



A novel method of multimodal medical image fusion using fuzzy transform [☆]



Meenu Manchanda ^{a,*}, Rajiv Sharma ^b

^a University Institute of Engineering & Technology, Maharshi Dayanand University, Rohtak, Haryana, India

^b Northern India Engineering College, New Delhi Guru Gobind Singh Indraprastha University (GGSIPU), New Delhi, India

ARTICLE INFO

Article history:

Received 12 May 2015

Revised 17 March 2016

Accepted 22 June 2016

Available online 27 June 2016

Keywords:

Medical imaging

Image fusion

F-transform (FTR)

Objective measures

ABSTRACT

Combined analysis of medical images obtained from multiple imaging modalities is extensively used by clinical professionals for quick diagnosis and treatment of critical diseases. Therefore, multimodal medical image fusion, that fuses information from different medical images into a single fused image, have gained potential interest of researchers in recent years. In this paper, a novel method of multimodal medical image fusion using fuzzy-transform (FTR) is proposed. FTR based fusion helps in preservation as well as effective transfer of detailed information present in input images into a fused image. To evaluate and prove better performance of the proposed fusion method, a number of experiments and comparisons with other existing methods of fusion have been carried out in this paper. Experimental results and comparative analysis prove that the proposed fusion algorithm is effective and generates better results.

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1. Introduction

In recent years, medical imaging is being used at large by clinical professionals for explicit diagnosis and treatment of diseases. Various imaging modalities like CT, MRI, SPECT, PET have allowed physicians to look into the complex body parts that are located in the interior of human body. However, these imaging modalities usually provide complementary information. For example, MRI and CT images provide only anatomical information whereas PET and SPECT images provide only functional information. To offer higher diagnostic accuracy, many studies prefer combined analysis of images in respect of the same patient obtained using different modalities [1]. This requirement of combined analysis led to the development of multimodal medical image fusion.

Image fusion is the process of combining two or more images of same modality or different modalities to produce a single fused image which is more informative than any of the individual input image. The main aim of image fusion is to preserve all salient, interrelated and relevant information present in input images without introducing any inconsistency, noise and artifact in the fused image. Image fusion not only provides enhanced information but also minimizes the storage cost by minimizing the memory requirement for storage of multiple input images to that needed

for storing only a single fused image. Due to unique and improved representation of information, image fusion is used in many medical applications [2,3] such as oncology, neurology, cardiology, and radiation therapy.

So far, many image fusion algorithms have been developed in literature. These algorithms can be categorized [4] into pixel-level, feature-level and decision-level image fusion algorithms. Pixel-level image fusion algorithms [5] fuse directly the raw input images based on their pixel intensities or on arbitrarily small regions of pixels. Feature-level fusion algorithms [6] fuse input images using their salient features such as edges and line segments. These algorithms assume that correspondence among features present in input images is usually known and are very much image dependent. Decision-level algorithms [7] fuses image descriptions directly, either in the form of probabilistic variables or in the form of relational graphs to produce a high quality fused image. These methods however completely rely on correct recognition of image descriptors and are very much application dependent. Compared to feature-level and decision-level image fusion algorithms, pixel-level algorithms [8] are capable of retaining most of the image information and are not only easy to implement but also computationally more efficient and are therefore preferred for multimodal medical image fusion.

Pixel-level image fusion can either be done in the spatial-domain or in the transform-domain. In spatial domain, individual pixels are fused linearly or non-linearly according to pre-defined fusion rules. Commonly used pixel-level image fusion algorithms are averaging based fusion and select maxima based fusion.

[☆] This paper has been recommended for acceptance by M.T. Sun.

* Corresponding author.

E-mail addresses: meenumanchanda73@gmail.com (M. Manchanda), rsap70@rediffmail.com (R. Sharma).

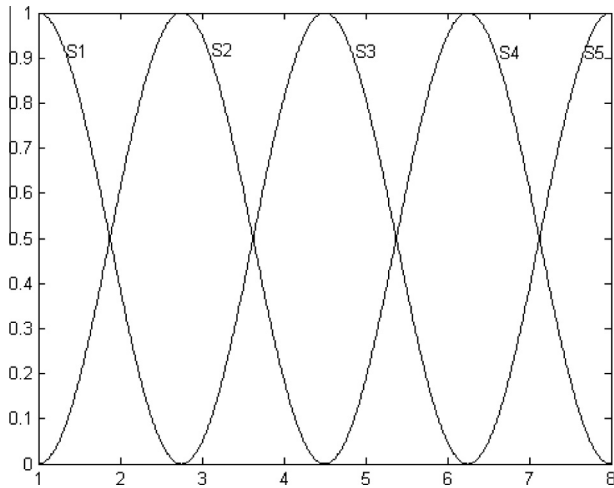


Fig. 1. An example of uniform fuzzy partition based on sinusoidal membership function.

