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"Dictionary Learning Based Super-Resolution Reconstruction Algorithm for Biomedical Images"

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Abstract -*High resolution 3D cardiac MRI is difficult to achieve due to the relative speed of motion occurring during acquisition. The lack of suitable reconstruction techniques that handle non-rigid motion means that cardiac image enhancement is still often attained by simple interpolation. In this paper, we explore the use of example-based super-resolution, to enable high fidelity patch-based reconstruction, using training data that does not need to be accurately aligned with the target data. By moving to a patch scale, we are able to exploit the data redundancy present in cardiac image sequences, without the need for registration. To do this, dictionaries of high-resolution and low-resolution patches are co-trained on high-resolution sequences, in order to enforce a common relationship between high- and low-resolution patch representations. These dictionaries are then used to reconstruct from a low-resolution view of the same anatomy. We demonstrate marked improvements of the reconstruction algorithm over standard interpolation.*

Key Words: training set, patch-based construction, reconstruction algorithm.........

1.INTRODUCTION

The speed of cardiac and respiratory motion present during Magnetic Resonance Imaging (MRI) of the heart makes the acquisition of high-resolution 3D cardiac image volumes a difficult task. Instead, Super-resolution image reconstruction is a very important task in many computer vision and image processing applications. The goal of image super-resolution (SR) is to generate a high-resolution (HR) image from one or more low-resolution (LR) images.

In this paper the high resolutions in 2D planar image formed by slices or form an image quality in photographic objects .improving the resolution of each image is an important in cardiac image visualisation and analysis. Improve the resolution image are carried out either improving speed of image or in post processing stage to achieve supper-resolution. The supper-resolution algorithm can classified into three main categories that means interpolation-based algorithm, learning based algorithm and reconstruction algorithm. The interpolation based algorithms are fast but result not fine. In learning based algorithms are need to careful selection of training set, the reconstruction algorithm with dictionary learning apply smoothness and HR image should reproduced LR image. in highly non-rigid motion present in MRI imaging with low resolution image make accurate registration difficult achieve, like wise reconstruction technique use in brain imaging which provide only rigid motion for this reason upsampling of to cardiac image via interpolation scheme such as bi-cubic are commonly used in MRI imaging. We have to perform that the idea of upsampling acquired data through the example-based-super resolution using image patches. Our aim to exploit the data redundancy at patch level across the sequence of image. The basic idea behind that low resolution (LR) image find super-resolution (SR) in database of high resolution (HR) image pair. The corresponding HR pair used to upsampled using relation between images. In previous work the database of image patches of the same anatomy. These case works on the assumption that the same relation between the construction of the HR and LR patches actually exits. In this paper the development of sparse representation and dictionary learning for single image reconstruction which applied to brain imaging such that LR patch based sparsity with respect to LR dictionary as corresponding to HR patch has to HR dictionary . We should use reconstruct HR image with upto 8 time upsampling without any registration.

2. SUPER RESOLUTION

Super-resolution (SR) imaging aims to overcome or compensate the limitation or shortcomings of the image acquisition device/system and/or possibly ill-posed acquisition conditions to produce a higher-resolution image based on a set of images that were acquired from the same scene. With rapid development and deployment of image processing for visual communications and scene understanding, there is a strong demand for providing the viewer with high-resolution imaging not only for providing better visualization (fidelity issue) but also for extracting additional information details (recognition issue). For examples, a high resolution image is beneficial to achieve a better classification of regions in a multi-spectral remote sensing image or to assist radiologist for making diagnosis based on a medical imagery. In video surveillance systems, higher-resolution video frames are always welcomed for more accurately identifying the objects and persons of interest. To understand the SR imaging, several fundamental concept are required to be clarified. First, it is important to note that an image's resolution is fundamentally different from its physical size. In our context, 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 limitation of SR computation mainly comes from the following factors interpolation error, quantization error, motion estimation error and optical-blur. A thorough study of SR performance bounds would understand the fundamental limits of the SR imaging to find the balance between expensive optical imaging system hardware's and image reconstruction algorithms.

