Journal of Visual Communication and Image Representation 51 (2018) 76–94

Contents lists available at ScienceDirect

Journal of Visual Communication and Image Representation

journal homepage: www.elsevier.com/locate/jvci

# An improved multimodal medical image fusion algorithm based on 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, Guru Gobind Singh Indraprastha University (GGSIPU), New Delhi, India

ARTICLE INFO

*Keywords:*
Multimodal medical image fusion
Fuzzy transform
Fusion performance measures

ABSTRACT

Multimodal medical image fusion has become a powerful tool in clinical applications. The main aim is to fuse different multimodal medical images, obtained from different imaging modalities, into a single fused image that is extensively used by the physicians for explicit diagnosis and treatment of diseases. In this paper, an improved multimodal medical image fusion algorithm based on fuzzy transform (FTR) is proposed. The core idea behind the proposed algorithm is to improve the performance of multimodal medical image fusion algorithm by taking into consideration the error images obtained using FTR pair. Subjective as well as objective evaluations demonstrate that the fusion quality in terms of edge strength, standard deviation, feature mutual information, fusion factor, feature similarity and structural similarity has significantly improved in the proposed algorithm as compared to other state-of-art multimodal medical image fusion algorithms.

## 1. Introduction

Over the last few years, medical imaging has developed from a state of infancy to a state of maturity. Various imaging modalities such as CT, MRI, PET and SPECT have enabled radiologists to look into the complex body parts located in the interior of human body. However, different imaging modalities provide highly complementary information. For example, CT and MRI provide images with excellent anatomical information and precise localization but cannot provide functional information. Whereas, PET and SPECT provide images containing highly functional information that is required for detecting metabolic abnormalities but cannot provide the anatomical details required for precise localization. Therefore, in order to obtain a single medical image that can provide both the anatomical information as well as the functional information, medical images of different modalities are required to be fused. This requirement, of obtaining a single fused medical image that possesses most of the relevant information, has attracted the attention of researchers towards multimodal medical image fusion.

Multimodal medical image fusion aims to combine information, from multiple medical images of same modality or of different modalities, to provide a single fused image. The fused image so obtained provides more accurate information to the physicians for explicit diagnosis and treatment of diseases. Multimodal medical image fusion has wide range of applications due to its compact and accurate representation of information. For instance, fusion of CT and PET images not only help oncologists to plan and monitor cancer treatment but also help cardiologists to assess the presence and extent of coronary artery disease [1]. Fusion of SPECT and CT images provide enhanced localization and staging of neuroendocrine tumor [2]. Fusion of MRI and CT is used for neuronavigation in skull-base surgery [3]. Further, fusion of PET and MRI images can be used to detect and follow variety of diseases from neurodegenerative disorders to cardiovascular diseases [4].

Many image fusion algorithms have been developed in literature [5,6]. These algorithms can be broadly grouped into three categories [7]: pixel-level, feature-level and decision-level. Pixel-level algorithms can preserve most of the original information as compared to feature-level and decision-level algorithms [8,9]. Further, pixel-level algorithms are easy to implement and are computationally more efficient and are therefore preferred for multimodal medical image fusion. The commonly used pixel-level image fusion algorithms [10] are average based fusion algorithm and select maxima based fusion algorithm. However, these algorithms often lead to undesirable side effects such as reduced contrast [11]. Other pixel-level image fusion algorithms are principal component analysis (PCA), intensity hue saturation (IHS) and Brovey transform (BT). However, the fused image obtained using these algorithms suffer from high spatial distortion and low SNR [12] and are therefore not preferred for medical image fusion. To overcome these

☆ This paper has been recommended for acceptance by Zicheng Liu.

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

https://doi.org/10.1016/j.jvcir.2017.12.011
Received 24 December 2016; Received in revised form 12 December 2017; Accepted 25 December 2017

drawbacks, multimodal medical image fusion algorithms based on multiresolution transforms have been developed by many researchers. The most commonly used multiresolution transforms include pyramid transforms and wavelet transforms. Pyramid transforms include Laplacian pyramid, Gaussian pyramid, contrast pyramid, ratio of low pass pyramid and morphological pyramid. However, pyramid transforms [13] fail to introduce spatial orientation selectivity in the decomposition process and occasionally introduce many undesired edges in the fused image. Wavelet transforms include discrete wavelet transform (DWT), lifting wavelet transform (LWT), Daubechies complex wavelet transform (DCxWT) and dual tree complex wavelet transform (DTCWT). However, wavelet transforms capture only limited directional information. Further, wavelets based decomposition is good at isolated discontinuities but fail at edges and textured regions [14,15]. In order to take into account the intrinsic geometrical structure of images, several multiscale geometric analysis tools such as curvelet transform [16], ripplet transform [17], contourlet transform, non-subsampled contourlet transform (NSCT) [18] and shearlet transform [19] have been used by many researchers for fusion of multiple images. Moreover, artificial neural networks based image fusion algorithms also exist in literature. However, the performances of neural network based algorithms depend upon the number of neurons in the hidden layer [20–22].

