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Analysis of Leaf Diseases using Learning Image Superresolution

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Abstract: Superresolution is a process of extracting higher details. The main objective of this paper is the study of patch based method for super-resolving low resolution of a leaf diseased image. The domain specific prior is incorporated into superresolution by the means of learning patch based estimation of missing high frequency details from infected leaf image. Images are decomposed into fixed size patches in order to deal with time and space complexity. The problem is modeled by Markov Random Field which enforces resulting images to be spatially consistent. The spatial interactions are coupled with a similarity constraint which should be established between high-resolution training image patches and low resolution observations of leaf diseased images. Through this proposed work, fine edges of SR images are preserved without applying complex mathematical algorithms based on wavelet, fast curvelet, etc. Also gives the better visual SR image as that of complex multi frame SR algorithms like reconstruction and registration. This concept is most useful for agricultural expert for helping our farmers. The experimental result shows the best visible SR result of an infected leaf along with MSE and PSNR.

Keywords: Markov Random Field, high-resolution, SR images.

1. INTRODUCTION

In agriculture, the analysis of infected leaf area is of great importance for the application of techniques such as pruning, fertilization and planting density [2]. A feature that can be extracted by analyzing the leaf area is the quantification of damage caused by pests and diseases. Such damage can be detected through the study of damaged leaf area by pests [2]. Detecting the precise amount of damaged leaf area is essential to determine control actions such as application of pesticides, since a small damaged leaf area may dispense control measures. In this paper, we have analyzed infected leaf image using learning based image superresolution techniques in order to recover the high frequency details such edges, various features, etc.

Obtaining a high-resolution (HR) image from single or multiple low-resolution (LR) images, known as "super-resolution" has been a classic problem. High resolution means high pixel density, also refered to as high-definition (HD). An HR image brings out details that would be blocked out in an LR image.

Super resolution problem is an ill-posed inverse problem. Estimating details is an inverse problem since low resolution observation is the result of a smoothing and downsampling process [3]. Basically, SR technique is broadly categorized in two parts. First is traditional image reconstruction and registration technique [5],[6] in these methods attempt to solve the problem by employing and fusing a number of low resolution images. The images are of an underlying scene are positioned into a common coordinate frame by sub-pixel shifts of images. Most of the literature available on super-resolution is for multi-frame and majority of them are based on the motion as cue. The super-resolution idea was introduced by Tsai and Hung, where a pure translation motion has been considered [1]. In such methods the quality of reconstructed SR image obtained from a set of LR images depends upon the registration accuracy of the LR images and some prior knowledge of imaging system [5, 6]. Nearly all SR reconstruction algorithms are based on the fundamental constraints that provide less useful information as the magnification factor increases also less computationally efficient to get more accuracy. Baker and Kanade found these limitations and developed a SR algorithm by modifying the prior term in cost to include the result of a set of recognition called as recognition based super-resolution or hallucination [11].

And second is single image learning based SR methods [7] which is more powerful and useful, when only a single observation image is available and several other high resolution images are present in the data set. All high resolution images from data set will act as training images. This method is classified under the motion free superresolution scheme as the new information required for predicating the HR image is obtained from a set of training images rather the subpixel shifts among low resolution observations.

This exploit the prior knowledge between the HR examples and the corresponding LR examples through the so-called learning process. Most example-based SR algorithms usually employ a dictionary composed of a large number of HR patches and their corresponding LR

patches. The input LR image is split into either overlapping or non-overlapping patches. Then, for each input LR patch, either one best-matched patch or a set of the best-matched LR patches are selected from the dictionary. The corresponding HR patches are used to reconstruct the output HR image.

In this paper, we propose a novel single image example-based super-resolution algorithm which combines the learning phase of [7] by searching for examples within the Gaussian pyramid of the input image itself and the reconstruction phase of [7], which uses the Markov Random Field (MRF) model to reconstruct the HR image. The main benefit of such learning approach is that no external database is required which results in faster search and absence of "hallucination" effect (when compared with [7]). On the other hand, using MRF in the reconstruction enables us to stay in the example based domain without combining it with classical SR as in [8]. There are a few advantages to this in comparison with [8]. First of all, we can use only one level of the pyramid as the search space whose sub-sampling factor corresponds to the magnification factor instead of multiple levels with non-integer sub-sampling factor and, thus, again decrease the computation time. Second, we reconstruct only the HR image of the desired resolution rather than employing course-to-fine reconstruction of images at intermediate resolutions. Finally, we avoid sub-pixel registration which often causes in accurate results.

