

Convolutional Sparsity Based Morphological Component Analysis of Medical Image Fusion

Dr.Shubhangi D C¹, Priyanka²

Professor and Program coordinator, Department of Computer Engineering, VTU Center for PG Studies Kalaburgi, Kalaburgi, Karnataka, India¹

PG Student, Department of Computer Engineering, VTU Center for PG Studies Kalaburgi, Kalaburgi, Karnataka, India²

ABSTRACT: For pixel-level medical image fusion a sparse representation (SR) model called convolutional sparsity-based morphological component analysis (CS-MCA) is introduced. Unlike the SR model norm, which is a single image component and overlapping patches, the CS-MCA model can simultaneously achieve multi-component and global source image SRs by combining MCA and CSR into a unified optimization system. For each source image, the CSRs of its cartoon and texture components are first obtained through the CS-MCA model using pre-learned dictionaries in the proposed fusion method. The sparse coefficients of all the source images are merged and the fused component is then reconstructed accordingly using the corresponding dictionary for each image component. The fused image is eventually measured as an overlay of the fused cartoon and texture components.

KEYWORDS: CS-MCA, CSR, Morphology, Convolutional, SR-Model

I. INTRODUCTION

DUE to the diversity of image capture mechanisms, medical images may reflect different categories of knowledge about organs / tissues. For example, the computed tomography (CT) images will clearly show dense structures such as bones and implants, while the soft tissue magnetic resonance (MR) images provide anatomical details of high resolution. The goal of the pixel-level medical image fusion technique is to combine the complementary information in multi-modal medical images by producing a composite image that is hoped to be more appropriate for physician observation or machine perception. During the last few decades a number of imaging fusion approaches have been proposed. These methods can generally be divided into four groups based on the accepted technique of image transformation: methods based on multi-scale decomposition (MSD), methods based on sparse representation (SR) conducted in other fields and methods based on the combination of different transforms. In this paper we concentrate above all on SR-based image fusion.



Fig. 1 Proposed System

II. RELATED WORK

[1] A. James and B. Dasarthy, "Medical image fusion: A survey of the state of the art," *Inf. Fusion*, vol. 19, pp. 4–19, 2014. Medical image fusion is the process of registering and combining multiple images from single or multiple imaging modalities to improve the imaging quality and reduce randomness and redundancy in order to increase the

