter H.

$$A_k = D H_{cam} F_k H_{atm} + n$$

$$A_k = D F_k H z = u_k \qquad k = 1, 2, ...N \tag{1}$$

Motion Estimation algorithms [5], [6] are used to calculate F_k. The inaccuracy of motion estimation is very important in super-resolution and it is important to reduce its effect in super-resolution.The other methods of super-resolution are time consuming but this approach is a non-iterative method hence fast. The approach presented here is using weighted median filtering with Gaussian weights.

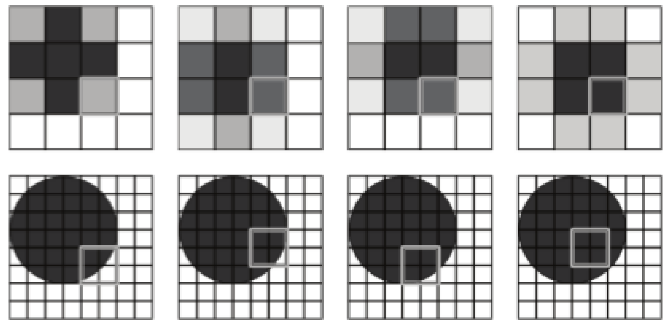

Figure II The correspondence between pixels of low-resolution images

III. PROBLEM DEFINITION

We have a high resolution image z and a set of low resolution images u_k defined on a discrete set $\{(i, j) : i, j \in Z\}$. The motion F_k operator defines a set of correspondences between the source image and the motion transformed image.

$$F_k z(i, j) = z(x^k_{i,j}, y^k_{i,j})$$

the downscaling is performed on the image with s as scale factor.

$$Dz(x, y) = z(sx, sy),$$

$$DF_k z(x, y) = z(x^k_{si,sj}, y^k_{si,sj}).$$

Hence the low resolution image can be obtained by

$$A_k z(i, j) = DF_k(Hz)(i, j) = (Hz)(x^k_{i,j}, y^k_{i,j}), i.e$$

$$(Hz)(x^k_{i,j}, y^k_{i,j}) = u^k_{i,j}.$$

The $(x^k_{i,j}, y^k_{i,j}, u^k_{i,j})$ are rewritten as (x_n, y_n, w_n). The final super-resolution image (Hz) with known values w_n will be in the given points will be (x_n, y_n)(see figure 2).

$$(Hz)(x_n, y_n) = w_n \tag{2}$$

IV. PROBLEM SOLUTION

The minute errors in the motion estimation results in serious degradation of the reconstructed image. So instead of constructing a high resolution image (Hz) which satisfies the equation (2) for each (xn, yn) we use the following approach:

The approach includes Gaussian filtering and median filtering. The median filter is a high pass filter so it produces sharp edges and Gaussian filter is a low pass filter so it smoothens the image. So the Gaussian filter takes care of the spatial distribution of points (xn, yn).

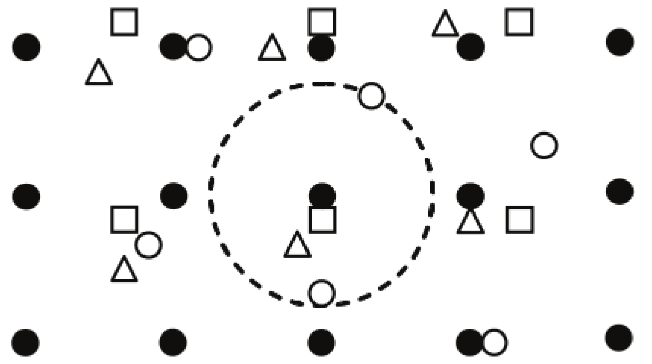

Figure III The illustration for super-resolution problem statement

The Gaussian filter approach is as follows. For each pixel (i, j) of high resolution image (Hz) we take all points (x_n, y_n) from a small neighborhood of (i, j) like in figure 2 and calculate the average of these values based on the Gaussian filtering.The sigma is chosen experimentally in accordance to scale factor and accuracy of motion vectors. Gaussian filtering causes image blur.