This paper achieves fast image super-resolution by reducing the size of trained dictionary. Thus, the reduced dictionary size makes it possible to significantly speed up SR processing and save the memory cost, while providing reasonable visual quality. Thus, the learning based approach is mostly advantageous over conventional reconstruction based SR approach.

2. LOW RESOLUTION IMAGING MODEL

We further assume that each of the measured image is contaminated by non-homogeneous additive Gaussian noise, uncorrelated between different measurements. Fig. 1 illustrates the image degradation model. In order to treat the most general case, it is assumed that each measurement is the result of different blur, noise, motion, and decimation parameters. Translating the above description to an analytical model, we get

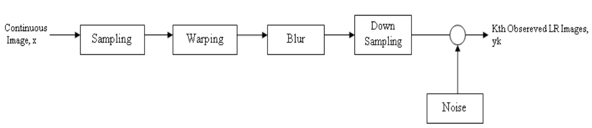


Fig. 1: Degradation Model.

$$y_k = DB_k M_k x + n_k \; for 1 \le k \le p \qquad (1)$$

The geometric warp matrix M_k is a one-to-one representation of the optic flow between the *nondecimated noiseless* version of the *kth* measured image and the ideal image x.

The assumption on the *a priori* knowledge of the blurring matrix, B_k can be explained in some applications by referring the blur to measurable phenomena, such as optics and sensor blur. In other cases, we may assume that the superresolution restoration process is robust to errors in the blurring function.

The decimation ratio between the ideal image and the *kth* measurement image can only be determined by parameter matrix D . This ratio is directly drawn from the ratio between the number of pixels in the measured image $[N_k \times N_k]$ and the ideal image $[L \times L]$ .The above restoration problem can be formulated in terms of the following equation

$$y_k = H \cdot x + n_k \; for 1 \le k \le p \qquad (2)$$

Where, $H = DB_k M_k$.

3. LEARNING BASED IMAGE SUPER-RESOLUTION

We propose a single-image example-based super-resolution method which uses MRF to model the HR image as a collection of overlapping HR patches whose

Possible candidates are obtained from the input LR image itself. The algorithm can be divided in to three main phases as shown in fig. (3): learning, reconstruction and post processing.

In the learning phase, we find candidate patches of each unknown HR patch by first searching for k-nearest neighbours of its corresponding known LR patch from the input image. This search exploits the patch redundancy across different scales of the Gaussian pyramid. We then extract the HR pairs of the found neighbours (called "parent" patches) from the input image and we use them as candidate patches for corresponding locations in the HR image, because we assume that the LR and HR patches are related in the same way across different scales [12].

The next is the reconstruction phase, which models the HR image as a MRF and performs inference on this model. MRF model has a great advantage over the simpler alternative, i.e. choosing the best match at each location, as we will demonstrate shortly.

Finally, we apply post-processing techniques to eliminate remaining artifacts such as edges. We use back-projection to ensure the consistency of the HR result with the input LR image. In case of a small input image and high magnification factor, the search space may become too small for good matches to be found. This will result in visible artifacts (edges) so we also use steering kernel regression [12,14] that produces a smooth and artifact (edge)-free image while still preserving edges, ridges and blobs. Post-processing together with MRF modeling allows us to obtain competitive SR result even with only having LR image as the algorithm's input.

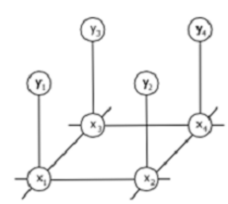


Fig. 2: RF Model : x_k – unknown HR patches;
Y_k - measured LR patches

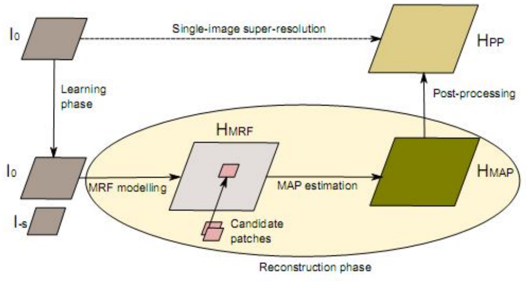


Fig. 3: Learning Based SR model.

