Super-Resolution of Cardiac MRI:Review

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ABSTRACT

The accurate measurement of 3D cardiac function is an important task in the analysis of cardiac magnetic resonance (MR) images. However, short-axis image acquisitions with thick slices are commonly used in clinical practice due to constraints of acquisition time, signal-to-noise ratio and patient compliance. In this situation, the estimation of a high-resolution image can provide an approximation of the underlying 3D measurements. In this paper, we develop a novel algorithm for the estimation of high-resolution cardiac MR images from single short-axis cardiac MR image stacks is proposed.

Keywords—*MRI Analysis, Patch, Super resolution, Reconstruction, Dictionary buildings etc.*

1.INTRODUCTION

3D cardiac magnetic resonance (MR) imaging has developed rapidly during the past few years, particularly in the acquisition of 3D cine MR images. The 3D cardiac MR images allow reliable assessment of complex cardiac morphology. Using 3D images also allows for a more accurate and reproducible estimation of cardiac functional indices. However, 3D cardiac MR imaging is not always available due to several limitations: First, 3D cardiac MR imaging often involves breath-holding for periods that are too long for many patients. In addition, it often has a low signal-to-noise ratio.Most super-resolution algorithms use an observation model which establishes a relationship between the high-resolution image and the observed low-resolution images. The observed low-resolution images are considered to be warped, blurred, down-sampled and noisy versions of the original high-resolution image.

2. LITERATURE REVIEW

Kanwal K. Bhatia1et.al. reported super-resolution reconstruction of cardiac MRI Using coupled dictionary learning that High resolution 3D cardiac MRI is difficult to achieve due to the relative speed of motion Instead, anisotropic 2D stack volumes are typical and improving the resolution of these is strongly motivated by both visualization and analysis. The lack of suitable reconstruction techniques that handle non-rigid motion means that cardiac image enhancement is still often attained by simple interpolation. 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.[1]
W. Shi1, J. Caballero1, et.al. reported Cardiac image super-resolution with global correspondence using multi-atlas Patch Match that the accurate measurement of 3D cardiac function is an important task in the analysis of cardiac magnetic resonance (MR) images. However, short-axis image acquisitions with thick slices are commonly used in clinical practice due to constraints of acquisition time, signal-to-noise ratio and patient compliance.[2]
Jose Caballero1 et.al. proposed Dictionary learning and time sparsity in dynamic MRI that Sparse representation methods have been shown to tackle adequately the inherent speed limits of magnetic resonance imaging (MRI) acquisition. Recently, learning-based techniques have been used to further accelerate the acquisition of 2D MRI. The extension of such algorithms to dynamic MRI (dMRI) requires careful examination of the signal sparsity distribution among the different dimensions of the data.[3]

W. Shi1, J. Caballero1, et.al. reported Cardiac image super resolution with global correspondence using multi-atlas Patch Match that the accurate measurement of 3D cardiac function is an important task in the analysis of cardiac magnetic resonance (MR) images. However, short-axis image acquisitions with thick slices are commonly used in clinical practice due to constraints of acquisition time, signal-to-noise ratio and patient compliance.[4]

Michal Aharon, et.al. reported K-SVD: An Algorithm for Designing Over completes Dictionaries for Sparse Representation that in recent years there has been a growing interest in the study of sparse representation of signals. Using an over complete dictionary that contains prototype signal-atoms, signals are described by sparse linear combinations of these atoms. Applications that use sparse representation are many and include compression, regularization in inverse problems, feature extraction, and more.[5]

Ali Gholipour, et.al proposed Robust Super-resolution Volume Reconstruction from Slice Acquisitions. Application to Fetal Brain MRI"that Fast magnetic resonance imaging slice acquisition techniques such as single shot fast spin echo are routinely used in the presence of uncontrollable motion. Current applications involve fetal MRI and MRI of moving subjects and organs. Although high-quality slices are frequently acquired by these techniques, inter-slice motion leads to severe motion artifacts that appear in out-of-plane views. Slice sequential acquisitions do not enable 3D volume representation.[6]

François Rousseau and The Alzheimer's Disease Neuroimaging reported a nonlocal approach for image super resolution using intermodality priors that Image enhancement is of great importance in medical imaging where image resolution remains a crucial point in many image analysis algorithms. In this paper, we investigate brain hallucination, or generating a high resolution brain image from an input low resolution image, with the help of another high resolution brain image. We propose an approach for image super resolution by using anatomical intermodality priors from a reference image.[7]

3.OBJECTIVE

The objective is recognition of high resolution MRI image from low resolution image to save time of acquisition.