**Motivation**: Apart from the above mentioned algorithms, researchers have also developed fuzzy logic based image fusion algorithms [23,24]. Fuzzy logic has the ease of implementation and the ability to deal with the uncertainty and non-linearity. Motivated from fuzzy logic and system modeling, Perfilieva et al. [25] proposed fuzzy transform (FTR) that associates an original continuous or discrete real function into a reduced set of real samples, thereby, making complex computations easier. Researchers have successfully used FTR in developing image fusion algorithms [26,27] as FTR possesses various important properties such as ability to provide better approximation, ability to preserve image edges, noise removing capability and smoothing ability. Multimodal medical image fusion algorithm based on FTR has already been proposed in [26] and produced good fusion results. However, the algorithm presented in [26] does not take into account the loss of information that is contained in the error images, obtained using FTR pair (i.e. FTR and its inverse transform). The error image is the difference between the original image and the reconstructed image obtained using FTR. Considering the accuracy required in medical field, the loss of information contained in error image cannot be neglected. Thus, in order to produce a highly informative fused medical image that takes into account the error images, an improved multimodal medical image fusion algorithm based on FTR is proposed in the paper.

**Contribution**: Considering the accuracy required in medical field, an improved multimodal medical image fusion algorithm based on fuzzy transform is proposed in the paper. The proposed algorithm produces highly informative fused medical images by taking into account the loss of information that is contained in the error images obtained using FTR pair. The proposed algorithm has been performed on different datasets of medical images. Results obtained using the proposed algorithm has been compared, subjectively as well as objectively, with recent state-of-art multimodal medical image fusion algorithms. The fused images obtained using proposed algorithm have better visual quality with sharp and smooth edges, fine texture and high clarity and these images are also free from the problem of artifacts.

The rest of the paper is organized as follows: the detail explanation of fuzzy transform is provided in Section 2, the proposed multimodal medical image fusion algorithm is presented in Section 3, the details of various measures used for evaluating the performance of the proposed fusion algorithm objectively are given in Section 4, experimental results are discussed and compared with the results of recent multimodal medical image fusion algorithms in Section 5 and finally, conclusion is drawn in Section 6.

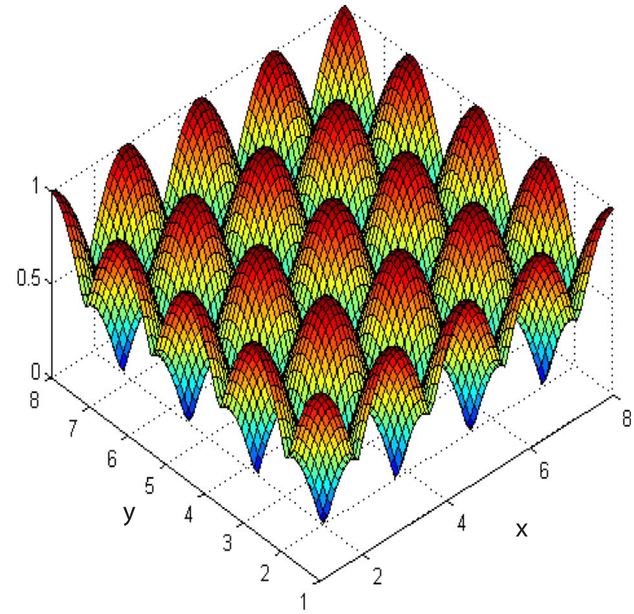


**Fig. 1.** An example of two-dimensional uniform fuzzy partition based on sinusoidal membership functions.

## 2. Fuzzy transform

Fuzzy transform (FTR), introduced by Perfilieva [25], is a powerful transformation technique that transforms an original continuous function or a discrete function into a finite set of real samples, by projecting the function on a fuzzy partition of its domain. It converts a complex function into a finite dimensional vector thereby making complex computations easier. It has been successfully used in many applications such as image processing [27,28], solving differential and integral equations [29,30], noise removal [31], data analysis [32], and time-series analysis [33]. In image processing, FTR has been applied to image compression [34,35], image reconstruction [36] and image fusion [37,26]. These applications are successful due to various properties and advantages of FTR [38,26,39] such as better approximation, shift invariance, noise removing abilities, smoothing abilities, capability of preserving image features, low computational complexity and faster implementation.

**Fuzzy partition of the universe:**

Let $[a,b]$ be a closed interval consisting of $M$ ($M \geq 2$) fixed nodes such that $a = x_1 < x_2 < \cdots < x_M = b$. The fuzzy sets $S_1,S_2,...,S_M$ with membership functions $S_1(x),S_2(x),...,S_M(x)$ constitutes a fuzzy partition of $[a,b]$ if the following conditions hold true, for every $i = 1,2,...,M$:

1. $S_i$: $[a,b] \rightarrow [0,1]$ and $S_i(x_i) = 1$.
2. $S_i(x)$ is continuous over $[a,b]$, as well as, strictly increasing on $[x_{i-1},x_i]$ and strictly decreasing on $[x_i,x_{i+1}]$.
3. $S_i(x) = 0$ for $x \notin (x_{i-1},x_{i+1})$.
4. For all $x \in [a,b]$, Ruspini condition [40] holds true i.e. $\sum_{i=1}^{M} S_i(x) = 1$.

If the nodes $x_1,x_2,...,x_M$ are equidistant, then the fuzzy partition formed is uniform if two additional conditions are met:

1. $S_i(x_i - x) = S_i(x_i + x)$ for all $x \in [0,\Delta]$ where $\Delta = (x_M - x_1)/(M-1)$ and $i = 2,3,...,M-1$.
2. $S_{i-1}(x) = S_i(x-\Delta)$ for all x and $i = 2,3,...,M-1$.

According to [41], uniform fuzzy membership functions retain useful properties of original functions and are therefore generally preferred. The following expressions represent the generic fuzzy partitions