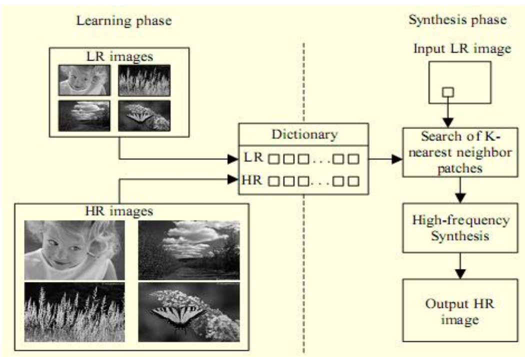


Fig. 4: HR-LR Dictionary Learning Based SR model.

As shown in fig. 4, at the learning phase, the training data, that is, a dictionary consisting of LR and HR patches, is constructed. The LR and HR patch pairs are obtained from various training images. During the synthesis phase, the input LR image is super-resolved by using the dictionary. For each LR patch in the input image, its nearest neighbor LR patches are explored from the dictionary. The high-frequency components of the input LR patch are synthesized using the best matched LR patches.

The performance of those learning-based SR algorithms highly rely on matching accuracy of an input LR patch with candidate LR patches in the dictionary. In order to improve the accuracy of matching, a sufficient number of LR-HR patch pairs must be included in the dictionary. Usually, existing learning-based SR methods require hundreds of thousands of training examples for reliable performance. However, such a dictionary size causes tremendous memory cost for storing the training samples as well as awfully large computational complexity in the matching process. In order to overcome this problem, we propose a fast learning-based SR algorithm with reduced dictionary based on k-means clustering.

3.1 Learning Based Preprocessing

Before learning preprocessing, the learned dictionary should possess various HF details lost by image degradation process and specific features to index them. The HF image I_{HF} is obtained by subtracting I_{UP} from I_H, and mid-frequency (MF) image I_{MF} stands for a high-pass filtered version of I_{UP} where, I_{MF} is employed as the features for indexing. They indicate lost HF and MF layers for predicting them, respectively.

As a result, as shown in fig. 5, we extract and store salient HR and LR patches from I_{HF} and I_{MF}, respectively. Those patches are properly overlapped with neighboring patches for local smoothness. Without loss of generality, we assume that the relationship between I_{HF} and I_{MF} is independent of the local image contrast. So, we normalize the contrasts of LR and HR patches by dividing them by the energy of the LR patch. Finally, these primitive patches including edges are chosen and they are required for the dictionary. In other words, the proposed synthesis may be applied only for the selected regions.

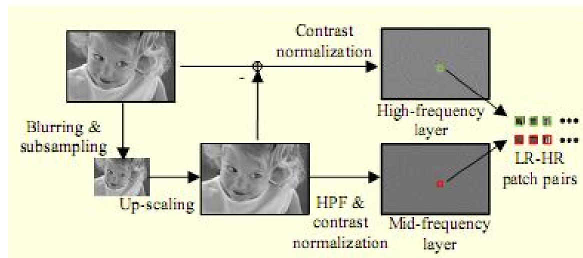


Fig. 5: Preprocessing for dictionary construction

3.2 Learning Based Dictionary Size Reduction

Now, we need to effectively reduce the number of LR-HR patch pairs in the dictionary so as to mitigate memory cost and computational burden in synthesis. This process is very significant in that the number of training examples in the dictionary generally dominates the performance of learning-based SR. Most of all, the small number of the samples can improve the practicality of the proposed SR algorithm.

So, we group adjacent LR-HR patch pairs into a single patch pair. We adopt k-means clustering to gather similar patches.

Fig. 6 illustrates this clustering process. Note that LR and HR patches in an LR-HR patch pair are always assigned into the same cluster. Finally, the center points of each cluster become new LR and HR patches belonging to the ordinary dictionary. In practice, we can determine *k* by considering memory cost and computational complexity of the synthesis phase.