$$(Hz)(i,j) = \frac{\sum_n w_n e^{\frac{-(x_n-i)^2+(y_n-j)^2}{2\sigma^2}}}{\sum_n e^{\frac{-(x_n-i)^2+(y_n-j)^2}{2\sigma^2}}}$$

A robust approach for median filtering is suggested in

9

. Median filtering up-samples the low resolution images and the up-sampled images are combined using median averaging. An adaptation of the median averaging to construct (Hz) in presented in

10

. It applies the median averaging to the values of all points in the neighborhood of the target pixel:

$$(Hz)(i,j) = med(w_n : (x-i)^2 + (y_n - j)^2 < R^2)$$

The combined method is based on weighted median averaging. In weighted median $wmed(w_n, c_n)$, every value w_n has a weight c_n. The value of c_n is chosen as:

$$c_n = exp(-\frac{-(x_n-i)^2+(y_n-j)^2}{2\sigma^2})$$

If the weights w_n are natural numbers, we calculate the weighted median as median average with w_n taken c_n times. For calculating $wmed(w_n, c_n)$ the pairs (w_n, c_n) are sorted in ascending order of w_n. Next, we find the value m which satisfies the conditions:

$$\sum_{k=1}^{m-1} c_k <= S/2 \quad \sum_{k=1}^{m} > S/2 \quad S = \sum_k c_k$$

and takes the value w_m as the result of the weighted median averaging.

Figure IV Weighted median averaging procedure

This process is illustrated in figure 3. We construct a long rectangle by concatenating rectangles of width S in ascending order of w_n where each rectangle represents a pair (w_n, c_n) with c_n as width and a fixed height. Finally we take value w_m of the rectangle in the middle of the constructed rectangle as the result of weighted median.

The result obtained is the approximation of blurred image Hz. The proposed method produces sharp images due to the behavior of median filtering. If we increase the radius of the median filtering then we do not increase the image blur of the resulting image and the resulting image tends to be piece-wise flat. Therefore we not apply deblur algorithms to the result and take the result of the weighted median averaging as the result of super-resolution.

V. RESULTS

To the test the approach we applied random shifts on high-resolution images and obtained a set of 7 down sampled images. Then the high resolution image is reconstructed using the set of low resolution images using the proposed approach and is compared with the reference high resolution image. To test the stability of the proposed method we added noise to the motion vectors. A randomly distributed value in [-1, 1] range was added to every motion vector of a quarter of input images and a random value between [-0.25, 0.25] is added to motion vectors of other images. The results of proposed super-resolution method are shown in figure 4. The results can be improved by varying the gauss radius sigma and the radius R for different pixels of the image. This will be part if future work.

VI. CONCLUSIONS

A Non-iterative image super-resolution method based on the weighted median averaging has been proposed. It was shown that weighted median averaging reduces the errors caused by inaccurate motion vectors.

REFERENCES

REFERENCES

[1] X. Li and M. Orchard, New edge-directed interpolation, IEEE transactions on image processing, vol. 10, no. 10, pp.15211527, 2001.

[2] S. Borman and R. Stevenson, Super-resolution from image sequences - a review, Midwest Symposium on Circuits and Systems, pp. 374378, 1998.

[3] K. Malczewski and R. Stasinski, Super resolution for multimedia, image, and video processing applications, Recent Advances in Multimedia Signal Processing and Communications, vol. 231, pp. 171208, 2009.

[4] S. Farsiu, D. Robinson, M. Elad, and P. Milanfar, Fast and robust multi-frame super-resolution, IEEE Transactions on Image Processing, vol. 13, no. 10, pp. 13271344, 2004.