However, these pixel-level fusion schemes [9] perform the operation right on the pixels of the input images and hence often have serious side effects such as reducing the contrast of image features. Other used spatial-domain fusion methods [4] are principal component analysis based (PCA), intensity-hue-saturation (IHS) based and Brovey transform based fusion methods. However, these spatial-domain methods result in reduced SNR and some spatial degradation in the fused image [10] and hence not suitable for medical applications. To overcome the drawbacks of

spatial-domain pixel-level image fusion methods, researchers have performed pixel-level image fusion in transform-domain. In these methods, the images to be fused are first converted into transform-domain and then fusion takes place in this domain. Finally, inverse transformation of fusion result produces a high quality of fused image. Majority of transform-domain fusion methods are based on multiscale approach that led to the development of pyramid transform based image fusion and wavelet transform based image fusion. However, pyramid transform based fusion [11] introduces some false edges into the fused image and may result in incorrect diagnosis and is therefore not preferred for clinical purposes. Wavelet transform [12] decomposes images into multiscale representation using wavelet and scaling functions. Standard wavelet transform i.e. discrete wavelet transform (DWT) fuses very little information along the three directions: horizontal, vertical and diagonal and is also shift-variant and therefore introduces some inconsistencies and artifacts in the fused image. Drawbacks of real wavelet transforms led to the development of complex wavelet transform [13]: dual tree complex wavelet transform (DT-CWT) and Daubechies complex wavelet transform (DCxWT). Complex wavelet solves the problem of limited directional information by extending the directional support from three to six (both magnitude and phase information) along the three directions: horizontal, vertical and diagonal), but this results in increased computational complexity and large memory requirement. Multiscale geometric analysis tool such as Curvelet [14], Shearlet [15], Non-Subsampled Contourlet Transform (NSCT) [16] were also developed for fusing multiple images.

Since fuzzy logic has revealed to provide a basis for the approximate description of different functions, researchers have also developed image fusion methods based on fuzzy logic [17–19].

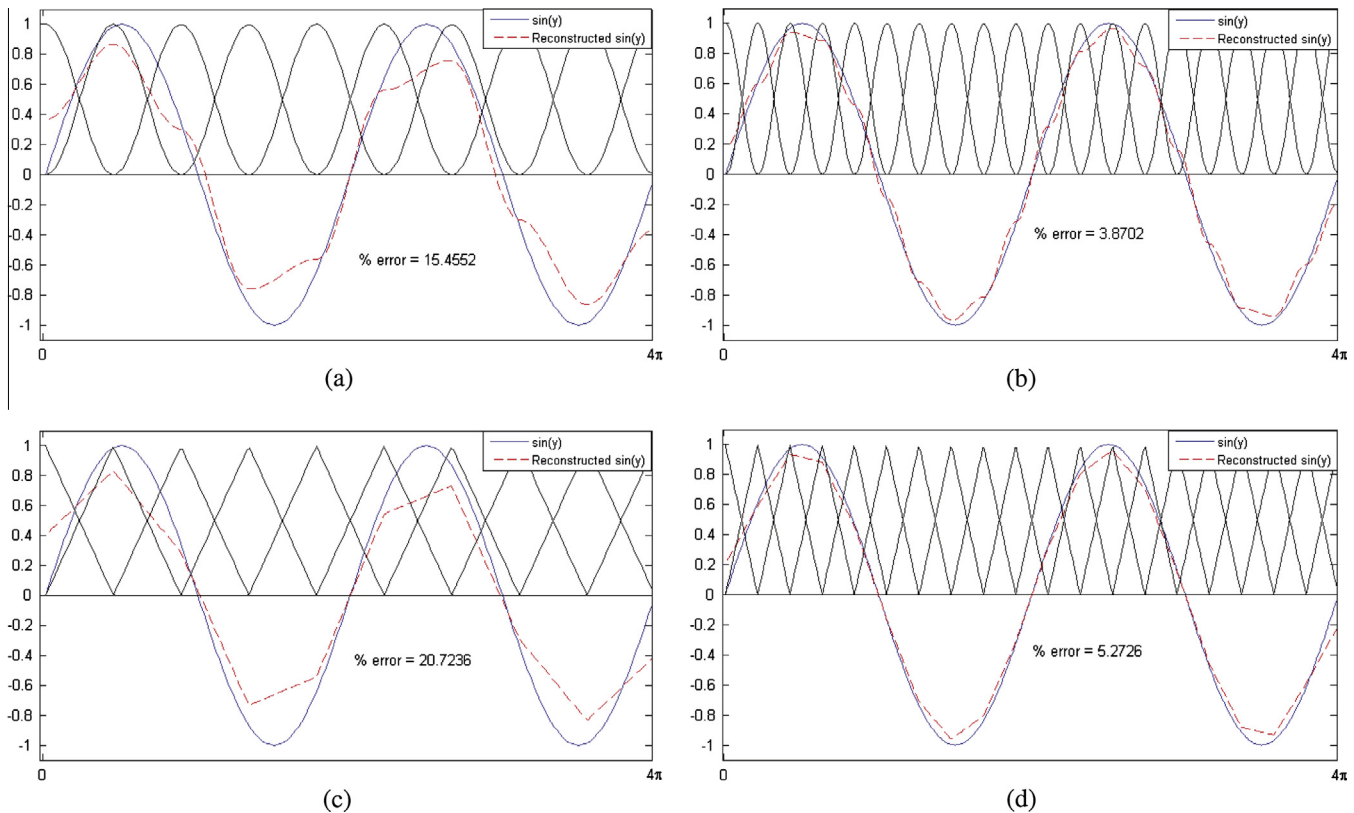


Fig. 2. $\sin(y)$ and its reconstruction using (a) 10 uniform sinusoidal shaped membership functions, (b) 20 uniform sinusoidal shaped membership functions, (c) 10 uniform triangular shaped membership functions and (d) 20 uniform triangular shaped membership functions.

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