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MEDICAL IMAGE FUSION USING WAVELET AND CURVELET TRANSFORM DOMAINS

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ABSTRACT

Medical image fusion has been used to derive useful information from multimodality medical image data. The idea is to improve the image content by fusing images like computer tomography (CT) and magnetic resonance imaging (MRI) images, magnetic resonance imaging (MRI) provides better information on soft tissue whereas computed tomography (CT) provides better information about denser tissue. In this project *a two stage multimodal fusion framework using cascaded combination of Stationary Wavelet Transform (SWT) and Non Sub-sampled Contourlet Transform (NSCT) domains is presented for images acquired using two distinct medical imaging sensor modalities (i.e. MRI and CT-Scan). The major advantage of using a cascaded combination of SWT and NSCT is to improve upon the shift variance, directionality and phase information in the finally fused image. The first stage employs Principal Component Analysis (PCA) algorithm in SWT domain to minimize the redundancy. Maximum fusion rule is then applied in NSCT domain at second stage to enhance contrast of the diagnostic features.*

INTRODUCTION

Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging.

Closely related to image processing are computer graphics and computer vision. In computer graphics, images are manually made from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from natural scenes, as in most animated movies. Computer vision, on the other hand, is often considered high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans). In modern sciences and technologies, images also gain much broader scopes due to the ever growing importance of scientific visualization (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real-time multi-asset portfolio trading in finance.

EXISTING SYSTEM

For one scene, many images can be simultaneously acquired by various sensors with development of numerous imaging sensors. Those images usually contain complementary information which is dependent on the natural properties of the sensors and the way the images are obtained. Image fusion can effectively extend or enhance information of the scene by combining the images captured by different sensors [1,2]. The fused image can improve edge detection, image segmentation and object recognition in medical imaging, machine vision and military applications. In the past two decades, many techniques and software for image fusion have been developed [3–5]. According to the stage at which the information is combined, image fusion algorithms can be categorized into three levels, namely pixel-level, feature-level, and decision-level [6]. The pixel-level fusion combines the raw source images into a single image. Compared to feature or decision-level fusion, pixellevel fusion can preserve more original information [7]. Feature-level algorithms typically fuse the source images using their various feature properties, such as regions or edges [8]. Thus, this kind of methods is usually robust to noise and misregistration. Decisionlevel fusion algorithms combine image descriptions directly, for example, in the form of relational graphs [9]. But the decision-level fusion methods are very much application dependent [1]. In this paper, we only focus on the pixel-level image fusion problem. The goal of pixel-level image fusion is to combine visual information contained in multiple source images into an informative fused image without the introduction of distortion or loss of information. In the past decades, many pixel-level image fusion methods have been proposed. In all of those methods, multiscale transform based methods are the most successful category of techniques. Typical multiscale transforms include the Laplacian pyramid [10], morphological pyramid [11], discrete wavelet transform (DWT) [12–14], gradient pyramid [15], stationary wavelet transform (SWT) [16,17], and dual-tree complex wavelet transform (DTCWT) [18,19]. Recently developed multiscale geometry analysis, such as ridgelet transform [20], curvelet transform (CVT) [21], the nonsubsampled contourlet transform (NSCT) [22,23], are also applied to image fusion. There are three basic steps for multiscale transform based image fusion: firstly, the source images are decomposed into multiscale representations with different resolutions and orientations. Then the multiscale representations are integrated according to some fusion rules. Finally, the fused image is constructed using the inverse transform of the composite multiscale coefficients [6,13]. Multiscale transform based image fusion methods assume that the underlying information is the salient features of the original images, which are linked with the decomposed coefficients [6]. This assumption is reasonable for the transform coefficients that correspond to the transform bases which are designed to represent the important features, such as edges and lines of an image.

