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EFFICIENT MEDICAL IMAGE FUSION BASED ON MORPHOLOGICAL BILATERAL FILTER AND AFOTV

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ABSTRACT

Medical image fusion and denoising main goal is integrating information from multimodality medical images are more accurate and clear understandable of the same image, Medical image fusion is used to access for image-guided medical diagnostic and treatment. Regrettably, medical images are often corrupted by noise in acquisition or transmission, and the noise gesture is easily mistaken for a meaningful characterization of the image, making the fusion effect deliver significantly. Medical image fusion and denoising is most challenging work nowadays. In proposed method is concentrate with this problem using an effective variation model for multimodality medical image fusion and denoising. Here, we used effective multiscale alternating sequential filter to get meaningful characterizations (e.g., details and edges) from noisy input medical images. Then, to guide the fusion of main features of input images a recursive filtering-based weight map is to be constructed. Additionally, Adaptive Fractional Order total variation (AFOTV) /bilateral filter constraint is developed for fused image, further effectively suppressing noise while avoiding the staircase effect of the TV. The experimental results indicate that the proposed method performs well with both noisy and normal medical images, outperforming conventional methods in terms of fusion quality and noise reduction.

KEYWORDS: AFOTV- Adaptive Fractional Order Total Variation

IMAGE FUSION

Image Fusion is the process of generating better quality image from two or more input images. Important features of all input images are retained by resultant images. The technology of Image fusion can be applied to many areas dealing with images such as medical image analysis, remote sensing, military surveillance, etc.

The fusion of images is often required for images acquired from different instrument modalities or capture techniques of the same scene or objects. Several approaches to image fusion can be distinguished, depending on whether the images are fused. The purpose of image fusion is to combine information from several different source images to one image, which becomes reliable and much easier to be comprehended by people. Image fusion can be broadly defined as the process of combing multiple input images or some of their features into a single image without the introduction of distortion or loss of information.

The objective of image fusion is to combine complementary as well as redundant information from multiple images to create a fused image output. Therefore, the new image generated should contain a more accurate description of the scene than any of the individual source image and is more suitable for human visual and machine perception or further image processing and analysis task. The fusion process should be shift and rotational invariant; it means that the fusion result should not depend on the location and orientation of an object the input image. The main principles of image fusion are the redundancy, the complementary, the time-limit and low cost.

Image fusion is an essential subject in vision processing. Image fusion is a process of combining the relevant information from a couple of pictures in to a single image where in fact the resulting merged picture may well be more helpful and complete than some of the input pictures. Picture fusion means the combining of two in to a single picture that has the maximum information content without producing details which are nonexistent in a given picture. With rapid development in technology, it's now possible to obtain information from multi-source pictures to generate a good quality merged image with spatial and spectral information. Caused by vision fusion is a new vision that retains the most desirable information and characteristics of input vision.

Most of the existing equipment is not capable of providing such records convincingly. In remote sensing and in astronomy, multi sensor merging can be used to reach high spatial and spectral resolution by merging visions from two sensors among that has high spatial resolution and the other one high spectral resolution. The key utilization of vision fusion is merging the grey level high resolution panchromatic vision and the colored low resolution Multispectral image. The vision fusion techniques enable the mixture of different information sources. The merged vision may have complementary spatial and spectral resolution features.

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When using the vision merging technique, some general requirements should be considered

- The fusion procedure shouldn't discard any information within the source pictures.
- The fusion procedure shouldn't introduce any artifacts or inconsistencies that may distract or mislead a human observer or any subsequent vision processing steps.
- The fusion procedure should be consistent, strong and have, as much as possible, the capacity to tolerate imperfections such as noise or miss registrations.

BASIC LEVELS OF IMAGE FUSION

Image fusion can be divided into three levels. This categorization is based according to merging stage.

- Pixel-level fusion
- Feature-level fusion
- Decision-level fusion.

Pixel Level Fusion

Pixel level fusion a fused image where generates in which information content associated with each pixel is determined from a set of pixels in source images. Fusion at this level can be performed either in spatial or in frequency domain. However, pixel level fusion may conduct to contrast reduction.