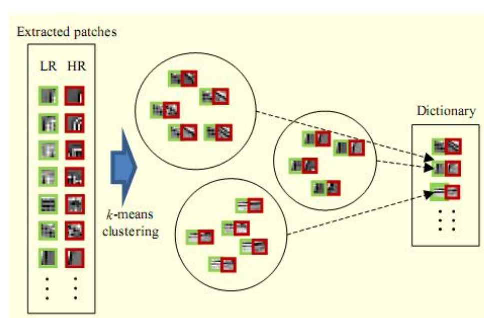


Fig. 6: Dictionary reduction using by *k*-mean clustering

3.3 Learning Based Image Synthesis

Fig. 7 describes the synthesis of learning based image SR. The input LR image is initially up-scaled using a linear scaler, and then LR patches are extracted from the MF layer of the input image as in the learning phase. Each input LR patch is compared with the candidate LR patches in the dictionary to find the best match. Next, the HR patch corresponding to the best matched LR patch is denormalized by multiplying with the energy of the input LR patch. Subsequently, a proper residue HF patch for each LR patch is explored from the residue dictionary, and the final HF patch is obtained by adding the residue patch to the best-matched HF patch selected from the ordinary dictionary. Note that the input MF residue patch, that is, the difference between the input LR patch and the best-matched LR patch, is compared with candidate MF residues in the residue dictionary. This process is applied to all the input patches. Averaging is only performed for pixels in overlapped regions. Finally, we obtain a synthesized HR image by adding the HF image I'_{HF} to the initially up-scaled image I_{UP}.

Note that the proposed algorithm selects the single best-matched patch unlike the conventional learning-based SR algorithms using multiple nearest patches. The single best-matched patch of the proposed algorithm may correspond to the average of multiple nearest neighbor patches because adjacent LR/HR patches on Euclidean space are clustered in the training phase of the proposed algorithm.

Therefore, even though we use a single best-matched patch for HF synthesis, we can obtain a similar results to synthesis using multiple nearest neighbor patches.

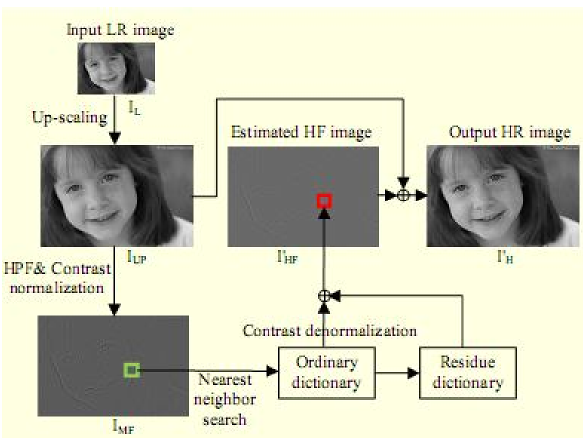


Fig. 7: Synthesis Phase

4. Mathematical Analysis

Mathematical analysis of SR is basically based on accurate MAP estimation [4]. According to the MAP estimator, the additive noise, the measurements, and the ideal image are all assumed stochastic signals. The MAP estimation of the unknown image *X* is done by maximizing the conditional probability density function of the ideal image given the measurements *P{X/Y}* . Based on Bayes rule, maximizing *P{X/Y}* is equivalent to maximizing the function *P{Y/X}P{X}* .

Bayesian approach provides a flexible and convenient way to model a priori knowledge concerning solution

X= arg max $P(x|y_1, y_2, \ldots\ldots\ldots, y_p)$

X= arg max {ln $P(x|y_1, y_2, \ldots\ldots\ldots, y_p)$+ ln $P(X)$}

The mathematical operation shows the final result as:

$$R = \hat{X} \cdot P$$

Where,

$$R = Q^{-1} + \sum_{k=1}^{p} H_k^T W_k H_k$$

and

$$P = \sum_{k=1}^{p} H_k^T W_k Y_k$$

If we assume that the measurements additive noise is zero mean Gaussian random process with auto-correlation matrix *W* with autocorrelation matrix *Q* for unique estimate image $\hat{X}$ using iterative technique.

By considering the stochastic least mean square filtering operation in order to minimize the error function as

$$e^2 = \min E\left\{\left[f(x,y) - \hat{f}(x,y)\right]^2\right\} \tag{10}$$

The solution can be achieved through following expression

$$\hat{F}(u,v) = \left[\frac{1}{H(u,v)} \frac{|H(u,v)|^2}{|H(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right] G(u,v) \tag{11}$$

Where, the ratio $S_\eta(u,v)/S_f(u,v)$ is called the *noise-to-signal* power ratio. For inverse filtering action it is equal to zero and $|H(u,v)|^2$ is the product of complex conjugate of $H(u,v)$ and self $H(u,v)$.

The analytical parameter such as MSE and PSNR can be calculated as, let, $x_{i,j}$ be the original image and $x'_{i,j}$ be the SR frame whose dimensions are M x N.