PROPOSED SYSTEM

Advancements' in large number of sophisticated medical imaging modalities like: Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), Ultrasound, X-ray, Single Positron Emission Computed Tomography (SPECT), Electrocardiography (ECG) etc. have added to the visual response from these devices in terms of interpretation and diagnostic analysis . Response(s) of these imaging modalities contain plenty of useful information that are extracted and analyzed by the radiologists for the purpose of analysis, detection and the diagnosis of diseases. Numerous image processing techniques like enhancement, denoising, de-blurring etc. are also used to further enhance and improve upon the visual responses obtained from these modalities . The obtained sensor responses of the various medical imaging modalities are often complementary in nature, i.e. a particular sensor modality is deprived of the features acquired by another sensor (imaging modality). For example, CT images deals with the demonstration of the extent of disease and provides information of denser tissues with less distortion; while MRI contains the information regarding soft tissues. Hence, a radiologist always purposes to analyze the sensor responses of the different modalities simultaneously. Also, image enhancement applied as post-processing on such images are restricted to improve the attributes of the individual images only . For instance, if contrast enhancement is performed on the CT and MRI scans, it can only serve to improve upon the contrast of the individual scans but still the problem of examining different modalities simultaneously prevails. This calls upon the need to integrate the useful as well as complimentary information from the images (which are the outcome of various sensor modalities for diagnosis) using fusion algorithms to yield a single image for optimum analysis and diagnosis.

PROPOSED FUSION METHODOLOGY

This section discusses the sub-band decomposition approaches along with fusion algorithms employed in the proposed methodology for compilation of the useful information from multimodal medical images. In this paper, an improved multimodal sensor fusion methodology involving a cascaded fusion framework of SWT and NSCT domains is proposed. The block diagram presenting the multimodal fusion framework for medical images is given in Fig. 1. The proposed methodology is initiated with pre-processing of the source images (from different modalities). This involves conversion of the RGB components of the image into the gray scale and it is also ensured during this step that the source images are appropriately registered. This is followed by the first decomposition stage using wavelets.

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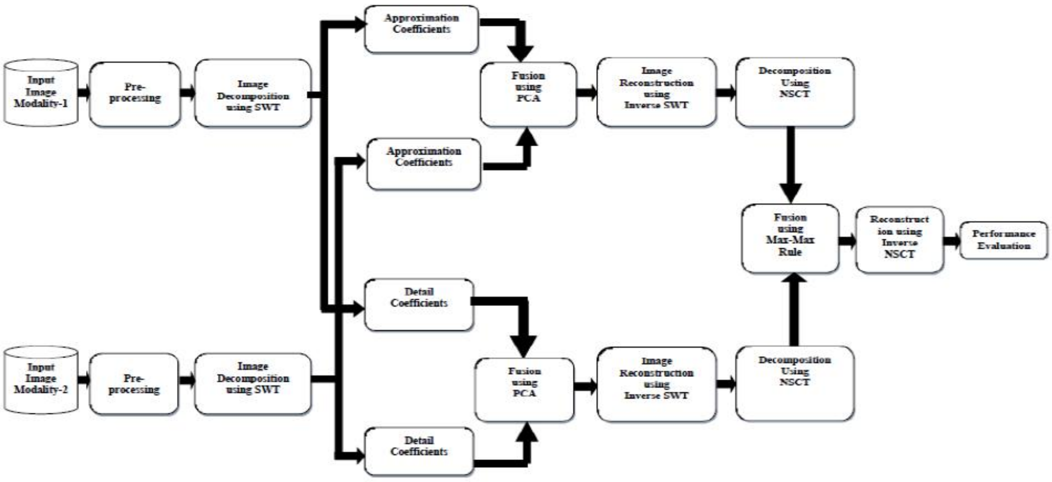

