PCA & CS based fusion for Medical Image Fusion

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Abstract **- Compressive sampling (CS), also called Compressed sensing, has generated a tremendous amount of excitement in the image processing community. It provides an alternative to Shannon/ Nyquist sampling when the signal under acquisition is known to be sparse or compressible. In this paper, we propose a new efficient image fusion method for compressed sensing imaging. In this method, we calculate the two dimensional discrete cosine transform of multiple input images, these achieved measurements are multiplied with sampling filter, so compressed images are obtained. we take inverse discrete cosine transform of them. Finally, fused image achieves from these results by using PCA fusion method. This approach also is implemented for multi-focus and noisy images. Simulation results show that our method provides promising fusion performance in both visual comparison and comparison using objective measures. Moreover, because this method does not need to recovery process the computational time is decreased very much.**

Keywords: Compressive Sensing, Image Fusion, Multi-Focus Images, Multi-Focus and Noisy Images

I. INTRODUCTION

Image fusion is defined as a process of combining two or more images into a single composite image. The single output image contains the better scene description than the individual input images. The output image must be more useful for human perception or machine perception. The basic problem of image fusion is determining the best procedure for combining multiple images. The main aim of image fusion is to improve the quality of information of the output image. The existing fusion algorithms and techniques shows that image fusion provide us an output image with an improved quality.

Only the objects of the image with in the depth of field of camera are focused and the remaining will be blurred. Fusion can be defined as the process of combining multiple input images into a smaller collection of images, usually a single one, which contains the relevant and important information from the inputs. Nowadays, many well-known fusion algorithms have been proposed. But most of them are based on the whole acquisition of the source images. A work demonstrated the possibility of fusing images without acquiring all the samples of the original images, if the images are acquired under the new technique – compressed sensing.

The noise should be removed prior to performing image analysis processes while keeping the fine detail of the image intact. Salt and pepper noise in an image are small, unwanted random pixels in areas where the surrounding majority of pixels are a different value, i.e. a white pixel in a black field or a black pixel in a white field. Many algorithms have been developed to remove salt and pepper noise in document images with different performance in removing noise and retaining fine details of the image. Median filter is a well known method that can remove this noise from images. The removal of noise is performed by replacing the value of window center by the median of center neighbourhood.

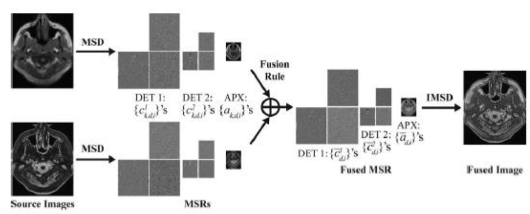

Fig 1 General procedure of MSD-based image fusion

Image fusion can be performed at three different levels, i.e., pixel/data level, feature / attribute level, and symbol/decision level, each of which serves different purposes Compared with the others, pixel-level fusion directly combines the original information in the source images and is more computationally efficient. According to whether multistage decomposition (MSD) is used, pixel-level fusion methods can be

Classified as MSD-based or non-MSD based. Compared to the latter, MSD-based methods have the advantage of extracting and combining salient features at different scales, and therefore normally produce images with greater information content.

The general procedure of MSD-based fusion is illustrated in Fig. 1. First, the source images are transformed to multi scale representations (MSRs) using MSD. An MSR is a pyramidal structure with successively reduced spatial resolution; it usually contains one approximation level (APX) storing low-pass coefficients and several detail levels (DETs) storing high-pass or band pass coefficients. Then, a certain fusion rule is applied to merge coefficients at different scales. Finally, an inverse MSD (IMSD) is applied to the fused MSR to generate the final image.

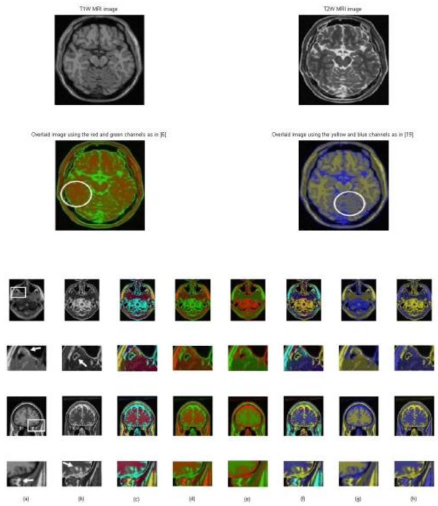

Fig 2 T1W and T2W M.R.I Scanning

Two directions can be explored in MSD-based fusion to enhance the fusion quality: advanced MSD schemes and effective fusion rules. Here, we focus on the latter and propose a novel cross-scale (CS) fusion rule, where the belongingness/ membership of each fused coefficient to each source image is calculated. Unlike previous methods, our fusion rule calculates an optimal set of coefficients for each scale taking into account large neighbourhood information, which guarantees intra scale and inter scale consistencies, i.e., coefficients with similar characteristics are fused in a similar way are avoided in the results.

II. Compressed Sensing

In this section we present a brief introduction to the Sparse model and compressive sensing background. Consider a real-valued, finite-length, one-dimensional, discrete-time signal X , which can be viewed as an N × 1 column vector in N R with elements x[n], n = 1, 2, . . . , N. Any signal in N R can be represented in terms of a basis of N × 1 vectors {ψ i } .

