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Super Resolution Using GMM in Scene Flow

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ABSTRACT

In the current years, many researches are done in super resolution methods due to its applications in various fields. An initiative for increasing the resolution of an image is proposed. We provide an efficient super resolution method for scene flow. This method is a combination of Gaussian kernel and gradient descent in Gaussian Mixture Model (GMM) which retrieves the data with high frequency. Without any external records, high resolution image is obtained by the application of the conversion function, thus we used to unpaired the valuation of depth from the motion. From the results obtained, the suggested method gives a precise increase in resolution and decreases the Minimum mean Square (MSE) when evaluated by other methods. It also enhances the quality of the image.

Keywords: Gaussian kernel, Gradient descent, Gaussian Mixture Model, Super resolution.

I. INTRODUCTION

The objective of Super resolution [1] (SR) is the conversion of low resolution (LR) image to high resolution (HR) image. High resolution image[2] provides a clear view and data for analysis in addition. The super resolution images are used in applications like surveillance system, remote sensing, and medical imaging. The methods of Super resolution can be broadly described as 1. The example based method, is the standard method for super resolution in single image. High resolution components are retrieved from the low resolution image by the application of image pairs in the records which has patches of low and high resolution images. 2. Reconstruction-based method, in this case the former knowledge is required for limitation of inverse problem in which we have to do lots of initialization works to get that former knowledge. 3.

Interpolation based method, it is very simple and rapid to carry out, but the main drawback is the results obtained are distorted [3].

Super resolution methods retrieve the components with high frequency that are lost due to various reasons from the original data [4, 5]. A new procedure for retrieving the components, which have high frequency, that uses conversion function is proposed. For conversion [6], image of low resolution characteristics are stored in the blur image of the lost component of high frequency is proposed. Initially, Gaussian Mixture Model (GMM) based conversion of voice was progressed. Converting the voice of one speaker to another voice of another speaker is the conversion function [7, 8]. This voice conversion is employed in converting low to high resolution image. The development of this function of conversion is between the original and its self-reduced image using GMM. High frequency components are retrieved by applying the function of conversion to the elaborated image.

The component of high frequency is integrated in this optimization method for super resolution for a single image using GMM [9]. We associate the GMM method with Gaussian kernel and gradient descent of the image. This method of super resolution is quicker and robust to distort with edge conversation [10]. The blurring effect is decreased in expanded images after multiple iterations. Gaussian mixture model is mainly used for the density estimation, clustering [11, 12] and data mining. These mixture models are widely used for completion of data, in particular for observing the hidden variables. In general, we used EM algorithm for estimation, here we used gradient descent for estimation of maximum likelihood.

II. GAUSSIAN MIXTURE MODEL

Let the input and output image can be expressed as, $A = [a_1, a_2, a_3, \ldots a_n]^TandB = [\, b_1, b_2, b_3, \ldots b_n\,]^T$. Then the probability density function of an input image A will be given by

$$G(a) = \sum_{j=1}^{n} a_j N(a; \mu_j \Sigma_j)$$

$$\sum_{j=1}^{n} \alpha_j = 1, \alpha \geq 0$$

Where mixture weight of j will be denoted asα_j, n is the number of mixtures. $N(a; \mu_j, \sum_j)$. Represents the normal distribution which includes mean μ_j and covariance matrix $\sum_j$ and the expression will be as

$$N\left(a; \mu_j, \Sigma_j\right) = \frac{1}{(2\pi)^{\frac{n}{2}} \, |\sum_{j=1}^{n}|} \exp\left[-\frac{1}{2}\left(x - \mu_j\right)^T \Sigma_j^{-1} \left(x - \mu_j^b\right)\right]$$

The conversion functions for input and output image will be,

$$B = F(a) = E[b|a]$$

$$\sum_{j=1}^{m} h_j(a)\left[\mu_j^b + \Sigma_j^{ba}(\Sigma_j^{ba})^{-1}\left(x - \mu_j^b\right)\right]$$

$$h_j(a) = \frac{\alpha_j N(a; \mu_j^a, \Sigma_j^{aa})}{\sum_j^n \alpha_j N(z; \mu_j^a, \Sigma_j^{aa})}$$

Where, the input and the output mixture mean will be given as μ_j^a and μ_j^b. then the covariance matrix will be as, μ_j^{aa} and μ_j^{bb} for the input and output images. For the converting the input image into output is achieved.

III. SUPERRESOLUTION USING GMM

Figure 1 provides the outline of our work, it has three significant steps: Construction of Pyramid Pair, conversion function and SR estimation.