In this case, it is 500 x500,

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(x_{i,j} - x'_{i,j}\right)^2$$

$$PSNR = 10 \log \frac{255^2}{MSE} dB$$

The MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio) shows the better analytical result as that of conventional SR interpolation methods.

Table I shows the improved performance of proposed patch based method over conventional SR methods in terms of visual assessment parameters MSE and PSNR.

5. Experimental Analysis

The experiments were executed on an Intel Core TM 2 duo CPU @ 2.5 GHz with 3 GB RAM and results are obtained using MATLAB 7.10 tool.

Low resolution images are captured by using a low cost LG mobile camera with resolution 125 x 125 which is pre-setted. Initially, we had captured all possible high resolution infected leaf images from surveying various farm fields in order to prepare a huge database i.e. dictionary.

In fig.8, we have taken a sample four test disease infected low resolution [125x125] leaf images for processing. Fig.9 (a) ,(b),(c),(d) shows the super-resolved high resolution images of the same of fig.8 (a),(b),(c),(d) with improved resolution of factor of 4, i. e. [500x500]

(a) (b) (c) (d)

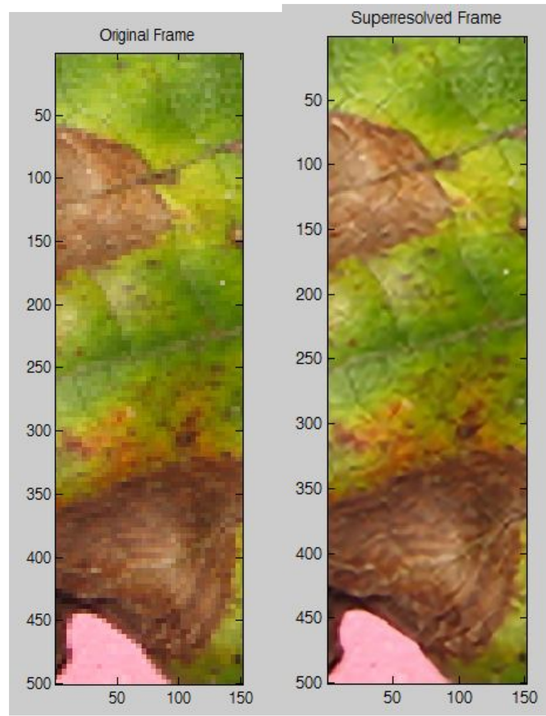
Fig.8 Low resolution leaf diseased images [125x125].

(a) (b)

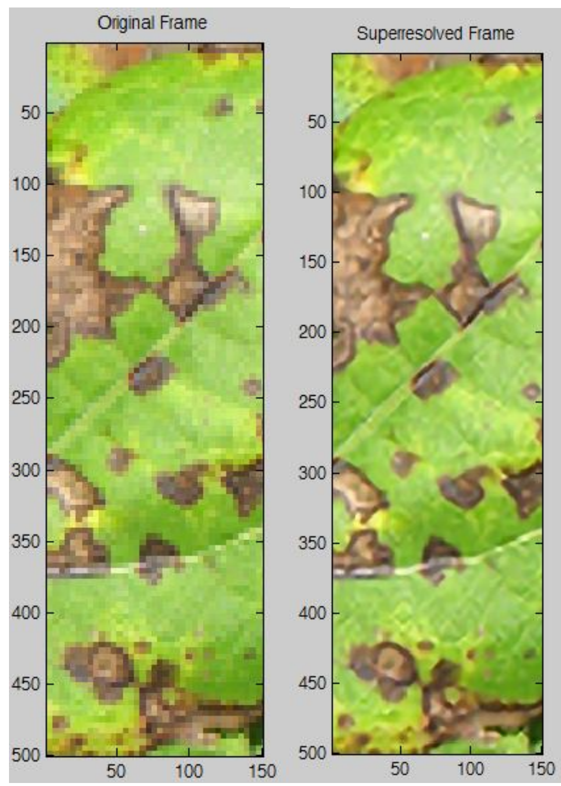
(c) (d)

Fig.9 R images of above LR leaf diseased images [500x500] with factor of 4.