clinical applicability of medical images for diagnosis and assessment of medical problems. Multi-modal medical image fusion algorithms and devices have shown notable achievements in improving clinical accuracy of decisions based on medical images. This review article provides a factual listing of methods and summarizes the broad scientific challenges faced in the field of medical image fusion. We characterize the medical image fusion research based on (1) the widely used image fusion methods, (2) imaging modalities, and (3) imaging of organs that are under study. This review concludes that even though there exists several open ended technological and scientific challenges, the fusion of medical images has proved to be useful for advancing the clinical reliability of using medical imaging for medical diagnostics and analysis, and is a scientific discipline that has the potential to significantly grow in the coming years. [2] S. Li, X. Kang, L. Fang, J. Hu, and H. Yin, "Pixel-level image fusion: A survey of the state of the art," *Inf. Fusion*, vol. 33, pp. 100–112, 2017. Pixel-level image fusion is designed to combine multiple input images into a fused image, which is expected to be more informative for human or machine perception as compared to any of the input images. Due to this advantage, pixel-level image fusion has shown notable achievements in remote sensing, medical imaging, and night vision applications. In this paper, we first provide a comprehensive survey of the state of the art pixel-level image fusion methods. Then, the existing fusion quality measures are summarized. Next, four major applications, i.e., remote sensing, medical diagnosis, surveillance, photography, and challenges in pixel-level image fusion applications are analyzed. At last, this review concludes that although various image fusion methods have been proposed, there still exist several future directions in different image fusion applications. Therefore, the researches in the image fusion field are still expected to significantly grow in the coming years. [3] H. Li, B. Manjunath, and S. Mitra, "Multisensor image fusion using the wavelet transform," *Graph. Models Image Process.*, vol. 57, no. 3, pp. 235–245, 1995. This paper discusses the image fusion based on wavelet transform and analysis of image fusion basic principal, method and advantage. The main objective of image fusion is to combine information from multiple image of the same scene based on a certain algorithm, the result of image fusion is a new result which can be more suitable for human and machine. This day's image fusion technology has been widely applied in many fields including remote sensing, automata recognition, computer vision, medical image processing. This document designs and realizes the method of image algorithm which is based on wavelet transform. [4] X. Qu, J. Yan, H. Xiao, and Z. Zhu, "Image fusion algorithm based on spatial frequency-motivated pulse coupled neural networks in nonsubsampling contourlet transform domain," *Acta Autom. Sin.*, vol. 34, no. 12, pp. 1508–1514, 2008. Introduces Convolutional neural networks (CNNs) into the field of image fusion. Discusses the feasibility and superiority of CNNs used for image fusion. Proposes a state-of-the-art CNN-based multi-focus image fusion method. Exhibits the potential of CNNs for other-type image fusion issues. Puts forward some suggestions on the future study of CNN-based image fusion. As is well known, activity level measurement and fusion rule are two crucial factors in image fusion. For most existing fusion methods, either in spatial domain or in a transform domain like wavelet, the activity level measurement is essentially implemented by designing local filters to extract high-frequency details, and the calculated clarity information of different source images are then compared using some elaborately designed rules to obtain a clarity/focus map. Consequently, the focus map contains the integrated clarity information, which is of great significance to various image fusion issues, such as multi-focus image fusion, multi-modal image fusion, etc. other-type image fusion issues is also briefly exhibited in the experiments.

III. PROPOSED SYSTEM

To overcome the existing system the sparse representations of cartoon and texture components of each source image. This component separation process can significantly improve the flexibility for designing more effective fusion strategies. On the other hand, to overcome the drawbacks caused by patch-based coding, Liu et al proposed a global SR-based image fusion method by introducing the convolutional sparse representation (CSR) model, where sparse coding is performed over the entire image rather than on overlapping patches to achieve better representations. SR-based image fusion that simultaneously addresses the above two issues: multi-component and global sparse representations. The contributions are two-fold: We introduce an SR model, the convolution sparsity based morphological component analysis (CS-MCA), into the field of image fusion. By integrating MCA and CSR into a unified optimization framework, this model can achieve multi-component and global sparse representations of source images at the same time. We propose a new medical image fusion method based on the CS-MCA model. Experimental results show that the proposed method outperforms several benchmarking and state-of-the-art SR-based fusion methods in terms of both visual quality and objective assessment.

IV. METHODOLOGY

Algorithm 1: Algorithm for Solving the CS-MCA model.

- 1: Input: $Y, \{dc, m\} M_c m=1, \{dt, m\} M_t m=1, \lambda_c, \lambda_t, L$
- 2: for $i = 1: L$
- 3: Calculate $X_{c,m}$ by solving Eq. (5);
- 4: Calculate $X_{t,m}$ by solving Eq. (6);

5: end for

6: Output: $\{X_{c,m}\}_{m=1}^M$ and $\{X_{t,m}\}_{m=1}^M$.

