ABSTRACT

Super-resolution (SR) is the process of generating a raster image with a higher resolution than its source. The source can consist of one or more images or frames. Since acquiring a magnetic resonance (MR) image with high spatial resolution is difficult, due to a number of limitations such as signal-to-noise-ratio (SNR), increased cost, data transfer rate, hardware, time limitations and patient's comfort. Conventional interpolation methods are not able to recuperate the high frequency (HF) information lost during the acquisition process. Interpolation techniques estimate new points assuming that the existing ones in the low-resolution (LR) image have the same value in the high-resolution (HR) images which is only valid within homogeneous regions. As a result, interpolated images are typically blurred versions of the underlying HR images. In this work a novel SR methodology namely the epipolar super-resolution technique is proposed. This technique recovers the lost HF information using epipolar HR images. The proposed method is based on the assumption that if a registered HR image/volume of the reference brain data from the same or other modality is available then anatomical information from this HR brain data can be used to recuperate additional structure in the SR reconstructed LR data. Furthermore, noise in the LR data can be minimized using mean correction. Even the images with highly anisotropic voxels can be reconstructed to have isotropic voxels (e.g. $1 \times 1 \times 9$ mm^3 to

$1 \times 1 \times 1$ mm^3) when HR data of an equal resolution is available. Isotropic voxels provide better segmentation and analysis results which aids in diagnosis of diseases. Nevertheless, it is vital to note here that the reconstruction can be performed in any dimension when appropriate data is available (e.g. $3 \times 3 \times 3$ mm^3 to $1 \times 1 \times 1$ mm^3). It is significant to note that no exceptional hardware or precise imaging sequences are required to apply the Epipolar SR approach. This method gives a significant 20-40 % peak–signal–to–noise–ratio (PSNR) improvement than other methods for LR dataset with and without noise. An additional work on sparse dictionary coding (SDC) technique for SR image reconstruction is also proposed. This technique integrates the feature patches of HR and LR images using sparse dictionary (SD). It fabricates a sparse connection between medium-frequency (MF) and HF image elements and concurrently comprehends match searching and optimization methods. When compared with learning-based SR methods, SDC requires only two compact learned dictionaries, instead of a large training patch database. The recovery of the sparse data is done using LR dictionary and the HR dictionary, which is used to calculate the final HR image. Sparse Kernel-Single Value Decomposition (SK-SVD) algorithm is applied for optimization to fasten the sparse coding process. Few experiments with general images depict that SDC technique surpasses all other learning-based SR algorithms in terms of peak–signal–to–noise–ratio (PSNR). The computed image adaptively selects the most relevant patch bases in the

dictionary to best represent each patch of the given low-resolution image. Moreover, the SDC technique is robust to noise, while most other methods cannot perform denoising and SR simultaneously. In comparison with other learning-based super-resolution methods, SDC method outperforms others in terms of quality, computation and efficiency. This method yields around 10- 15% better PSNR than previous learning-based SR methods.