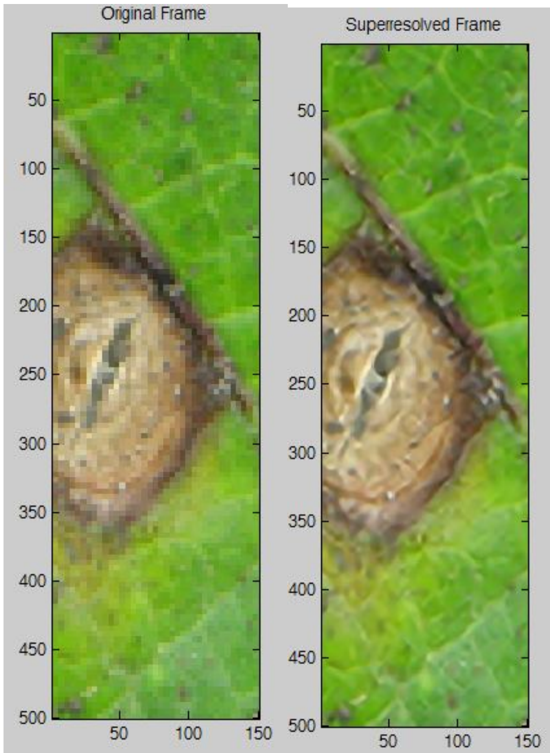
Fig. 10 shows the comparison of super fine edge quality of original frame with respect to SR frame of cropped portion of infected leaf. If the original leaf image get cropped, edge information is lost as shown in each of left side image of (a), (b), (c), (d), respectively. And on the same right side, we observe that all the edge informations are restored for the further analysis. This is the main difference between conventional algorithms and this proposed one.



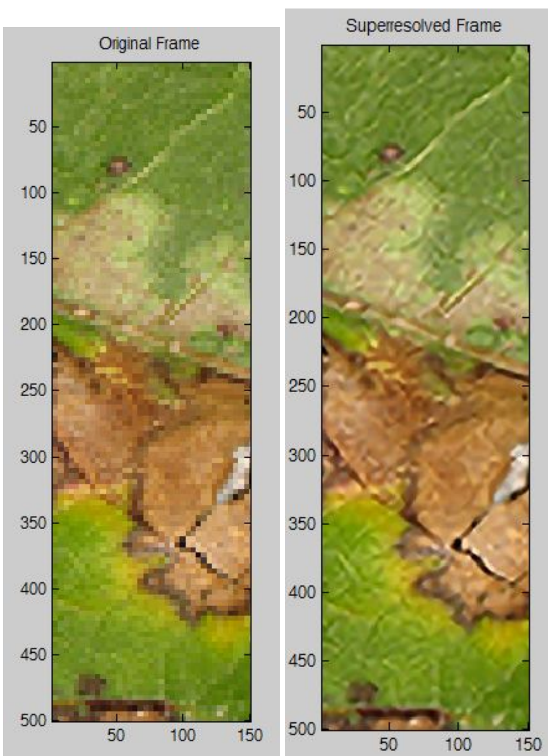
(a)



(b)



(c)



(d)

Fig.10 Comparison of Super fine edges between original image and SR image

Diseases	**MSE**		**PSNR, dB**	
	Convent.	***Proposed***	***Convent..***	***Proposed***
Disease 1	0.092	0.0020	33.13	34.94
Disease 2	0.049	0.0053	28.35	30.88
Disease 3	0.023	0.0015	32.67	36.31
Disease 4	0.044	0.0073	28.44	29.30

Table : Comparison of MSE and Psnr Between conventional Methods and proposed Method.

6. Conclusion and Future Scope

From the observational result, it is verified that the disease infected single LR image with low cost camera is only sufficient to improve its resolution with better visual quality. Information from leaf edges are recovered successfully. The proposed algorithm is very much fast with reduced size of database due to *k*-means clustering, hence memory requirement is low. Patch based learning SR technique gives improved MSE and PSNR over analytical as well as appearance result.

Properly analyzed infected leaf images are mostly useful for plant pathologist for the following purposes:

1) Identification of diseased leaf, stem, fruit ;

2) Identification and quantification of affected area by disease;

3) Identification of intensity of diseases and their effect on productivity.

Our proposed methodology is the best option for costly and complex hyper spectral satellite imagery system.

This paper will definitely bring some smile on farmer's face for improvement is crop production and agricultural development through agricultural experts.

In future, this concept can be extended to different plant pathologist for solve various agricultural engineering problems. There is a great scope for doing further research on the creation of self-learning database for any kinds of single image SR. Also, the work should be independent from the interpolating factor.

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