[5] A. Bruhn, J. Weickert, and C. Shnorr, Lucas/Kanade Meets Horn/Schunck: Combining Local and Global Optic Flow Methods, International Journal on Computer Vision, vol. 61, no. 3, pp. 211231, 2005.
[6] H. Le and G. Seetharaman, A super-resolution imaging method based on dense subpixel-accurate motion fields, Proc. of the Third International Workshop on Digital and Computational Video, pp. 3542, 2002.
[7] A. N. Tikhonov and V. Y. Arsenin, Solutions of Ill-Posed Problems. Washington DC: WH Winston, 1977.
[8] A. S. Krylov, A. V. Nasonov, and O. S. Ushmaev, Video super-resolution with fast deconvolution, Pattern Recognition and Image Analysis, vol. 19, no. 3, pp. 497500, 2009.
[9] A. Zomet, A. Rav-acha, and S. Peleg, Robust super- resolution, Proc. of the IEEE Workshop on Applications of Computer Vision, pp. 645650, 2001.
[10] A. Sanchez-Beato and G. Pajares, Robust super-resolution using a median filter for irregular samples, Lect. Notes in Comp. Science, vol. 5524, pp. 298305, 2009.
[11] A. Nasonov and A. Krylov, Adaptive image deringing, Proceedings of GraphiCon2009, pp. 151154, 2009.

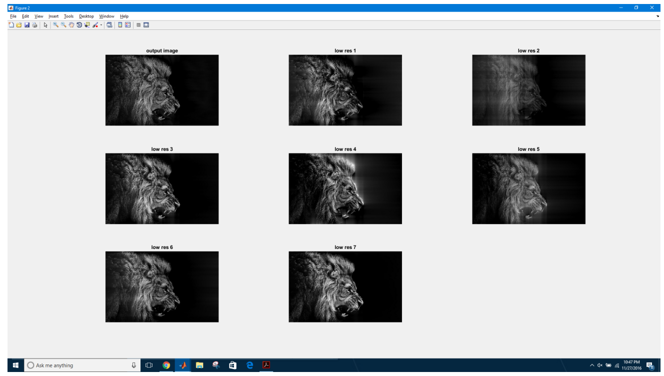

Figure VI Set of low resolution images


Figure VI High-resolution image

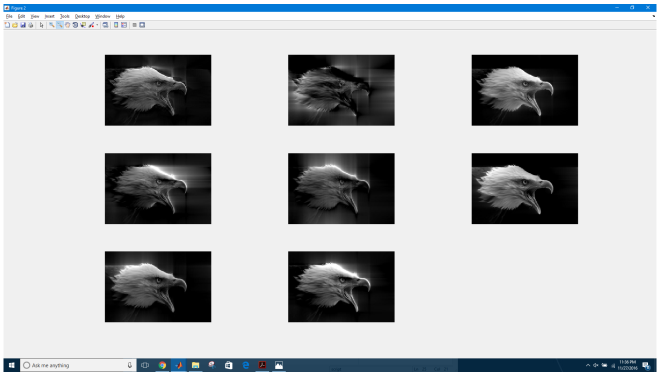

Figure VI Set of low resolution images

Figure VI High-resolution image

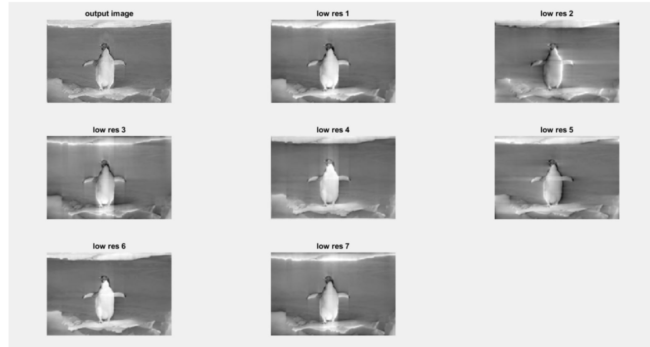

Figure VI Set of low resolution images

Figure VI High-resolution image