In Pixel based image fusion, the fusion process is performed on a pixel-by-pixel basis. It generates a fused image in which information associated with each pixel is determined from a set of pixels in source images to improve the performance of image processing tasks such as segmentation. Pixel level image fusion is the process which contains detailed information. Most of the medical image fusion process employs Pixel level image fusion due to the advantage of easy implementation, original measured quantity and efficient computation.

Feature Level Fusion

The extractions of salient features which are depending on their environment such as pixel intensities, edges or textures are required by feature level fusion. These similar features from the input images are fused. This fusion level can be used as a means of creating additional composite features. The fused image can also be used for classification or detection. Feature level image fusion is extracting the feature from different images that are to be fused in order to form a new image.

Decision Level Fusion

Decision level is a higher level of fusion. Information extraction individually processed for Input images. Information is combined by applying decision rules to reinforce common interpretation.

Decision level image fusion contains compact data. It requires the extraction of important features which are depending on their environment such as pixel intensities, edges or textures. These similar features from input images are fused. Decision level image fusion is effective for complicated system which is not suitable for general applications. Decision level fusion consists of merging information at a higher level of abstraction it combines the results from multiple algorithms to yield a final fused decision.

MEDICAL IMAGE FUSION

Different Types of Medical Images

In Medical field there are different types of medical scan are available in order to diagnosis a tumor of a patient in absolute manner. Some of the examples of medical scan are CT image, MRI image, and PET image and SPECT image.

CT Image

A CT Image used to determine information of hard bone and it provides the structure of the body, including internal organs, blood vessels, bones and tumors. CT image is a type of X-ray technology used for broken bones, blood clots, tumors, blockages and heart disease. CT image provides better information about structure of tissue and it is better visualized in CT image.

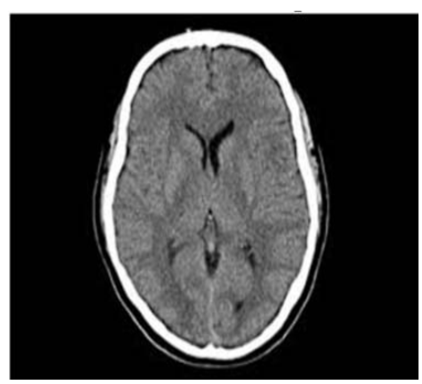

Figure 1: CT image

MRI Image

MRI image is a type of medical diagnostic imaging used to look at the blood vessels, brain, heart, spinal cord and other internal organs. MRI image provides better information on soft tissue. Normal and Pathological soft tissues are better visualized. The composite image not only provides salient information from both image but also reveal the position of soft tissue with respect to the bone structure. Normally MRI images are typically used to visualize soft tissue information.

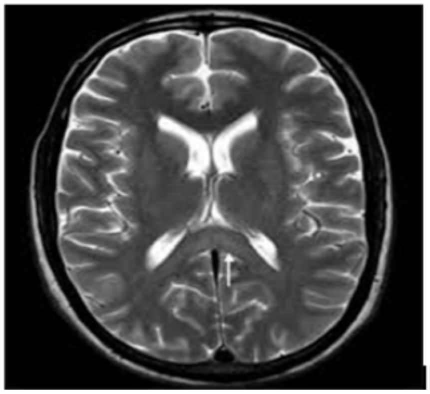

Figure 2: MRI image

PET Image

A PET image shows chemical and other changes in the brain on comparing to that of CT and MRI images. These detailed information of the brain activity of PET image, help doctors to diagnose a problem, choose the best treatment and see how well the treatment is working.

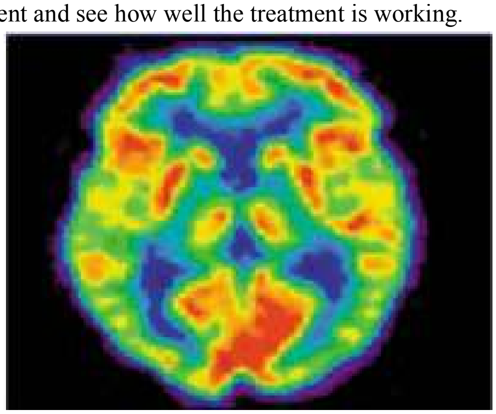

Figure 3: PET image

SPECT Image

SPECT (A Single Photon Emission Computed Tomography) scan is a type of nuclear test that shows how blood flow changes in brain, tissues and organs. The SPECT image differs from a PET image tracer stays in your blood stream rather than being absorbed by surrounding tissues. A Single Photon Emission Computed Tomography scans are cheaper and more readily available than higher resolution PET scans.