Fig 1 Block Diagram Of Proposed Method

Decomposition Stage 1

SWT (or RDWT) is also commonly referred to as a trous algorithm [26]. This transform is a variant of Fast Wavelet Transform (FWT) excluding the sub-sampling. Unlike, the conventional FWT, the high and the low-pass components are not sub-sampled during the filtering. SWT poses certain advantages over conventional DWT or FWT. Firstly, SWT is translation invariant and therefore can be extended to dyadic inputs. Secondly, SWT possesses redundancy, i.e. the reconstruction of wavelet coefficients gets doubled and is no more unique. Therefore, as a remedy, an average of the various possible inverse transforms is computed that leads to smoothing effect, which is beneficial for noise suppression [27]. SWT decomposes the source image into its respective approximation and detailed coefficients. These sub-bands coefficients are generally the low frequency and the high frequency sub-bands of the image. The approximation coefficients are the low frequency components while the detailed coefficients lie in the high frequency band. SWT also known as un-decimated DWT is the member of wavelet family. Wavelets can be termed as the combination of two types of function namely wavelet and scaling. These functions can also be referred as the father wavelet and the mother wavelet Ψ(x). Also, the transformation of the parent wavelet gives the daughter wavelet. Mostly, the daughter wavelet undergoes normalization so as to inherit all the property of the mother wavelet. The daughter wavelet $\Psi_{a,b}(x)$ is defined in the following wavelet family plays a considerable role in defining the output image. Different wavelet families have separate features that advocates for different attributes in the fused image. In addition, the level of decomposition to be applied is also an important feature; as there is loss of features or changes in the degree of reconstruction as the level of decomposition changes. In this stage, the decomposed approximation and the detailed coefficients from each of the source images are fused by PCA [9], [28]-[29]. PCA being an orthogonal transform helps to reduce the redundancy present in both the source images as well as serves to improve upon the non-directionality limitation of SWT. Now, the obtained approximation and detailed coefficients after application of PCA are reconstructed using the inverse SWT (in both the cases). The entire processing carried out in this stage serves to provide significant localization leading to a better preservation of features in the fused image.

Decomposition at stage 2

After reconstruction at Stage-1, fusion algorithm is again applied at stage 2 in Contourlet domain. The significance of such an approach is to overcome the limitation of shift variance introduced due to wavelets (in stage-1). This issue is functionally removed by the use of a highly shift invariant transform NSCT [18]-[19], [30]. NSCT does not involve the down-sampling as in SWT, hence it is unaffected by any shift in the source images. After applying sub-band decomposition using NSCT, a set of coefficients are obtained (for both the images) where: f_a and f_b are the source images, aj represents the low frequency coefficients and b_j represents the high frequency coefficients that are set in scale (j). The respective coefficients are then fused using the maximum fusion rule [31] that chooses the maximum valued coefficients (among each set of high/low frequency coefficients from source images). Maximum fusion rule helps to improve upon visual quality of the finally fused image in terms of better contrast. The fused coefficients are then reconstructed using the inverse NSCT transform. The fusion algorithm in this domain serves to provide processing in coherence to human perception. This is necessary as these medical images will be finally analyzed for diagnostic purposes by human observers (radiologists and medical experts).

Evaluation of the Proposed Fusion Approach

The customary requirements of an image fusion process include that all the reasonable and functional information from the source images should be safeguarded. In the mean time, the subsequent reconstruction of the fused one must not be hindered due to the unwanted introduction of artifacts. Evaluating the performance of the fusion algorithm can be ascertained effectively via Image Quality Assessment (IQA) of the fused image. Image fidelity metrics based on error estimation, i.e. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) are commonly employed for objective evaluation of fused image quality. Other than this, fusion metrics based on Entropy (E), Standard Deviation (SD) and Fusion Factors (FF) account for the restored information content in the fused image. As regards evaluation of edge preservation; Edge Strength ( ) is employed whereas Measure of Enhancement (EME) accounts for degree of contrast improvement in the finally fused image. The fusion process, accompanies various changes in the fused image; not merely in information content but also in terms of radiometric contrast, structural content and edge preservation. These metrics are therefore collectively employed for IQA to escort for the more effective assessment of the fusion along with efficient benchmarking of image fusion algorithms. These fusion metrics are essential not only for the sake of performance comparisons but also provide a versatile means of tuning parameters of the fusion algorithm (aiding in performance improvement).

