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Super-Resolution Rebuilding Of Cardiac MRI Using Coupled Dictionary Analyzing

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ABSTRACT

3D Cardiac MRI with high resolution is tricky to attain due to the absolute speed of motion going on during throughout acquisition. Instead, anisotropic 2D pile volumes are distinct and humanizing the resolution of these is strongly provoked by both visualization and analysis. The sustain of suitable reconstruction techniques that hold non-rigid activity way to cardiac image enhancement is tranquil repeatedly attain by simple interpolation. This paper presents, we search the use of example based super-resolution, to enable high fidelity patch-based reconstruction techniques that hold non-rigid motion, and 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.

KEYWORDS: MRI Analysis, Patch, Super resolution, Reconstruction, Dictionary building.

1. INTRODUCTION

Medical research and diagnosis rely heavily on magnetic resonance imaging (MRI) for the visualization of anatomical structures and physiological function. This technology is non-invasive, non-ionizing and offers an unmatched quality in soft tissues contrast. However, physical and physiological limits on scanning speed make this an inherently slow process. Sampling constraints are particularly challenging for dynamic MRI (dMRI). The use of compressed sensing (CS) theory [1, 2] has been shown repeatedly to be successful at reducing acquisition time. The philosophy behind CS is that if a signal is known a-priori to be sparse in some transform domain, much fewer samples are needed for its acquisition than those dictated by the Nyquist rate.

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, stacks of high resolution 2D planar slices are typically acquired, resulting in anisotropic volumes of, for example, 1.25 × 1.25 × 10 mm voxels as standard. Improving the resolution of such images is an important challenge in cardiac image visualization and analysis. Attempts to improve resolution of images of moving structures are typically carried out either in the acquisition stage, by aiming to improve speed, or in the post processing stage, based on the fusion of data from multiple acquisitions to achieve super-resolution.

Previous work in the latter approach depends on the quality of alignment of the images. Unfortunately, the highly non-rigid motion present in cardiac imaging, together with the low resolution of the acquired images makes accurate registration difficult to achieve, setting a limit on the possible enhancement obtainable. Likewise, reconstruction techniques used for brain imaging, which compensate only for rigid or affine motion between acquisitions, are insufficient for cardiac image super-resolution. For this reason, up sampling of cardiac images via intensity based interpolation schemes, such as b-spline or Bicubic, are still commonly used in cardiac imaging.

We explore instead the idea of up sampling acquired data through example-based super-resolution using image patches. This enables the integration of information from multiple views but without the need for any non-rigid alignment or modelling of the underlying motion. Instead, we aim to exploit the data redundancy - at a patch level - across a cardiac sequence. Recent work using patch-based approaches for reconstruction has focused on brain MRI, for example to reconstruct low-resolution T2-weighted images from corresponding high-resolution T1-weighted images. The motivation for patch-based super-resolution in cardiac imaging is even stronger than in brain imaging, due to the lack of existing acquisition techniques or post-processing algorithms that deal robustly with non-rigid motion.

The basic idea behind these approaches is that of pattern matching. Given a low-resolution (LR) image, find similar LR images in a database of LR and high-resolution (HR) image pairs. The corresponding HR pairs are then used to up sample the test image using the observed relationship between images. Since this is not possible on whole images, the methods use image patches of, for example, size 5 × 5 × 5 voxels, instead. In previous works, the database of training patches consists of either other patches within the image itself or those from a HR view of the same anatomy. Most recently, patch-based reconstruction using HR external atlases has been proposed. These cases however, work on the assumption that the same relationship between the construction of HR and LR patches actually exists.

2. BACKGROUND

Standard cardiac imaging techniques typically involve the acquisition of multiple 2D slice stacks creating an anisotropic 3D volume which is HR in-plane, but LR in the through-plane direction. Given an underlying unknown HR imagey_H, the acquired LR image yL can be modelled as:

$$y_L = (y_H * B) \downarrow s + \eta \qquad (1)$$

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 regularisation on the nature ofy_H. In this work, we adopt the prior that small image patches of y_H can be sparsely reconstructed with respect to an appropriate

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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 hypothesise 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.

