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Study on Different Approaches for Super Resolution

Engineering

KEYWORDS: Super Resolution , Frequency domain based approach,) Interpolation-based approach, Regularization-based approach, Iterative back projection approach

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ABSTRACT

Super Resolution is a technique of enhancing the resolution of an image or video using different signal processing techniques. The objective of SR imaging is to produce an image with a clearer content from its low resolution counterpart rather than simply achieving a larger size of image. In other words, the main goal and the first priority of super-resolution imaging is to 'fuse' the contents of multiple input images in order to produce one output image containing with more clear and detailed contents. The physical size of the output image (in terms of total number of pixels) could be the same as any one of the input images or subject to further enlargement using an image interpolation method. Second, in our context, the term resolution of super-resolution is referred to the spatial resolution of the image, not the temporal resolution of the image sequence.

A. Super Resolution Approaches

The key objective of *super-resolution* (SR) imaging is to reconstruct a higher-resolution image based on a set of images, acquired from the same scene and denoted as 'low-resolution' images. In general, the SR image techniques can be classified into four classes:

(i) Frequency domain based approach
(ii) Interpolation-based approach ,
(iii) Regularization-based approach and
(iv) Iterative Back Projection Approach
(v)Learning-based approach

The first four categories get a higher-resolution image from a set of lower resolution input images which are typically aligned with sub-pixel accuracy, while with learning based approach, one achieves the same objective by exploiting the information provided by an image database, which includes LR and HR image pairs .

a. Frequency domain based approach:

The first frequency-domain SR method can be credited to Tsai and Huang [3], where they considered the SR computation for the noise-free low-resolution images. They proposed to first transform the low-resolution image data into the *discrete Fourier transform* (DFT) domain and combined them according to the relationship between the aliased DFT coefficients of the observed low-resolution images and that of the unknown high-resolution image. The combined data are

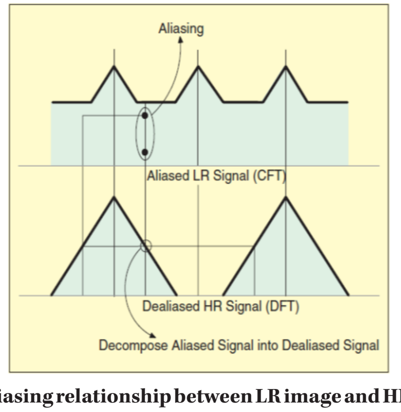

Fig..1 Aliasing relationship between LR image and HR image

then transformed back to the spatial domain where the new image could have a higher resolution than that of the input images. Rhee and Kang [4] exploited the *Discrete cosine transform* (DCT) to perform fast image deconvolution for SR image computation.

The frequency-domain-based SR approaches have a number of advantages. First, it is an intuitive way to enhance the details (usually the high-frequency information) of the images by extrapolating the high-frequency information presented in the low-resolution images. Secondly, these frequency-domain-based SR approaches have low computational complexity. However, the frequency-domain based SR methods are insufficient to handle the real-world applications, since they require that there only exists a global displacement between the observed images and the linear space-invariant blur during the image acquisition process.

b. Interpolation-based approach :

The *interpolation*-based SR approach constructs a high resolution image by projecting all the acquired low-resolution images to the reference image, then fuse together all the information available from each image, due to the fact that each low-resolution image provides an amount of additional information about the scene, and finally deblurs the image. Note that the single image interpolation algorithm cannot handle the SR problem well, since it cannot produce those high-frequency components that were lost during the image acquisition process. The quality of the interpolated image generated by applying any single input image interpolation algorithm is inherently limited by the amount of data available in the image. The interpolation-based SR

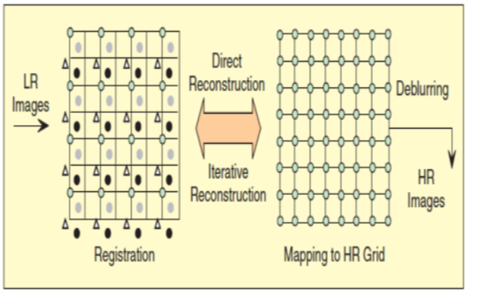

Fig. 2 Registration – Interpolation based reconstruction Approach

usually consists of the following three stages, as depicted in Fig. 2 : (i) the registration stage for aligning the low-resolution input images, (ii) the interpolation stage for producing a higher-resolution image, and (iii) the deblurring stage for enhancing the reconstructed high-resolution image produced in the step ii).

The interpolation stage plays a key role in this framework. There are various ways to perform interpolation. The simplest interpolation algorithm is the *nearest neighbour* algorithm, where each unknown pixel is assigned with an intensity value that is same as its neighbouring pixels. But this method tends to produce images with a blocky appearance. Ur and Gross [6] performed a nonuniform interpolation of a set of spatially shifted low-resolution images by utilizing the generalized multichannel sampling theorem. The advantage of this approach is that it has low computational load, which is thus quite suitable for real-time applications. However, the optimality of the entire reconstruction process is not guaranteed, since the interpolation errors are not taken into account.

c. Regularization-based approach :

The basic idea of these regularization- based SR approaches is to use the regularization strategy to incorporate the prior knowledge of the unknown high-resolution image. From the Bayesian point of view, the information that can be extracted from the observations (i.e., the low-resolution images) about the unknown signal (i.e., the high-resolution image) is contained in the probability distribution of the unknown. Then, the unknown high-resolution image can be estimated via some statistics of a probability distribution of the unknown high-resolution image, which is established by applying Bayesian inference to exploit the information provided by both the observed low- resolution images and the prior knowledge of the unknown high-resolution image. Two most popular Bayesian-based SR approaches are *maximum likelihood* (ML) estimation approach and *maximum a posterior* (MAP) estimation approach.