2.1 SUPER-RESOLUTION IMAGE RECONSTRUCTION

The objective of SR image reconstruction is to produce an image with a higher resolution based on one or a set of images captured from the same scene. 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) learning-based approach. The first three categories get a higher-resolution image from a set of lower resolution input images,

2.1.1 FREQUENCY-DOMAIN-BASED SR IMAGE APPROACH

The first frequency-domain SR method can be credited to Tsai and Huang 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 then transformed back to the spatial domain where the new image could have a higher resolution than that of the input images.

2.1.2 INTERPOLATION-BASED SR IMAGE APPROACH

The interpolation-based SR approach constructs a high resolution image by projecting all the acquired low-resolution images to the reference image, then fuses 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.

2.1.3 REGULARIZATION-BASED SR IMAGE APPROACH

Motivated by the fact that the SR computation is, in essence, an ill-posed inverse problem numerous regularization based SR algorithms have been developed for addressing this issue. 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.

3. LITERATURE SURVEY

Super-Resolution Image Reconstruction

The objective of SR image reconstruction is to produce an image with a higher resolution using one or a set of images captured from the same scene. In general, the SR image techniques are classified into four classes:

- Frequency domain-based approach
- Interpolation-based approach
- Regularization-based approach
- Learning-based approach

The first three categories get a HR image from a set of LR input images, while the last one achieves the same objective by exploiting the information provided by an image database.

The first frequency-domain SR method can be credited to Tsai and Huang (1984), where they considered the SR computation for noise-free LR images. They used the frequency domain approach to demonstrate the ability to reconstruct one improved resolution image from several down-sampled noise-free versions of it, based on the spatial aliasing effect. Rhee and Kang (1999) exploited the discrete cosine transform (DCT) to perform fast image de-convolution for SR image computation. .

The aim is to estimate the finer scale sub-band coefficients, followed by applying the inverse wavelet transform to produce the HR image. Woods et al. (2006) presented an iterative expectation maximization (EM) algorithm (Dempster et al. 1977) for simultaneously performing the registration, blind de-convolution, and interpolation operations.

Bose and Ahuja (2006) used the Moving Least Square (MLS) method to estimate the intensity value at each pixel position of the HR image via a polynomial approximation using the pixels in a defined neighborhood of the pixel position under consideration.

Motivated by the fact that the SR computation is, in essence, an ill-posed inverse problem (Bertero et al. 1998), numerous regularization-based SR algorithms have been developed for addressing this issue (Tom et al. 1995, Tian et al. 2010, Schultz et al. 1996, Suresh et al. 2007, Belekos et al. 2010, Shen et al. 2007). The basic idea of these regularization-based SR approaches is to use the regularization strategy to incorporate the prior knowledge of the unknown HR image. Recently, learning-based techniques were proposed to tackle the SR problem (Hertzmann et al. 2001, Chang et al. 2004, Freeman et al. 2000, Pickup et al. 2003). In these approaches, the high frequency information of the given single LR 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 LR image. Hertzmann et al. (2001) proposed an image analogy method to create the high-frequency details for the observed LR image from a training image database. It contains two stages: an off-line training stage and an SR reconstruction stage. In the off-line training stage, the image patches serve as ground truth and are used to generate LR patches by simulating the image acquisition model. Pairs of LR patches and the corresponding (ground truth) high-frequency patches are collected. In the SR reconstruction stage, the patches extracted from the input LR 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 HR image.

Chang et al. (2004) proposed that the generation of the HR image patch depends on multiple nearest neighbors 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 an HR image patch, which depends on only one of the nearest neighbors in the training set as used in the aforementioned SR approaches (Hertzmann et al. 2001, Freeman et al. 2000, Pickup et al. 2003), this method requires fewer training samples. Another way is to jointly exploit the information learnt from a given HR training data set, as well as that provided by multiple LR observations.