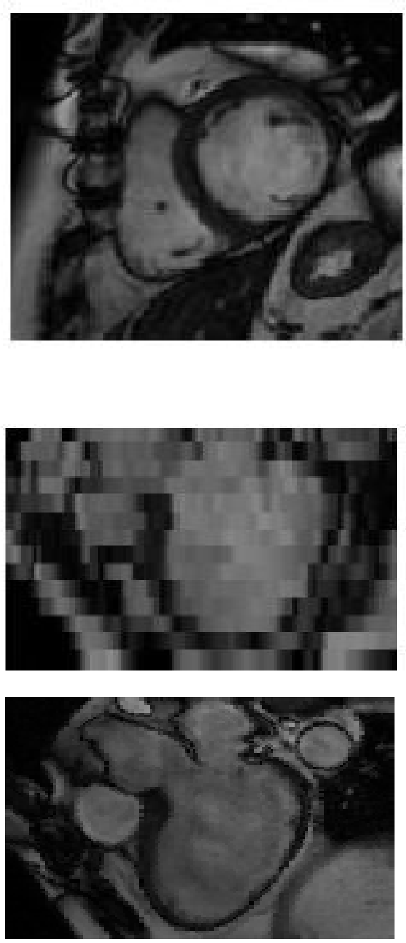

Figure 1: Typical cardiac image acquisitions. L-R: HR SA slice, LA stack of short-axis slices, frame of HR LA slice sequence.

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. A review of SRR in general medical imaging can be found. Techniques fall into two main categories: those based on reconstruction through the fusion of multiple views of an object, and example-based super resolution, which aims to up sample LR images via knowledge of the relationship between HR and LR image features from example data. Due to difficulties in aligning cardiac images to sufficient sub-pixel accuracy, we here adopt the latter approach. We use HR LA slices through time as training examples to reconstruct the LR orientation of a stack of SA slices.

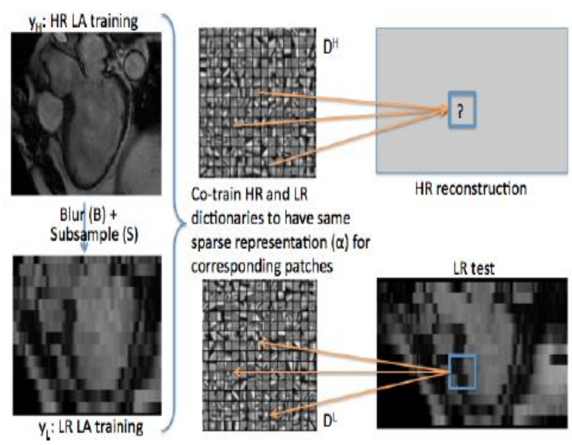

Figure 2: Reconstruction using co-trained dictionaries. HR and LR dictionaries are co-trained to encode corresponding patches with the same sparse representation. LR patches from a test image are then sparse coded using the LR dictionary, and the resulting sparse code applied to the HR dictionary to reconstruct a corresponding up sampled 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. Using dictionary learning for image SRR has recently been proposed in, for example. These work on the idea that dictionaries trained from HR and corresponding LR examples can be used to reconstruct from new LR input. In the following, we describe the method and show its application to cardiac images.

3. PROPOSED 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. The method is summarised in Fig. 2.

Training

Our training data consists of frames from a HR LA sequence, $Y_H = \{y_H\}$ and corresponding LR sequences obtained through blurring and down sampling according to Eq. 1. By using training data that covers the whole cardiac cycle, we can account for the variation of motion likely in the test image. A Gaussian kernel, with full width half max (FWHM) equal to the slice thickness, is used to blur in the slice-select direction only, in order to simulate the acquisition process [9]. The resulting LR images are then up sampled using bi-cubic interpolation back to the original size, giving. $Y_L = \{y_L\}$. Corresponding patches $P = \{p_k^H, p_k^L\}_k$ are extracted from these images: $p_k = R_k y$, where R_k is an operator to extract a patch of size of size $n \times m$ from location k. These patches are used to co-train the HR and LR dictionaries.