V. EXPERIMENTAL RESULTS

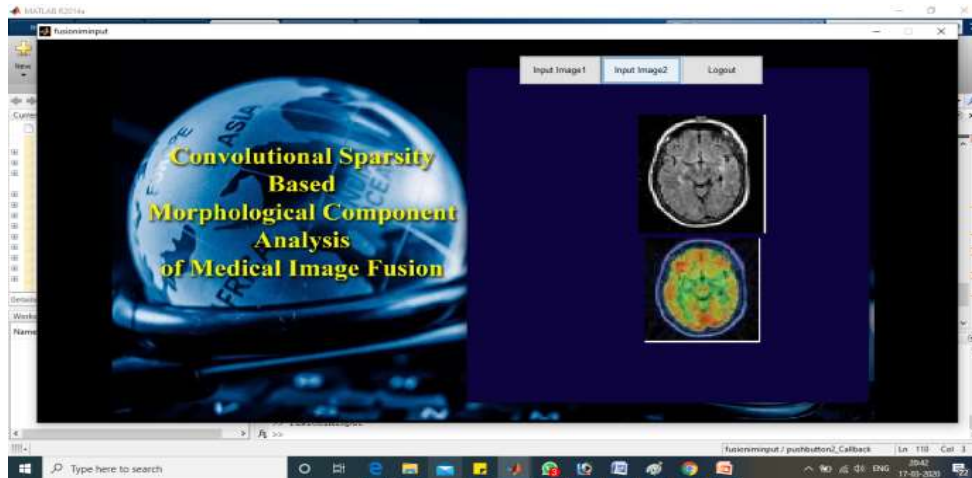


Fig 2: Read Image

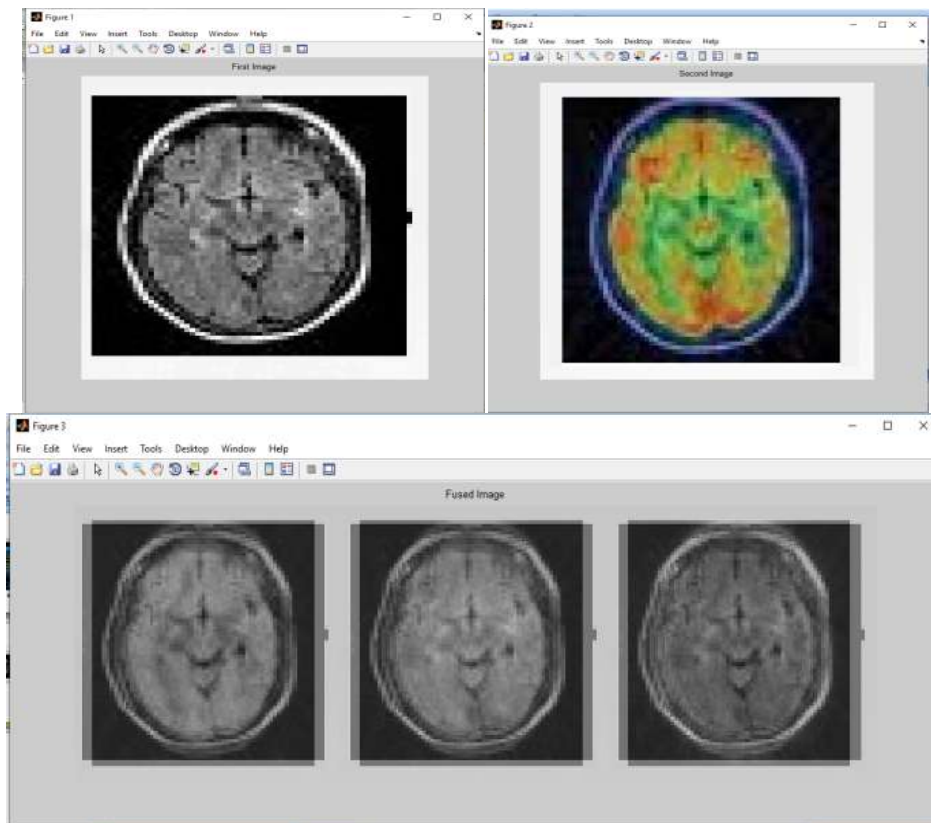


Fig 3: Fusion Image



VI.CONCLUSION

We are launching a new CS-MCA Image Fusion SR model. The CS-MCA model can simultaneously achieve multi-component and global sparse representations of source images by combining MCA and CSR into a single optimisation system. A new method of medical image fusion based on the existing CS-MCA model. Experimental findings check the effectiveness of the existing process.

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