4.SCOPE

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 project,we explore the use of example-based super resolution to enable high fidelity patch-based reconstruction,using raining 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 patches.

5.BLOCK DIAGRAM

A. Image Acquisition

Image acquisition in image processing can be broadly defined as the action of retrieving an image from some source, usually a hardware-based source, so it can be passed through whatever processes need to occur afterward. Performing image acquisition in image processing is always the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed and is the result of whatever hardware was used to generate it, which can be very important in some fields to have a consistent baseline from which to work.

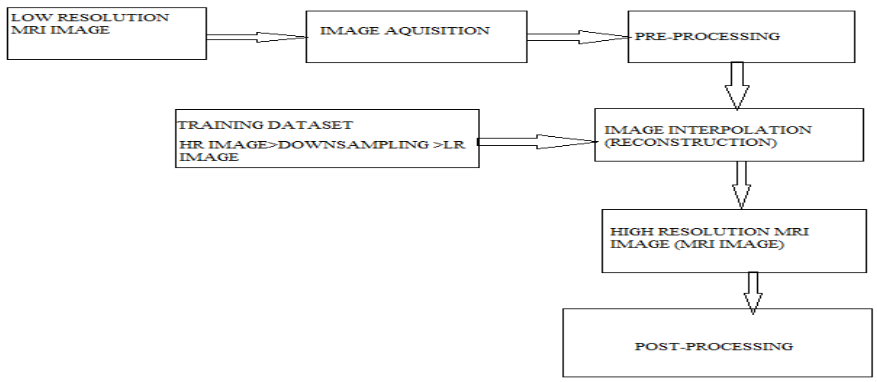

Fig.1. Block Diagram of Proposed System

One of the ultimate goals of this process is to have a source of input that operates within such controlled and measured guidelines that the same image can, if necessary, be nearly perfectly reproduced under the same conditions so anomalous factors are easier to locate and eliminate.

B.Image pre-processing

Image pre-processing can significantly increase the reliability of an optical inspection. Several filter operations which intensify or reduce certain image details enable an easier or faster evaluation. Users are able to optimize a camera image with just a few clicks.

C. Image interpolation

Image interpolation occurs in all digital photos at some stage whether this is in bayer demosaicing or in photo enlargement. It happens anytime you resize or remap (distort) your image from one pixel grid to another. Image resizing is necessary when you need to increase or decrease the total number of pixels, whereas remapping can occur under a wider variety of scenarios: correcting for lens distortion, changing perspective, and rotating an image.Even if the same image resizes or remap is performed, the results can vary significantly depending on the interpolation algorithm. It is only an approximation; therefore an image will always lose some quality each time interpolation is performed.

D. Training Dataset

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.

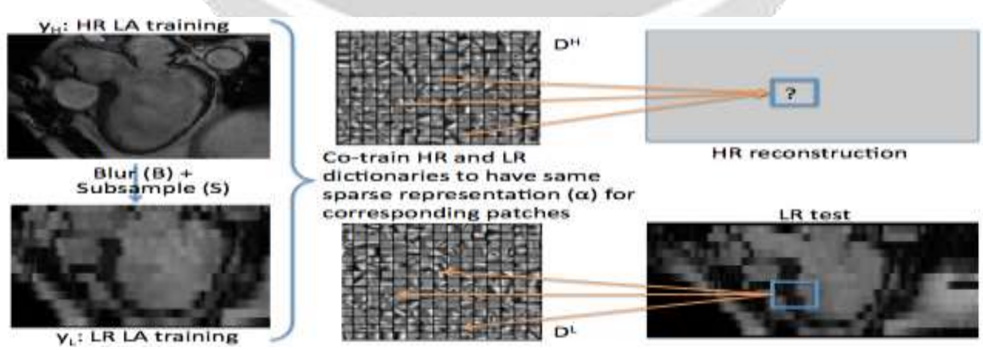

Fig. 2. Reconstruction using co-trained dictionaries. HR and LR dictionaries are co-trained to encode corresponding patches with the same sparse representation. LR patches from a test image are then sparse coded using the LR dictionary, and the resulting sparse code applied to the HR dictionary to reconstruct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