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: $\hat{p}_k^L = f_k * y_L$. Finally, Principal Component Analysis is used to reduce the feature vector extracted: $p_k^L = C\,\hat{p}_k^L$, where C is a projection operator that transforms $\hat{p}_k^L$ to a low-dimensional subspace preserving 99.9% of its average energy. Image intensities are used for the HR patches $p_k^H = R_k\, y_E$. This gives pairs of co-occurring patches at each location k, $P = \{p_k^H, p_k^L\}_k$.

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:

$$D^L, \alpha = \min_{D^L, \alpha_k} \sum_k \| p_k^L - D^L, \alpha_k \|_2^2 \quad subject\ to\ \|\alpha\|_0 < \lambda \qquad (2)$$

Where λ denotes the desired sparsity of the reconstruction weights vector . This standard dictionary learning equation is solved sequentially for D^L and α using the method of [10]. The resulting sparse code , α_k for each patch k, is then used to solve for the HR dictionary by minimising:

$$D^H = \min_{D^H} \sum_k \| p_k^H - D^H \alpha_k \|_2^2 = \min_{D^H} \sum_k \| P^H - D^H A \|_F^2 \qquad (3)$$

where columns of P are formed by the HR training patches$p_k^H$and columns of A are formed by the atoms α. Denoting A^+ as the Pseudo-Inverse of A, the solution is given by:

$$D^H = P^H A^+ = P^H A^T (AA^T)^{-1} \qquad (4)$$

Reconstruction

Patches from a LR test image are extracted in the same way as for the LR training images (3.1.1). The sparse code for each patch with respect to the LR dictionary, D^L, is found by:

$$\alpha_k = \underset{\alpha_k}{argmin} \sum_k \| p_k^L - D^L \alpha_k \|_2^2 \quad subject\ to\ \|\alpha_k\|_0 < \lambda \qquad (5)$$

again as in [10]. Crucially, this is the same sparse coding equation as in the training phase. The reconstruction weights vector α_k for each test patch are used to approximate HR patches by $\{\tilde{p}_k^H\}_k = \{D^H \alpha_k\}_k$. To create a smooth overall reconstruction, overlapping patches are used, and the up sampled image given by their average reconstruction. The final HR image is given by adding the LR interpolated approximation $\tilde{y}_H = y_L + (\sum_{k \in \Omega} R_k^T R_k)^{-1} \sum_{k \epsilon \Omega} R_k^T \tilde{p}_k^H$.

SIMULATION RESULTS

Method	PSNR	CSNR
Bicubic	30.5184	35.2248
Proposed	30.6630	34.9355
Extension	32.9892	27.0626

Table.1. PSNR & CSNR values for dataset1

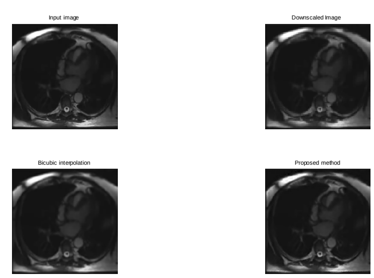

Figure.1. Reconstructed cardiac images for database1 with different methods

Method	PSNR	CSNR
Bicubic	32.5424	31.1768
Proposed	32.5281	31.2054
Extension	33.6347	25.7717

Table.2. PSNR & CSNR values for dataset2

4. CONCLUSION

A novel approach is proposed in this paper which accurately precise the High resolution 3D cardiac MRI in easy way. 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.

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[4] J. V. Manjon, P. Coupe, A. Buades, D. L. Collins, and M. Robles, “Mri superresolution using self-similarity and image priors,” Int J. Biomed. Imaging, 2010. Fig. 4. Example reconstruction of real MRI frames. First two rows: adult dataset. Bottom two rows: neonatal dataset. (j) Original (k) Bicubic (l) Proposed

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