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DENOISING AND SUPER-RESOLUTION OF MEDICAL IMAGES BY SPARSE WEIGHT METHOD

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ABSTRACT
High resolution images are needed for many applications like medical imaging for diagnosis and treatment. Denoising and super-resolution of medical images is proposed in this paper. Construct a database of high and low resolution image patch pairs and with the help of this database estimate a high resolution image from a single noisy low resolution image. In order to find out a high resolution version from the given input low resolution version, get the non-negative sparse linear representation of the input patch over the low resolution patches from the database. Non-negative quadratic programming approach is used for the sparse process. For the low resolution and noisy images, it is a widely adequate method. Edges of the super resolved image can be enhanced by using the blind deconvolution algorithm.

INTRODUCTION
Number of pixels in an image represents the resolution of an image. The total number of pixels in the image and the width and height of the image represents the image resolution. It is the detail an image occupies. Resolution of image applies to a number of images like raster digital images, film images etc. An image with high resolution is the one which contain more image detail. A number of ways exist to measure the image resolution. Resolution measures how close lines can be to each other. It is the ability of the sensor to observe or measure the smallest object clearly with distinct boundaries. There is a distinction between the resolution and a pixel. A pixel is in fact a unit of the digital image. Resolution depends upon the pixel size. If we consider a lens with smaller the size of the pixel, higher the resolution will be and the clearer the object will be in the image. Images with smaller pixels might consist of more pixels. The amount of information within the image and the number of pixels is correlated. The aim of this work is to estimate a high resolution image from a single noisy low resolution image. This technique is known as super-resolution.

Smoothing and interpolation techniques for noise reduction have been commonly used in image processing as simple resolution enhancement techniques. Gaussian, Wiener, and median filters are the spatial filters which are generally used for smoothing. Bicubic interpolation and cubic spline interpolation are the commonly used interpolation techniques. Compared to simple smoothing method, interpolation methods give improved performance. These methods smooth edges as well as regions with slight variations creating blurring problems.
Optical images could be captured efficiently by an array of solid state detectors by the invention of charge coupled piece of equipment. Image resolution is determined by the detector size and its number. Most imaging areas require high resolution images. Improving detector array resolution is not always a feasible approach to increase resolution .There is a tendency to decrease signal-to-noise ratio (SNR) and light sensitivity with the use of higher resolution image sensor devices. For most legacy imaging systems it is very difficult to change detectors due to practical cost and physical restrictions. Image processing area is developing a set of algorithms known as super-resolution as a solution to this problem generating high resolution image from systems having low-resolution imaging detectors [2].

Medical imaging is one of the applications which are using high resolution images. Medical imaging is one area which uses high resolution images for treatment. Images with high resolution have applications in several fields. Applications like surveillance, forensic and satellite need zooming of particular region of concern that is the reason for high resolution images becomes vital in such fields. A high resolution image is created in two methods. One way is to create a high resolution image from many lower resolution images or make a high resolution image from a single low resolution image with the help of a database that learns relationship between low and high resolution images. High resolution images are able to provide images with high pixel density and more details about the original. The need for high resolution is common in computer vision applications for better performance in pattern recognition and analysis of images.

High resolution images have use in many areas. Medical imaging is one of the significant area which are using high resolution images for treatment and analysis. Doctors need very clear images for the identification of infirmity. It has applications in satellite, observation and forensic which need some specific part for processing. To generate a high resolution image, there exist two methods. One way is to create a high resolution image from a single low resolution image and another way is to create a high resolution image from many low resolution images. Characteristics existing with high resolution images are images with high pixel density and more information's.

High resolution images are not always accessible. Because of the shortcomings of the sensor and optics building methods, images with high resolution is not always feasible and it is somewhat expensive. Super resolution is an answer for this difficulty, it uses some image processing algorithms. The merits of using super resolution is that the existing low resolution method can still be utilized and it is inexpensive.

Early fast and precise detection of imaging biomarkers of the onset and progression of diseases is of great significance to the medical community since early detection and intervention often results in optimal treatment and recovery [2]. The advent of novel imaging systems has for the first time enabled clinicians and medical researchers to visualize the anatomical substructures, pathology, and functional features in vivo. However, earlier biomarkers of disease onset are often critically smaller or weaker in contrast compared to their corresponding features in the advanced stages of disease. Therefore, medical imaging community strives for inventing higher-resolution/contrast imaging systems. Super-resolution can be beneficial in improving the image quality of many medical imaging systems without the need for significant hardware alternation [2].

For optimal treatment and recovery, early detection of diseases is of great importance in the medical field [2]. It is possible to visualize the anatomical structures and other features by the advent of novel imaging systems. In the advanced stages of the disease if we consider the earlier biomarkers of the disease, it will be smaller or weaker. So high resolution or high contrast images are needed for medical imaging community. With no need for significant hardware alternation, there is a technique called super-resolution to improve the quality of image [2]. Super resolution methods are categorized into multi-image super-resolution and single image super-resolution methods. Single image super resolution methods are also called example learning based methods. Multi-image super-resolution techniques take a number of low resolution images to make a high resolution image as result. Registration is one of the complicated task in a multi-image super-resolution technique, the other two steps are deblurring and fusion. Motion estimation in case of multiple blurred and noisy low resolution images is a very difficult step in the image resolution. This is the reason for preferring single image super-resolution. From a single low resolution image example based super-resolution or single-image super-resolution methods generate a high resolution image [1]. This technique does not need many low resolution images of the same view and the registration procedure. In this approach, the correlation between low resolution images and corresponding high resolution images is learnt from a database of known low and high resolution image pairs.