2.1.5 Iterative Back Projection Approach

Irani and Peleg formulated the iterative back-projection (IBP) SR reconstruction approach that is similar to the back projection used in tomography. In this approach, the HR image is estimated by back projecting the error (difference) between simulatedLRimages via imaging blur and the observed LR images. This process is

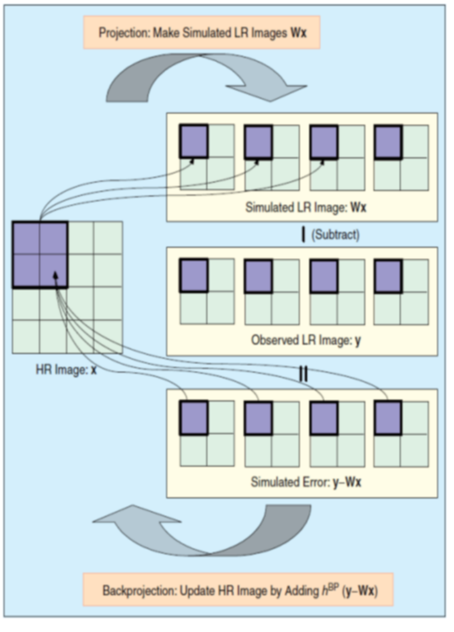

Fig. 3 Iterative Back-Projection Approach

repeated iteratively to minimize the energy of the error. The scheme for IBP is illustrated in figure 5. Unlike imaging blur, *h*BP can be chosen arbitrarily. It is pointed out that the choice of h^{BP} affects the characteristics of the solution when there are possible solutions. Therefore, h^{BP} may be utilized as an additional constraint which represents the desired property of the solution. Mann and Picard extended this approach by applying a perspective motion model in the image acquisition process. Later, Irani and Peleg modified the IBP to consider a more general motion model.

The advantage of IBP is that it is understood intuitively and easily. However , this method has no unique solution due to the ill-poised nature of the inverse problem.

e. Learning-based approach :

Several learning-based (example-based) methods have been proposed for super-resolution images [2]-[8]. Such methods are quite different from conventional signal processing methods. An HR image is not obtained by filtering a single LR image, but from a different training set of HR images. Figure 4 shows the flow diagram of a conventional learning-based method.

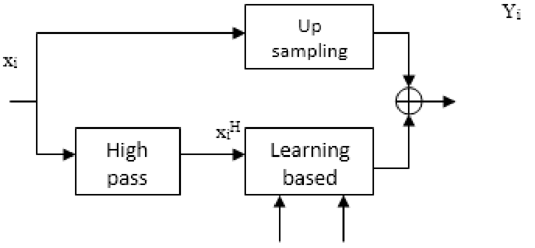

Fig.4 Flow diagram of conventional Learning – based method

In learning based approaches, the high frequency information of the given single low-resolution image is enhanced, by retrieving the most likely high-frequency information from the given training image samples based on the local features of the input low-resolution image. Hertzmann [10] proposed an image analogy method to *create* the high-frequency details for the observed low-resolution image from a training image database. It contains two stages: an off-line training stage and a SR reconstruction stage. In the off-line training stage, the image patches serve as ground truth and are used to generate low-resolution patches through the simulating the image acquisition model. Pairs of low-resolution patches and the corresponding (ground truth) high-frequency patches are collected. In the SR reconstruction stage, the patches extracted from the input low-resolution images are compared with those stored in the database. Then, the best matching patches are selected according to a certain similarity measurement criterion (e.g., the *nearest distance*) as the corresponding high-frequency patches used for producing the high-resolution image. Chang et al. [11] proposed that the generation of the high-resolution image patch depends on multiple nearest neighbours in the training set in a way similar to the concept of manifold learning methods, particularly the *locally linear embedding* (LLE) method. In contrast to the generation of a high-resolution image patch, which depends on only one of the nearest neighbourrs in the training set as used in the aforementioned SR approaches. The disadvantage of all above approaches is that they either obtain LR images in database by down sampling the high resolution images. Such a database does not represent the true spatial features between LR-HR pairs as they do not correspond to the images captured by real camera.

IV. Conclusion

I have presented a study & overview on various Super Resolution approaches to get HR images namely Frequency domain based , Interpolation-based, Regularization-based approach, Iterative back projection & Learning based approach. The first four categories get a higher-resolution image from a set of lower resolution input images which are typically aligned with sub-pixel accuracy, while with learning based approach, one achieves the same objective by exploiting the information provided by an image database, which includes LR and HR image pairs.

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