Datsenko and Elad (2007) first assigned several high quality candidate patches at each pixel position in the observed LR image. These are found as the nearest-neighbors in an image database that contains pairs of corresponding LR and HR image patches. These found patches are used as the prior image model and then merged into an MAP cost function to arrive at the closed-form solution of the desired HR image. Recent research on the studies of image statistics suggest that image patches can be represented as a sparse linear combination of elements from an over-complete image patch dictionary (Wang et al. 2010, Kim et al. 2010, Yang et al. 2010). The idea is to seek a sparse representation for each patch of the LR input, followed by exploiting this representation to generate the HR output. By jointly training two dictionaries for the LR and HR image patches, the sparse representation of a LR image patch can be applied with the HR image patch dictionary to generate an HR image patch.

4. BACKGROUND

Standard cardiac imaging techniques typically involve the acquisition of multiple 2D slice stacks creating an anisotropic3D volume which is HR in-plane, but LR in the through-plane direction. Given an underlying unknown HR image Y_H, the acquired LR image y_l can be modelled as:

$$\mathbf{y}_L = (\mathbf{y}_H * \mathbf{B}) \downarrow s + \eta$$

where B represents a blur operator, ↓ s is a down sampling operator that decreases the resolution by a factor of s and η represents an additive noise term. Recovering the high resolution image y H from y L is under-determined and requires some regularization on the nature of y H . In this work, we adopt the prior that small image patches of y H can be sparsely reconstructed with respect to an appropriate dictionary, in the same way as y L , under particular circumstances.

Typically, orthogonal HR short-axis (SA), four-chamber and two-chamber long-axis (LA) views are acquired. Given a HR sequence covering the same anatomy as the LR sequence, we hypothesis that (if working with small enough image patches), there should be enough redundant information in the sequence to reconstruct a HR patch from the available data, even without information about spatial correspondences.

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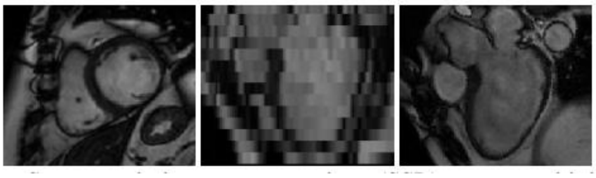
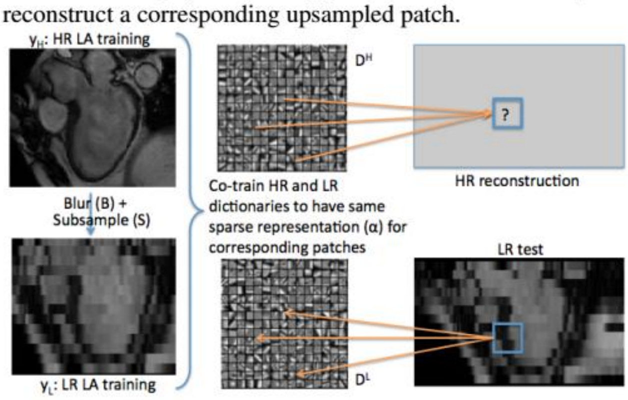
Fig. 1. Typical cardiac image acquisitions. L-R: HR SA slice, LA stack of short-axis slices, frame of HR LA slice sequence.



Super-resolution reconstruction (SSR) uses multiple views of an object to improve image resolution. Its application to cardiac image enhancement is attractive due to the potential to combine data acquired over time and in multiple orientations.

Fig. 2. Reconstruction using co-trained dictionaries. HR and LR dictionaries are co-trained to encode corresponding patches with the same sparse representation. LR patches from a test image are then sparse coded using the LR dictionary, and the resulting sparse code applied to the HR dictionary to reconstruct a corresponding upsampled patch.



Recent advances in computer vision have shown that signals such as image patches may be represented by a sparse combination of atoms from a dictionary. Such a dictionary can be pre-defined for general images e.g.: DCT, or learnt by training examples of similar images. A standard method of training a dictionary D to sparsely represent a set of signals x is the K-SVD method

5. METHOD

We aim to reconstruct a LR orientation (the through-plane view of a 2D slice stack) sequence, from frames of a HR sequence of the corresponding anatomy. To ease explanation, we assume in the following a LR SA stack sequence and single slice HR LA sequences. However, the same methods equally apply to any pair of orthogonal views that yield HR in-plane. By using orthogonal views of the same anatomy, we eliminate the need for affine registration

5.1. Training

Our training data consists of frames from a HR LA sequence YH = $\{y_h\}$,and corresponding LR sequences obtained through blurring and downsampling according to Eq. By using training data that covers the whole cardiac cycle, pk = Rk y, where Rk is an operator to extract a patch of size of size n × m from location k. These patches are used to co-train the HR and LR dictionaries.