LITERATURE REVIEW

In [3], H Chang projected a novel method for solving single-image super-resolution issues. By means of a set of training examples create a high resolution image from an image with low resolution image. For a given input low resolution patch, find out its nearest low resolution patches and replace the low resolution patches with its corresponding high resolution patch by using a method called locally linear embedding.

Single image super resolution method have a requirement for low and high resolution images that the number of patches needs to be same and there found an inter patch relationship. Patch wise image processing is happening here. Euclidean distance matric is used for getting the nearest neighbors which are available in the database. Take the equivalent high resolution patches and calculate the weighted combination by considering all the k high resolution patches. It need patch overlapping to make use of the entire information. Performance of the neighbor embedding method is affected by the k-candidates selection procedure and its quality. When the image is degraded by noise, nearest embedding method become inefficient scheme [4].

In [4] J Yang et al. projected a single-image super-resolution, based on sparse signal representation. It use the over-complete dictionary concept. In order to represent image patches, it use sparse linear representation of

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elements from the dictionary. For low and high resolution patches there exist two dictionaries. Sparse representation in corresponding patches is used for creating the high resolution image patch.

Representation of an input vector as a weighted linear combination of basis atoms (small number of basis vectors) is the aim of sparse coding. This method make use of sparse representation for super-resolution. Independent coding is performed on each patch unlike k- nearest neighbor based method. One of the issue of sparse coding based method is it is a time consuming process of creating dictionary and another issue is when dealing with noisy images.

PROPOSED METHOD

Super resolution and denoising is proposed in the sparse wait model for single image super-resolution. Super-resolution is performing on each image patch. In the example learning based method imagine a set of quality images (example images). To create a LR (low resolution) image from a HR (high resolution) image do the following,

$$Y = D_S HX + \eta \qquad (1)$$

Here H is the blur operator, η is the additive noise component and D_s is the decimation operator with a factor s. Database construction and super resolution are the 2 phases in single image super resolution (example learning based) method. From the example images, take the low resolution and high resolution patch pairs $\{(p_i^l, p_i^h), i \in I$. 'I' denotes the index set and the database is $(P_l, P_h) = \{(u_i^l, u_i^h) \in R_m \times R_n\}$, i ∈ I, where $u_i^l = F_l\, p_i^l$ and $u_i^h = F_h\, p_i^h$.

Features of LR and HR patches like first and second order derivatives, edge information and contours are taken by the operators F_l and F_h.

By using the co-occurrence association between the vector pairs (u_i^l, u_i^h) in the database (P_l, P_h), we get the missing high frequency components $x_j^h \subset R^n$. For each LR input y_j^l, x_j^h is the corresponding HR output.

In the sparse weight method, find the non-negative sparse representation of the input y_i^l over the training database P_l = { u_k^l, k ∈ I} where the non-zero representation coefficients can be assigned to example patches u_k^l which are congruent to y_i^l.

The LR image can be represented as,

Y = { y_i^l, i = 1,2,..., N} where N is the number of overlapping patches and y_i^l is a $\sqrt{m} \times \sqrt{m}$ image patch. In the same way the HR patches can be represented as { x_i^h, i = 1,2,..., N}. Low and high resolution patches are associated by, $y_i^l = D_s H x_i^h + \eta_i$, here the noise in the i^{th} patch is η_i and consider that the noise is $\eta_i \sim N(0, \sigma_i^2)$.

Consider a Gaussian, white, noise with zero-mean, and with variance σ_i^2 . $x_i^h \in R^n$ And $y_i^l \in R^m$. If the image is a noisy one, then first denoise the image and then do the super resolution.

For the accomplishment of the method, it need a good database. Images with variety of intensities, little noise in addition to shapes is required in the database as example images. To build the database standard images are needed and are as shown in the figure 1.

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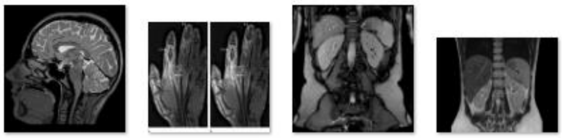
Figure 1: Standard Images in Database



Standard Images in Database

DATABASE CONSTRUCTION

From the database a set { p_k^h, k ∈ I} of vectorized image patches of size $\sqrt{n} \times \sqrt{n}$ is first extracted. For each HR patch p_k^h, a matching vectorized LR patch $p_k^l \in R^m$ is find out by,

$$p_k^l = D_s H p_k^h \qquad (2)$$

LR patch is considered as a noise free one.
At this time the database of patch pairs (HR & LR) is,

$$(P_l, P_h) = \{(u_k^l, u_k^h) = \left(\frac{p_k^l}{\|p_k^l\|}, \frac{p_k^h}{\|p_k^l\|} \right), k \in I\} \qquad (3)$$

We can indicate the training set as,

$$(P_l, P_h) = \{(u_k^l, u_k^h) \in R^m \times R^n, k \in I\} \qquad (4)$$

Patch super-resolution and reconstruction of the entire HR image is the two steps in the super resolution.