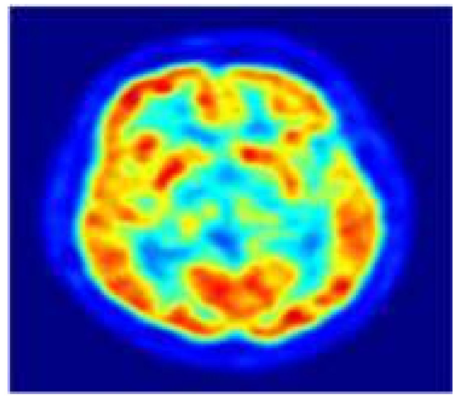

Figure 4: SPECT image

MEDICAL IMAGE FUSION METHODS

Medical image fusion attracts much attention in the recent years due to being a vital component of machine vision. It is a significant technology for diagnostics and treatments in the field of medical instrumentation and measurement. It is based on the fact that each imaging modality reports on a restricted domain and provides information in limited domains that some are common and some are unique. For instance, computed tomography (CT) image provides the best information on dense structures with less distortion like bones and implants, but it cannot detect physiological changes. Magnetic resonance (MR) image provides better information on soft tissue.

Medical image fusion aims at integrating information from multimodality medical images to obtain a more complete and accurate description of the same object. It provides an easy access for radiologists to quickly and effectively report CT/MR studies. In fact, in many applications, the medical images obtained from medical instruments are noisy due to imperfection of image capturing devices. Unfortunately, noise is easily mistaken for the useful feature of the image, making the traditional image fusion algorithms invalid, although they can efficiently fuse noise-free images. Thus, it is necessary and challenging to investigate joint fusion and denoising for multimodality medical images. Fusion of images is more suitable for human/machine perception for object detection in the field of remote sensing and diagnosis in case of medical imaging.

The medical imaging field demands more complementary information for disease diagnosis purpose. However, this is not possible using single modality medical images as X-ray computed tomography (CT) is suited only for recognizing bones structure, MRI giving clear information about the soft tissues and so on.

Here, two input images from different image modalities are shown figure 5 and figure 6. First image is a Computed Tomography (CT) image and the second image is a Magnetic Resonance Imaging (MRI). Each image has its own limitation, which can be solved by creating the fused image from two different image modalities as shown in figure 7.

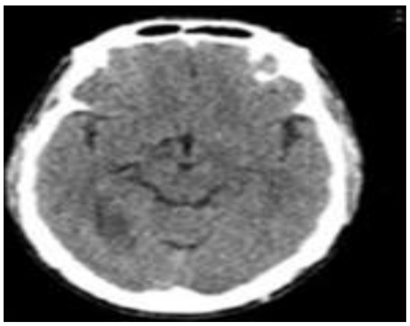

Figure 5: CT image

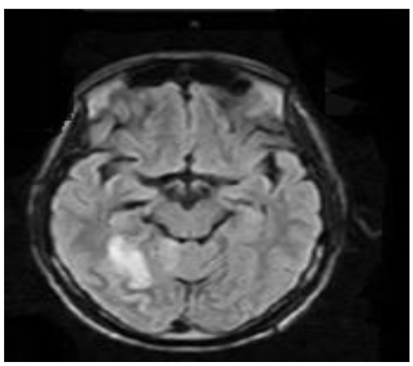

Figure 6: MRI image

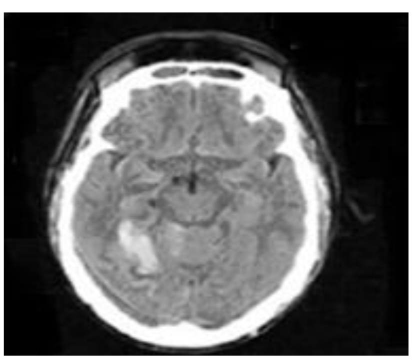

Figure 7: Fused Image

This would lead to improved diagnosis, better surgical planning, more accurate radiation therapy and countless other medical benefits. The main advantage of Image fusion (IF) is integrating complementary, as well as redundant information from multiple images to create a fused image for providing more complete and accurate information.