5.2 Patch pairs construction

To focus the training on the relationship between LR patches and high-frequency information (edges and textures), patches are extracted from a LR image, y L , and a difference image given by y E= $Y_H - Y_L$. For the LR patches, features containing high frequency information are extracted from y L by convolving with 2D Gaussian / Laplacian filters: $p_k^L = f_k \times y_l$. Finally, Principal Component Analysis is used to reduce the feature vector extracted p_k^L = Cp_k^L, where C is a projection operator that transforms p_k^L to a low-dimensional subspace preserving 99.9% of its average energy. Image intensities are used for the HR patches p_k^H = $R_k \times y_l$ This gives pairs of co-occurring patches at each location k, P = {p_k^L , p_k^H} k .

5.3 Correlated dictionary learning :

Correlated dictionaries ensure that a HR patch and its LR counterpart have the same sparse representations in their respective dictionaries. We also need to ensure that the LR patches can be encoded sparsely and in the same way for both train and test data. When reconstructing a LR test patch, we find the sparse representation of that patch in terms of the LR dictionary only. The LR dictionary D L is therefore also constructed using LR patches only

$$\mathbf{D}^L, \alpha = \min_{\mathbf{D}^L,\alpha_k} \sum_{L} \|\mathbf{p}_k^L - \mathbf{D}^L\alpha_k\|_2^2 \text{ subject to } \|\alpha\|_0 < \lambda$$

Where λ denotes the desired sparsity of the reconstruction weights vector α. This standard dictionary learning equation is solved sequentially for D L and α using the method. The resulting sparse code αk for each patch k, is then used to solve for the HR dictionary by minimizing

$$\mathbf{D}^H = \min_{D_H} \sum \|\mathbf{p}_k^H - \mathbf{D}^H\alpha_k\|_2^2 = \min_{\mathbf{D}^H} \|\mathbf{P}^H - \mathbf{D}^H\mathbf{A}\|_F^2$$

where columns of P are formed by the HR training patches, p H k and columns of A are formed by the atoms α. Denoting A + as the Pseudo-Inverse of A, the solution is given by $\mathbf{D}^H = \mathbf{P}^H A^+ = \mathbf{P}^H \mathbf{A}^T(\mathbf{A}\mathbf{A}^T)^{-1}$ resulting in correlated dictionaries, D H and D L .

5.4 Reconstruction :

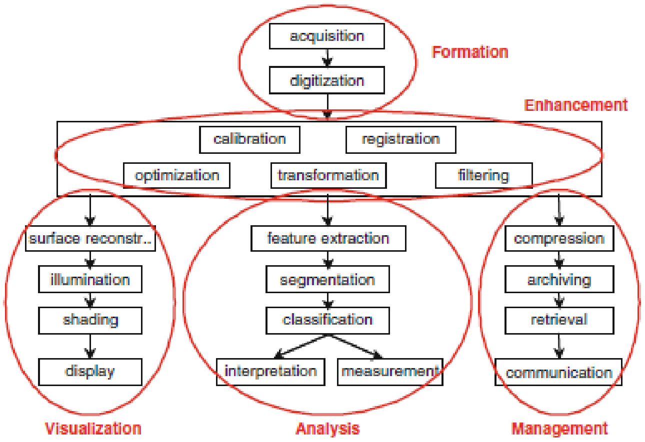
Patches from a LR test image are extracted in the same way as for the LR training images. The sparse code for each patch with respect to the LR dictionary, DL, is found

$$\alpha_k = \arg\min_{\alpha_k} \sum_k \|p_k^L - \mathbf{D}^L\alpha_k\|_2^2 \text{ subject to } \|\alpha_k\|_0 < \lambda$$