Patch Super-Resolution

Calculate the HR patch x_i^h, denoted by $\hat{x}_i^h$, from y_i^l by way of the database (P_l, P_h). Think about a subset of patches $u_k^h \in P_h$ which have related structures as those in x_i^h for determining the estimate $\hat{x}_i^h$. That is x_i^h $\in R^n$ can be projected as a sparse non-negative linear combination of the HR patches in p_h as,

$$x_i^h = \sum_{k \in I} \alpha_{ik} u_k^h \qquad (5)$$

The coefficient $\alpha^i = [\alpha_{i1}, \alpha_{i2}, \ldots\ldots,]^T \geq 0$. Here we can approximate the HR patch x_i^h by multiplying this representation by the database P_h, $\hat{x}_i^h = p_h \alpha^i$. It shows the central part behind the proposed method. As a result of penalizing on α_{ik}, we can use small α_{ik} for high dissimilarity w_{ik}, which indicates weak similarity between x_i^h and u_k^h. The penalty coefficient is defined as,

$$w_{ik} = \phi_i \left(d\left(y_i^l, u_k^l \right) \right) \qquad (6)$$

The dissimilarity between y_i^l and u_k^l is estimated by the function d(y_i^l, u_k^l).
Assume the mean of noise component η_i, E(η_i) ≈ 0.

$$E(y_i^l) = \mu_{ik} E(u_k^l) + E(\eta_i) \Rightarrow \mu_{ik} = \frac{E(y_i^l)}{E(u_k^l)} \qquad (7)$$

We can infer,

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$$\{E(y_i^l - \mu_{ik}u_k^l) \approx 0$$
$$\{Var(y_i^l - \mu_{ik}u_k^l) - \sigma_i^2 \approx 0 \qquad (8)$$

It use the parameter a_{ik},

$$a_{ik} = \left|E(y_i^l - \mu_{ik}u_k^l)\right| + \left|Var(y_i^l - \mu_{ik}u_k^l) - \sigma_i^2\right| \approx 0 \qquad (9)$$

Also consider that, d($y_i^l, u_k^l) \le \gamma\left(m\sigma_i^2\right)$. Here m is the number of elements in vector y_i^l ($y_i^l \in R^m$), and γ is a positive constant.

Use the following multiplicative updates algorithm for solving the sparse decomposition problem $\alpha^i = \underset{\alpha \ge 0}{\arg\min} \|\alpha\|_0 + \sum_{k \in I} w_{ik} a_{ik}$ (10)

Multiplicative updates algorithm

Input: $\alpha = \alpha_0 > 0,$

Updating: t=0

While $t < T$ & $\left\|y_i^l - U_i\alpha_t\right\|_2^2 > m\sigma_i^2$

$\alpha_{t+1} = \alpha_t .*(U_i^T y_i^l)./(U_i^T U_i \alpha_t + w_i)$

T=t+1

End

Output: $\alpha^i = \alpha_t$

After solving the sparse decomposition problem, estimate the HR patch by,

$$\hat{x}_i^h = \sum_{k \in I} \alpha_{ik} u_k^h \qquad (11)$$

Non-negative sparse linear combination of the LR patch in the database represent the denoised patch,

$$\hat{y}_i^l = U_i \alpha^i = \sum_{k \in I_i} \alpha_{ik} u_k^l \qquad (12)$$

Creation of HR image

Final HR image is constructed by averaging in overlapping regions. Similarly we can do the denoising by replace the noisy patches by noiseless patches and perform averaging in overlapping regions. Use iterative back projection algorithm to solve the following problem:

$$X_{t+1} = X_t + ((Y^{denoise} - D_s H X_t) \uparrow s) * p \qquad (13)$$

Here p is a symmetric Gaussian filter, ↑s denotes up-scaling by factor s and X_t is the HR image at the t-th iteration. It is possible to reduce the reconstruction error with a competent iterative procedure.

Edge enhancement

Recovery of a target scene from blurred images is possible with blind deconvolution. To improve the sharpness of an image, we mainly focus on edge enhancement. Even if the blur kernel is not known, it is possible to recover the sharp version of a blurred image when the blind deconvolution algorithm is used.

CONCLUSION

An example based method for denoising and super-resolution is proposed in this paper. It require a database that contains HR and LR patch pairs created using these standard images. By using the sparse positive representation of the HR patches, solve the sparse decomposition optimization problem to generate the HR image. For the noise corrupted and low resolution image this method is very useful. Use the blind deconvolution algorithm to perform the edge enhancement for better diagnosis.

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