The signal X is K-sparse if it is a linear combination of only K basis vectors, that is, only K of the i S coefficients in are nonzero and (N − K) are zero. The case of interest is when K<< N. The signal X is compressible if the representation has just a few large coefficients and many small coefficients.

III. Image Fusion Method

Our method for two input source images and then we can generalize it for multiple input images. We compute two-dimensional discrete cosine transform of two input images and then these measurements are multiplied with sampling filter, so compressed images are obtained. We take inverse discrete cosine transform of them.

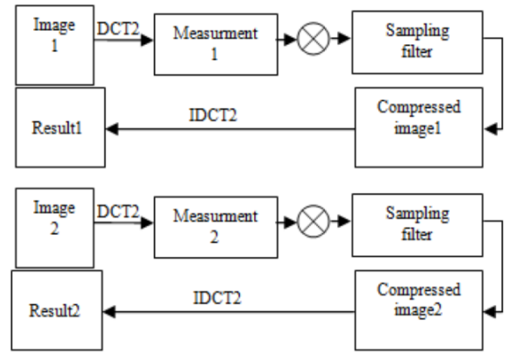

Fig 3 Block diagrams of computing

PCA is a statistical method for transforming a multivariate data set with correlated variables into a data set with new uncorrelated variables. For this purpose search is made of an orthogonal linear transformation of the original N-dimensional variables such that in the new coordinate system the new variables be of a much smaller dimensionality M and be uncorrelated. In the Principal Component Analysis (PCA) the sought after transformation parameters are obtained by minimizing the covariance of error introduced by neglecting N-M of the transformed components.

The contrast sensitivity function of luminance shows band pass characteristics, while the contrast sensitivity functions of both red–green and yellow–blue show low-pass behaviour. Therefore, luminance sensitivity is normally higher than chromatic sensitivity except at low spatial frequencies. Hence, the fused monochrome image, which provides combined information and good contrasts, should be assigned to the luminance channel to exploit luminance contrast.

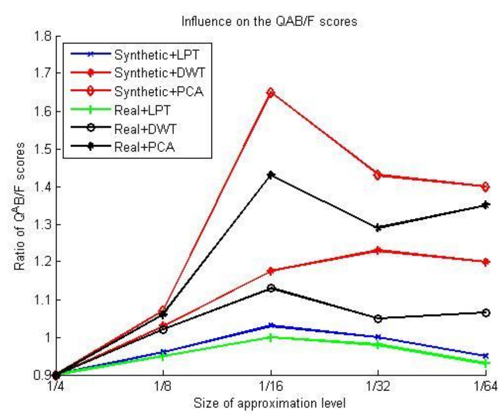

Fig 4 Graph 1

In addition, the colour-fused image should also provide good contrasts in the red–green and/or yellow–blue channels in order to fully exploit human colour perception. To achieve this, we can consider that red, green, yellow, and blue are arranged on a colour circle as in, where the red– green axis is orthogonal to the yellow–blue axis and colour (actually its hue) transits smoothly from one to another in each quadrant.

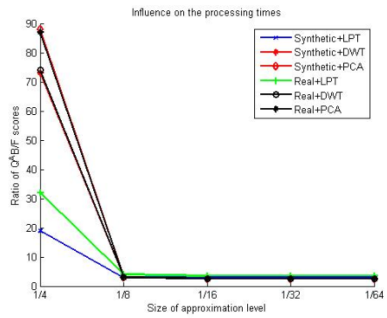

Fig 5 graph 2

IV. Simulation Results

The performance of our CS fusion rule was evaluated on volumetric image fusion scans using both synthetic and real data. After this validation, we demonstrate the capability of our fusion rule to fuse other modalities. In addition, we have consulted a neurosurgeon and a radiologist. In their opinion, our method not only provides enhanced representations of information, which is useful in applications like diagnosis and neuro navigation, but also offers them the flexibility of combining modalities of their choice, which is important because the data types required are normally application dependent.

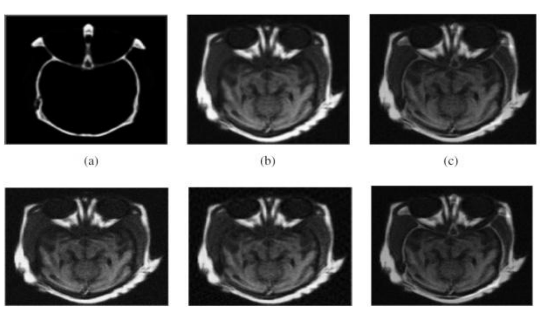

Figure 6. (a) CT image. (b) MRI image. (c) Fusion result by FAR method. (d) Fusion result by DS_MS method . (e) Fusion result by Han's method . (f) Fusion result by our method

With regard to the visual comparison of the second group, the fusion result by using our method in Fig. 3 (f) contains more information than the input images in Fig.3 (a) and (b). Noise sensitivity is a common concern for many pixel-level fusion methods. For noisy images, one could employ a denoising activity-level measure or pre-processing step

Conclusion

In this paper, we present a new image fusion method based on the CS theory and compare it with other methods. Our method is done on blurred images. Visual analysis and the quantitative evaluation show our fusion method performs better than others. For blurred and noisy images, first salt and pepper noise is removed from images ,then our fusion method is applied on them. Finally, wiener filter minimized variation the pixel value. In this case, also, we achieve better performance with this new fusion method.

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