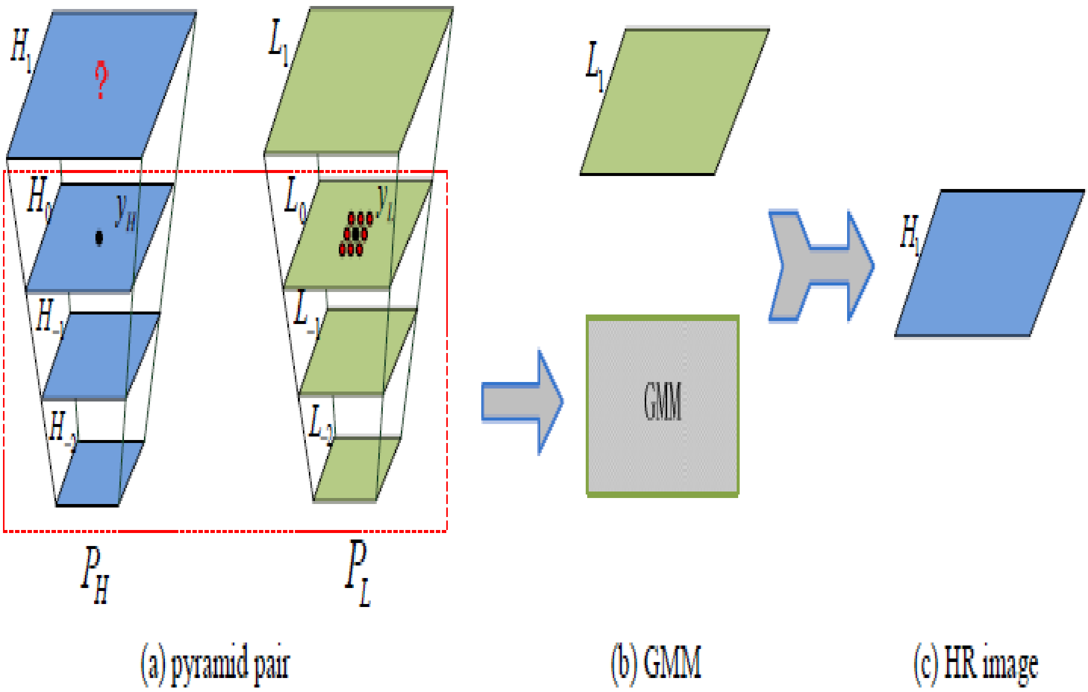

Fig 1. Architecture

IV. PYRAMID PAIR

The pyramid pair [14] consists of the pyramid for ground truth P_G and the pyramid of interpolation P_I. The arrangement of the pyramid pair P_H and P_L are shown in Fig. 1 (a). P_H includes the image set $\{H_i\}$, I = -2, …, 1. H_0 and H_1 are the input image of low resolution and output image of high resolution to be estimated respectively. H_{i+1} is used for generating H_i with this operation,

$$H_i = (H_{i+1} * B) \downarrow$$

Where * is the convolution function and B is the Blur matrix ↓ indicates the operation for down sampling and the scale reduction factor S is between H_i and H_{i+1}. The P_I pyramid includes the image set $\{L_i\}$, I = -2, …, 1. H_{i+1} is used for generating image L_i by using bi-cubic [14] interpolation with the scale factor S.

It is evident that both the pyramids P_H and P_L correspond to each other. H_1 is the final image with high resolution, which is approximated by the relationship between H_i and L_i. Unlike the previous example - based method, no external image record is used, but only H_0lower resolution image is used as input.

V. CONVERSION FUNCTION

A pixel with a like neighborhood, whose intensity changes sped in perpendicular direction. Intensities are invariant within neighborhoods in smooth regions [15]. The similarity in a pixel has corresponding similarities in the neighboring pixels. This method uses the relationship between the pixel in P_H and the 8-neighbored pixel B of the corresponding pixel in pyramid P_L.

Here the self-reduction image A_R will be obtained by the reduction of input image A with the high resolution image A_H and then bi-cubic interpolation will be used to expand A_R. by introducing various high pass filters; we root out the high-frequency components like A_{LH1}, A_{LH2}, A_{LH3}, A_{LH4} from the low resolution image A_L.

The structure of the training data A is given in figure 1 (a). The black point b_hCorresponds toy_l. The red point in L_0 indicates 8-pixel neighborhood pixels of Y fory_L. Every data for training includes $b_h$and B, and A can be given as,

A = [Z, B],

For every image pair H_i and L_i, i= -2, -1, 0. The training data is the random variable of A.

