Chapter 50
Effective and Accurate Diagnosis Using Brain Image Fusion

Sivakumar Rajagopal
https://orcid.org/0000-0001-8486-7960
Vellore Institute of Technology, India

Babu Gopal
Velammal Institute of Technology, India

ABSTRACT

Medical imaging techniques are routinely employed to create images of the human system for clinical purposes. Multi-modality medical imaging is a widely used technology for diagnosis, detection, and prediction of various tissue abnormalities. This chapter is focused on the development of an improved brain image processing technique for the removal of noise from a magnetic resonance image (MRI) for accurate image restoration. Feature selection and extraction of MRI brain images are processed using image fusion. The medical images suffer from motion blur and noise for which image denoising is developed through non-local means (NLM) filtering for smoothing and shrinkage rule for sharpening. The peak signal to noise ratio (PSNR) of improved curvelet based self-similarity NLM method is better than discrete wavelet transform with an NLM filter.

INTRODUCTION

The imaging process in medicine is mainly used to provide visual information about the internal parts to provide better decision making for clinical purposes and further procedures (Anjali Wadhwa et al., 2019). An important advantage is the extraction of prior knowledge for the prevention of diseases. Nowadays the most frequent and severe syndrome created by Alzheimer's disease, which affects the human memory and thinking process to lead everyday life (Yujun Hou et al., 2019). Multimodal Image acquisition is generally affected by the faulty instrument noise, manual handling of medical instruments,

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the imperfect process followed in the acquisition procedure and improper fusing methods used, and due to the error introduced by the transmission process and the type of compression techniques used for transmission (Mzoughi et al., 2019).

Magnetic Resonance Imaging (MRI) image acquisition depends on the various parameters. It depends on the strength of the magnet used to generate static field, the patient size, handling the of the machine, selection radio frequency (RF) coil, frequency of radiofrequency coil, pulse sequence used to transmit and receive RF pulse, positioning of gradient coils for slice selection, various parameters set for acquisitions process, the type reconstruction technique (Gudjartsson & Patz, 1995).

Image restoration often requires the decomposition of a degraded image as approximation and details. In this research work, smoothening by improved Non-Local Means Filter (NLM) (Buades et al., 2011) and sharpening by Soft thresholding shrinkage rule (Chang et al., 2000) play the role of decomposition. The decomposition of degraded image restores line discontinuities by employing Fast Discrete Curvelet Transform.

The three-dimensional imaging can be used to identify the depth information which can be realized by the vision system (Cootes et al., 1992). The anatomical variations in the different individual's images can be analyzed using brain image registration. It is useful to combine information from different sources, analyze the individual variations, localizing and detecting various diseases and fuse the images for better decision making (Babu & Sivakumar, 2017). The similarity-based brain image registration is initiated for minimizing geometric distortion.

Multimodal fusion techniques applied to brain image analysis is used to reduce the redundant information and increase the required details from different imaging techniques. A multimodal image fusion provides clear feature details to enable the clinician to make an efficient decision for disease analysis Data fusion in medical images is introduced to merge multimodal (anatomical and structural information) and multi-patient images for the identification of structures (Piao et al., 2019; Padmavathi et al., 2019). Image fusion is focused on data combination, identification of anatomical structure based on image geometrical features and statistical image features (Barillot et al., 1993). The main drawbacks are poor resolution and mis-registrations which are overcome by improved curvelet based self-similarity measured in MRI.

A fuzzy-based algorithm proposed by Stelios Krinidis and Vassilios Chatzis (2010) integrates both the gray level and spatial level details. The performance of the integrating process can be enhanced by fuzzy local information C Means (FLICM) (Zhang et al., 2019). The FLICM is mainly used to retain most of the image details and make image insensitive to noises. The image segmentation and clustering process can be made effective using the Fuzzy based. They utilize a fast, generalized, Fuzzy C Means (FGFCM) algorithm to integrate both the gray level and spatial level image information. In their research work, the improved curvelet based NLM method is applied in Fuzzy C Means (FCM) to classify aging syndrome from due to Alzheimer's disease.

The majority of older people are suffering from Alzheimer's disease. It is also affecting the people in the age group between the forties and fifties. The effect of the disease becomes more severe at the later stages. It is a degenerative disease, where symptoms gradually worsen over several years. The effect of disease on memory loss at the initial stage is less, but it becomes worse at a later stage, individuals finding it difficult to respond to any conversation. The progress of the disease can be classified into four different levels (Robert Katzman et al., 1988). The early level does not make any significant change in everyday routine and it is known as Mild Cognitive Impairment (MCI) (Peterson, 2004). The cognitive loss and decrease in independence are increased in the second and third levels of the disease and are

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