WAVELET TRANSFORM

Continuous Wavelet Transform

The 1-D continuous wavelet transform is given by:

$$W_f(a, b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \quad \text{------------ (2.3)}$$

The inverse 1-D wavelet transform is given by:

$$x(t) = \frac{1}{C}\int_{0}^{\infty}\int_{-\infty}^{\infty} W_f(a,b)\psi_{a,b}(t)db\frac{da}{a^2} \quad \text{------ (2.4)}$$

$$\text{Where } C = \int_{-\infty}^{\infty} \frac{|\psi\omega)|^2}{\omega} d\omega < \infty$$

$\Psi(\omega)$ is the Fourier transform of the mother wavelet $\Psi(t)$. C is required to be finite, which leads to one of the required properties of a mother wavelet. Since C must be finite, then $\Psi(0) = 0$ to avoid a singularity in the integral, and thus the $\Psi(t)$ must have zero mean. This condition can be stated as $\int_{-\infty}^{\infty} \psi(t)dt = 0$ and known as the admissibility condition.

1-D Discrete Wavelets Transform

The discrete wavelets transform (DWT), which transforms a discrete time signal to a discrete wavelet representation. The first step is to discretize the wavelet parameters, which reduce the previously continuous basis set of wavelets to a discrete and orthogonal / orthonormal set of basis wavelets.

$\psi_{m,n}(t) = 2^{m/2}\,\psi(2^m t - n)$; $m, n \in Z$ such that $-\infty < m, n < \infty$ -------- (2.5)

The 1-D DWT is given as the inner product of the signal x(t) being transformed with each of the discrete basis functions.

$W_{m,n} = < x(t), \psi_{m,n}(t) >$; $m, n \in Z$ --- (2.6)

The 1-D inverse DWT is given as:

$$x(t) = \sum_{m}\sum_{n} W_{m,n}\psi_{m,n}(t)\text{ ; m, n} \in Z\text{-----} \quad (2.7)$$

2-D Wavelet Transforms

The 1-D DWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. As depicted in Figure 8 (c), the four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

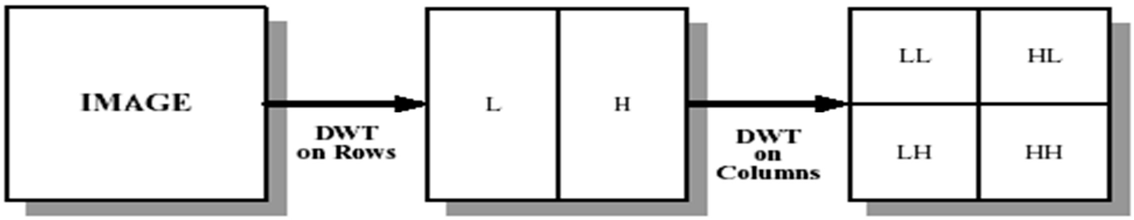

Figure 8: Block Diagram of DWT (a) Original Image (b) Output image after the 1-D applied on Row input (c) Output image after the second 1-D applied on row input

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank.

Figure 9: DWT for Lena image (a) Original Image (b) Output image after the 1-D applied on column input (c) Output image after the second 1-D applied on row input

The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas of figure 9(b), respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2D-DWT output image is shown in figure 9(c).

We can use multiple levels of wavelet transforms to concentrate data energy in the lowest sampled bands. Specifically, the LL sub band in figure 8(c) can be transformed again to form LL2, HL2, LH2, and HH2 sub bands, producing a two-level wavelet transform. An (R-1) level wavelet decomposition is associated with R resolution levels numbered from 0 to (R-1), with 0 and (R-1) corresponding to the coarsest and finest resolutions.

The straight forward convolution implementation of 1D-DWT requires a large amount of memory and large computation complexity. An alternative implementation of the 1D-DWT, known as the lifting scheme, provides significant reduction in the memory and the computation complexity. Lifting also allows in-place computation of the wavelet coefficients. Nevertheless, the lifting approach computes the same coefficients as the direct filter-bank convolution.