again. Crucially, this is the same sparse coding equation as in the training phase. The reconstruction weights vector αk for each test patch are used to approximate HR patches by $\{p_k^H\}$ k = $\{D^H_{\alpha_k}\}$ k . To create a smooth overall reconstruction, overlapping patches are used, and the upsampled image give by their average reconstruction. The final HR image is given by adding the LR interpolated approximation

$$\tilde{\mathbf{y}}_H = \mathbf{y}_L + \left(\sum_{k\in\Omega} \mathbf{R}_k^T\mathbf{R}_k\right)^{-1} \sum_{k\in\Omega} \mathbf{R}_k^T\tilde{\mathbf{p}}_k^H .$$

k-svd algorithm : In the K-SVD algorithm, the *D* is first to be fixed and t e best coefficient matrix *X* . As finding the truly optimal *X* is impossible, we use an approximation pursuit method. Any such algorithm as OMP, the orthogonal matching Pursuit in can be used for the calculation of the coefficients, as long as it can supply a solution with a fixed and Predetermined number of nonzero entries *T*0 . After the sparse coding task, the next is to search for a Better dictionary *D* . However, finding the whole dictionary all at a time is impossible, so the process then update only one column of the dictionary *D* each time while fix *X*



6. FMRI EXPERIMENT ANDANALYSIS

The functional Magnetic Resonance Imaging (fMRI) is a powerful imaging tool that can be used to perform brain activation studies non-invasively in vivo while subjects are engaged in meaningful behavioral task. Before the emergence of fMRI, radioisotope based techniques, such as positron emission tomography (PET) which measures regional cerebral blood flow (rCBF), were widely used for mapping the brain function. However, these techniques are invasive and have a low spatial and temporal resolution. Developing successful fMRI experiments requires careful attention to experimental design, data acquisition techniques, and data analysis. The experimental design is at the heart of any cognitive neuroscience investigation.

6.1 Analysis of Imaging Data:- Data analysis mainly consists of motion correction, corcgistration, normalization to a template (if required), smoothing, estimation of parameters of a statistical model (statistical modeling), and statistical inference to determine significant areas of brain activation. The fMRI images are prcprocessed and a General Linear Model would be setup to investigate the candidate brain regions that arc activated preferentially by the sequence tasks. This section outlines the analysis procedure used for image analysis The major steps of data analysis include:

- Data Acquisition
- Preprocessing
- Model Setup and Estimation
- Statistical inference (Results assessment)

SPM stands for Statistical Parametric Mapping(SPM), which is the main output of the software. Statistical Parametric Mapping refers to the construction and assessment, of spatially extended statistical process used to test hypotheses about [neuro] imaging data obtained from PET (Positron Emission Tomography) and fMRI. The parameterized value is generally some form of Student's t-test estimating the likelihood that a comparison of two image groups matches a given model that explains their possible differences.

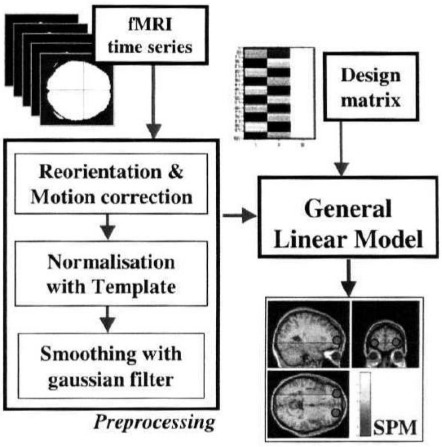


Figure 3.1: Data Processing Steps in SPM

6.2 Data Acquisition:-Issues of data acquisition are included here because it is crucial that the data are acquired in a way that the experimental hypothesis can be addressed. This includes the experimental design as well as technical questions of modality, acquisition parameters, and reconstruction. The most important consideration is the actual design of the experiment. In conducting a hypothesis-based experiment, we wish to be able to attribute any observed effects to experimentally manipulated conditions. This can be guaranteed only if conditions are randomly allocated to a presentation order for each subject in a sensible manner. Further, this randomization should be appropriately balanced, both across and within subjects.