RESULTS AND DISCUSSION

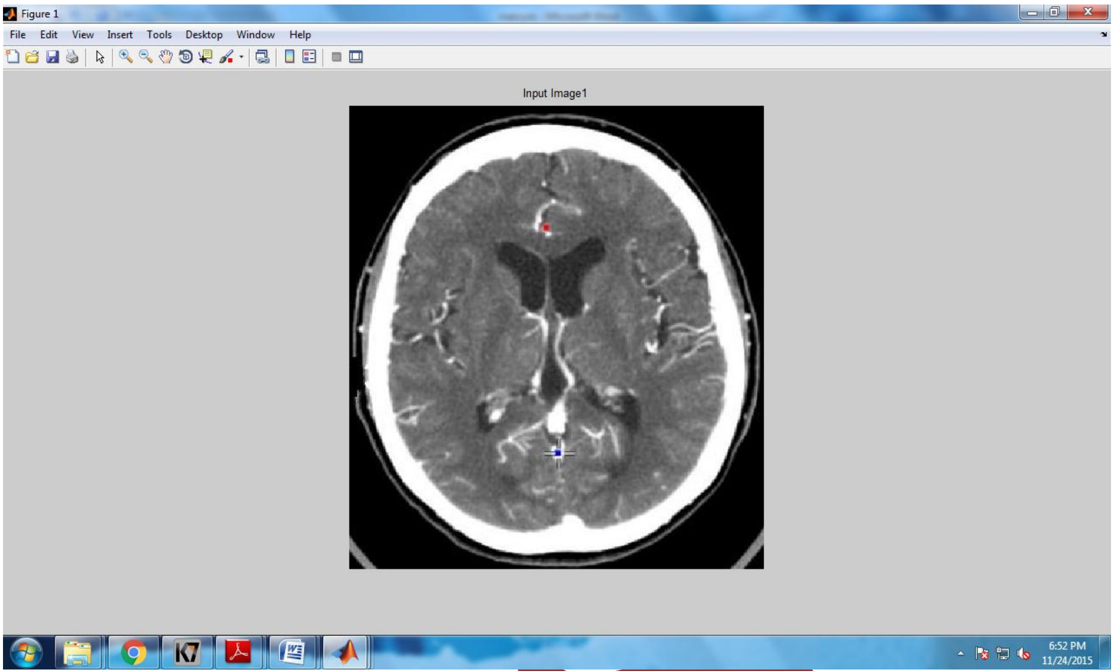

Fig 2 Input Image 1

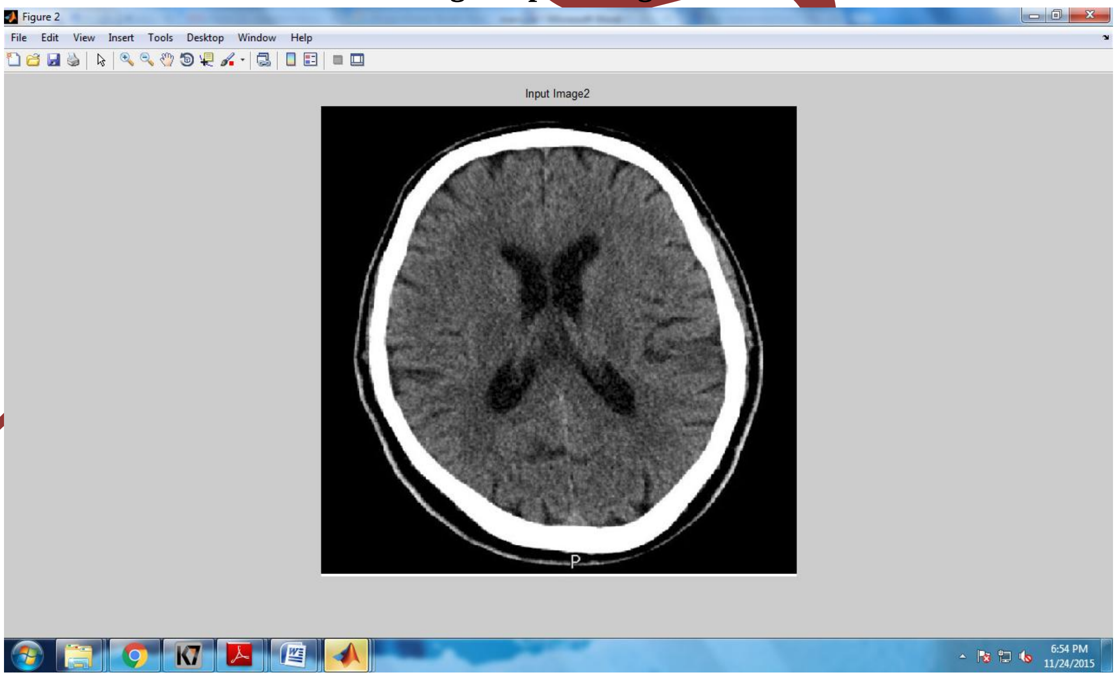

Fig 3 Input Image 2

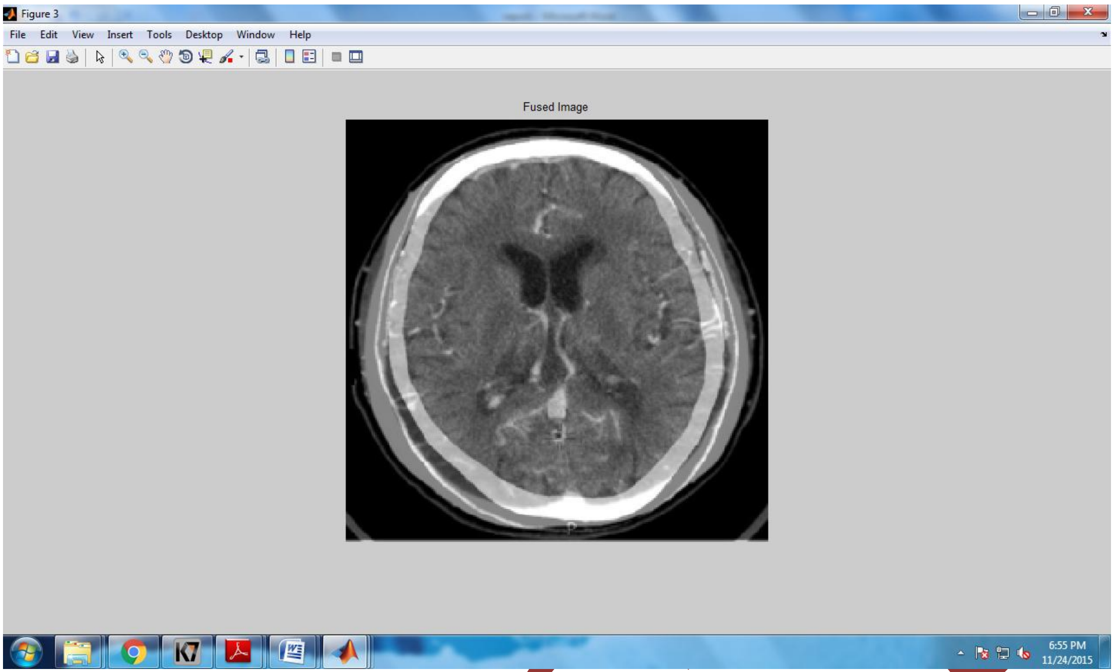

Fig 4 Fused Image

CONCLUSION

The state of art multimodal image sensing modalities yields discernable information of the region of interest depicting disease affirmation. Transformation of multimodal images via image processing algorithms should not disturb the spectral and the spatial features in these images. SWT when used for sub-band decomposition results in the fused image with increased frequency and time localization but with shift variance. On the other hand NSCT is a shift invariant transform. The present work explores the key potential of cascading the Wavelet (SWT) and Contourlet transform (NSCT) domains in restoring the aforesaid features of medical images supported with fusion of complementary structures. PCA and maximum fusion rule adds to the performance of the fusion approach in terms of minimization of redundancy, better restoration of morphological details and improved contrast. The qualitative examination of the resultant (fused) image and the obtained fusion metrics also shows coherence with the human perception. Thus, confirming the suitability of the proposed sensor fusion methodology for precise and efficient clinical diagnosis.

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