VI. SR ESTIMATION

The conversion function parameters will be trained by using the joint probability function of vector $[k = [a^T b^T]^T]$ Which can be expressed as,

$$\mu_j = [\mu_j^a, \mu_j^b], \Sigma_j = \begin{bmatrix} \Sigma_j^{aa} & \Sigma_j^{ab} \\ \Sigma_j^{ba} & \Sigma_j^{bb} \end{bmatrix}$$

$$P(k) = \sum_{j=1}^{n} \alpha_j N\left(k; \mu_j, \Sigma_j\right)$$

Where μ_j^k and Σ_j^k are given as,

$$\Sigma_j^k = \begin{bmatrix} \Sigma_j^{aa} & \Sigma_j^{ab} \\ \Sigma_j^{ba} & \Sigma_j^{bb} \end{bmatrix}, \mu_j^k = \begin{bmatrix} \mu_j^a \\ \mu_j^b \end{bmatrix}$$

In learning phase, the enlarged input image $A_L^{'}$will be separated into patches. Features a low resolution image will be obtained by using these image patches [16]. By using these image patches we get the low resolution features. The function for conversion of the image patches will be used for obtaining the features of high resolution image $A_F^{'}$.

Thus, by the addition of lost feature of high-resolution image $A_F^{'}$To the magnified input image $A_L^{'}$the output, Super resolution image $A_s$will be obtained.

VII. RESULTS

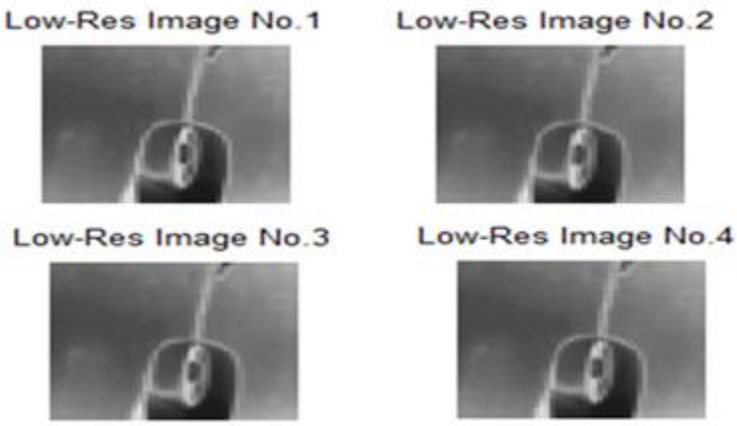

Figure (a)

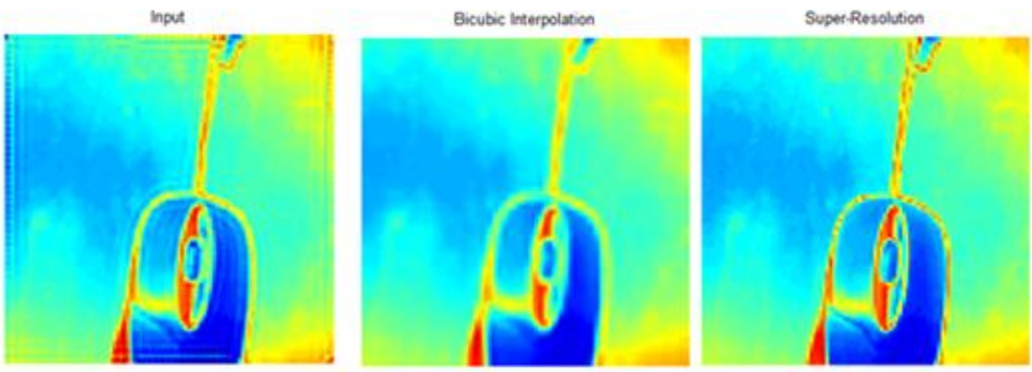

Figure (b)

Fig (a) pyramid image and fig (b) input image (left), bicubic interpolation (center), and the super-resolution(right) images

Table 1: MSE comparison between Bicubic and GMM

	Bicubic interpolation	GMM
Mouse (. png)	0. 0098	0. 0097
Tiger(. bmp)	0. 0768	0. 0759
Lena(. gif)	0. 00425	0. 0042

VIII. CONCLUSION

In this paper, we compared the proposed and the previously used bicubic method for super resolution. A new technique for achieving the super resolution in scene flow has been given. Thus, here we get the super resolution image using the conversion function of GMM with the self-reduction image in scene flow. Here we used to reduce the resolution of the input image as one-third in both vertical and horizontal directions. Thus the Gaussian descent method for GMM has been used for obtaining the conversion function.

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