6.3Preprocessing: This stage includes several steps, all of which are aimed at massaging the data so that it is suitable to be statistically analyzed by SPM99. In our experiment, the scanner was operated continuously for a session. Two additional scans acquired at the beginning of each session were discarded to account for the transients in the magnetic field of the scanner. Further, one scan at the beginning of every block that corresponded to the block instruction was also discarded from analysis.

6.4 Smoothing: The normalized functional images are spatially smoothed with a gaussian filter using a suitable full width half maximum (FWHM of 6mm in our case i.e., double the voxel size). The smoothing process not only increases the signal to noise ratio (SNR), but also validates the underlying gaussian assumption for the BOLD activity that is in turn used in the statistical inference step.

7. QUANTITATIVE RESULTS

In order to obtain an objective measure of performance for the SR algorithms under comparison, For performance evaluation, a typical 512× 512 gray-level HR image is chosen We synthetically generate some LR images from this HR image and later reconstruct an HR image from these generated LR images. Finally, we compute the peak signal-to-noise ratio (PSNR) and SSIM as the quantitative measures of quality of reconstructed HR image with respect to the original HR image

Tablel . Atomic particles. The given values for mass and charge are only rough estimates. The atomic mass unit 1 u = 1.660538782 · 10−27 kg. The elementary charge 1 e = 1.602176487 · 10−19 C

Name	Symbol	Mass	Charge
Proton	p	1 u	+1 e
Neutron	n	1 u	0 e
Alpha particle	α	4 u	+2 e
Electron	β	0 u	−1 e
Positron	β^+	0 u	+1 e
Photon	γ	0 u	0 e

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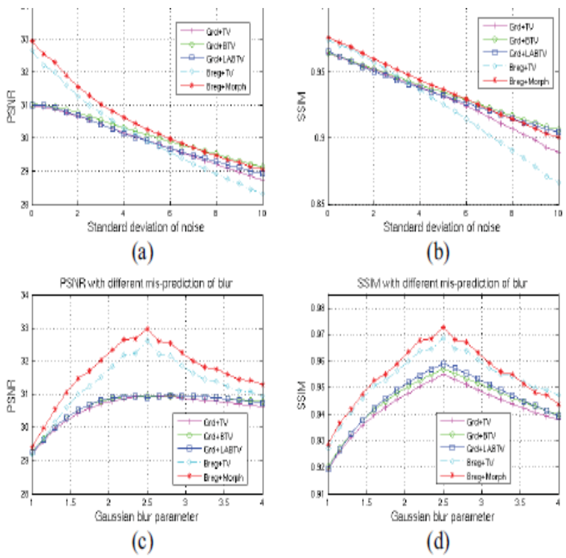
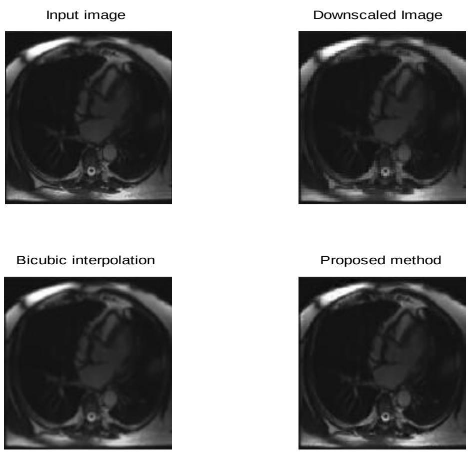


Fig. 8. Analysis of the performance of SR image reconstruction algorithms applied on different gray images and then average quantitative measures are plotted. (a)–(b) PSNR and SSIM of SR algorithms for noisy LR images with additive Gaussian noise. (c)–(d) PSNR and SSIM for different amount of misprediction in The blurring parameter.



8. CONCLUSION

We have demonstrated how we can already achieve marked improvement over Bicubic interpolation on real MRI data. Extensive validation of real cardiac datasets is difficult due to the lack of ground truth and is the subject of ongoing work.

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