Given an underlying unknown HR image yH, the acquired LR image yL can be modelled as:

$$yL = (yH * B) \downarrow s + n \quad (1)$$

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

6. EXPERIMENTAL RESULTS

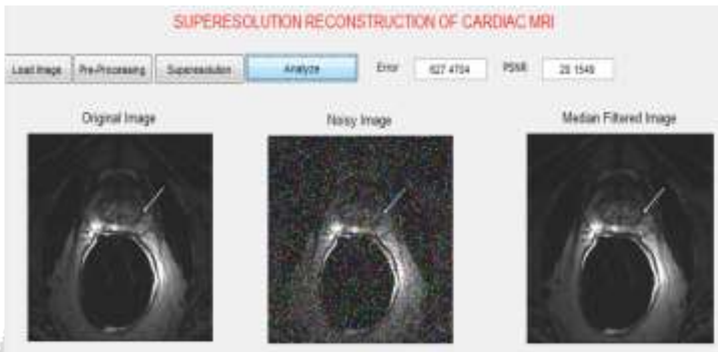

Fig.3.Original image and filter image Output

The PSNR and Error value are

PSNR=20.1549

Error=627.4704

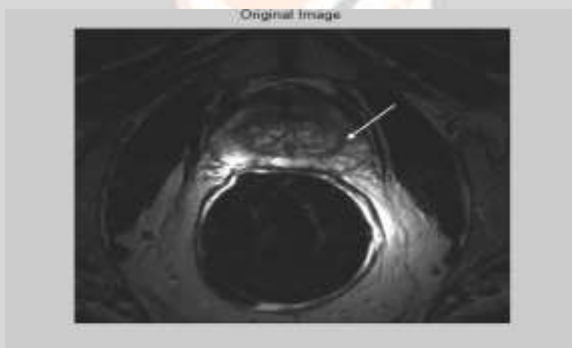

Fig.4.Original image

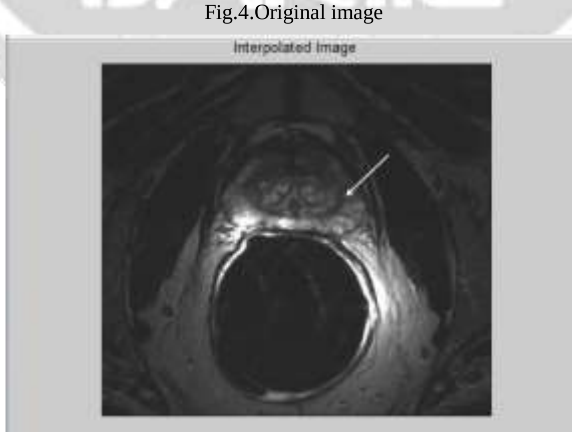

Fig.5.Interpolated Image

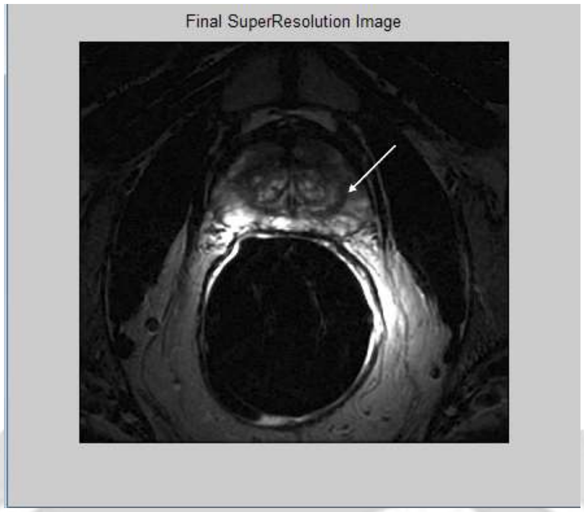

Fig.6.Final Super resolution Image

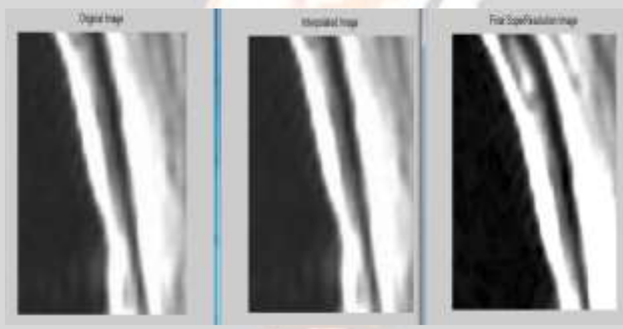

Fig.7.Output of Interpolated and Super resolution Image

7. CONCLUSION

The proposed system reconstruct a super-resolution (SR) cardiac MR image from a single short axis (SA) cardiac MR image with a set of 3D atlases available as the training database.We use a novel approximate global search approach to find patch correspondence between the short axis MR image and a set of atlases. 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 patches.

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