Dual Tree Complex Wavelet Transform

In this method, fusion is executed using the masks to remove information from the decomposed structure of DTCWT. Figure demonstrates the complex transform of a signal using two split DWT decompositions: Tree a and Tree b. It can be observed that the DT-CWT structure, involves both real and complex coefficients. It is known that DT-CWT is relevant to visual sensitivity.

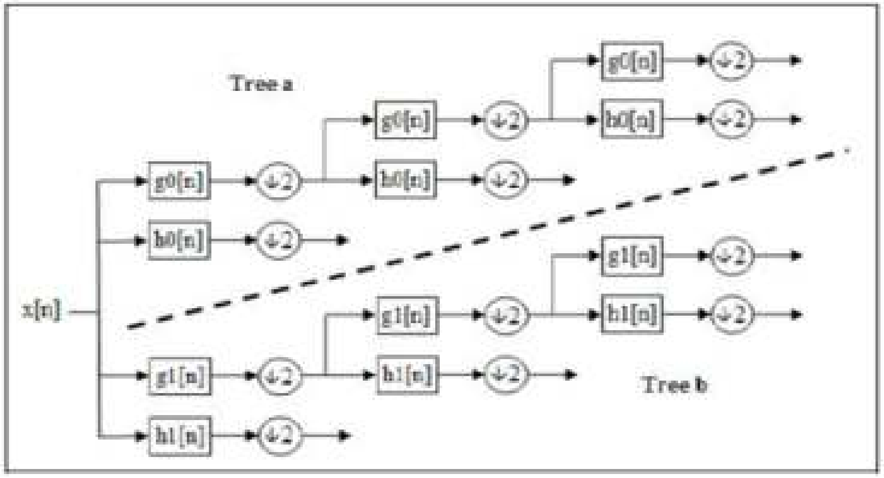

Figure 10: Dual Tree Complex Wavelet Transform

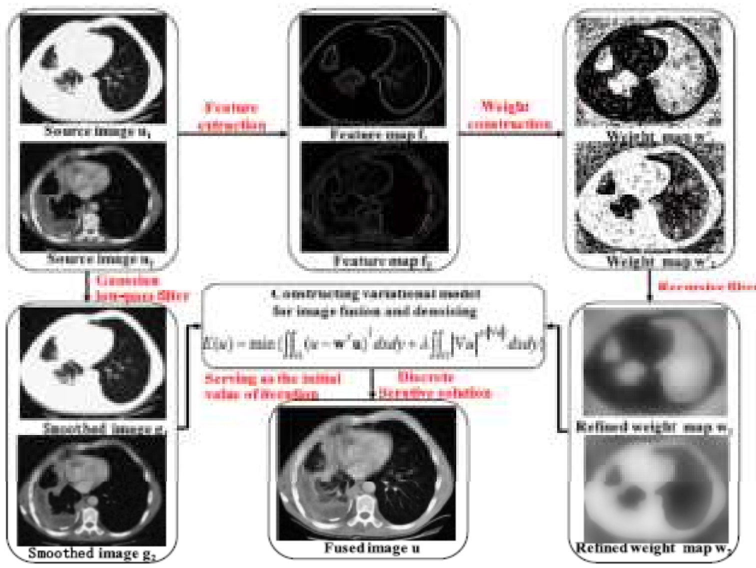

Figure 11: Algorithm flow

CONCLUSION AND FUTURE WORK

The existing methods can produce effective fusion results when the input medical images are noise free. However, if the input medical images are noisy, noise, generally concentrating in high-frequency part of the image, affects the extraction of image details and edge features. Hence, medical image fusion and denoising is a challenging problem.

Thus, the proposed method is more robust to noise. Several advantages of the proposed image fusion approach are highlighted as follows.

1) An effective variation model is proposed to estimate the fused medical image. The proposed fusion framework not only can be used for noisy multimodal medical image fusion, but also can be used for noise-free medical image fusion.

2) A multiscale alternating sequential filter is first innovatively integrated into the multimodal medical image fusion framework by recursive filtering-based weight map technique. It can effectively extract the main characteristics from noisy input medical images, preventing noise interference.

3) TV is developed by constructing an adaptive fractional order p ($|\nabla u|$) instead of parameter 1, called AFOTV. Through the isotropic diffusion in the flat part of the image andffusion along the tangential direction of the

edge, noise is suppressed while avoiding the staircase effect.

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