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A Survey on Multimodal Medical Image Fusion

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Abstract: *Multimodal medical image fusion (MIF) is a method ofextracting complementary information fromdifferent sourceimages and combining them into a resultant image. Theintegration of multimodality medical images can providemore complete pathological information for doctors, which greatly helps their diagnosis and treatment.In this paper a survey is carried out over the approaches proposed in earlier for medical image fusion. The complete approaches are categorized into various classes like Morphological methods, knowledge based methods, wavelet based methods, neural network based methods, fuzzy logic based methods, contourlet based methods and the non-subsampled contourlet transform based methods.*

Keywords: *Medical image fusion, Morphology, Wavelet, contourlet, ANN, fuzzy logic.*

I. Introduction

The rapid and significant advancements in medical imaging technologies and sensors, lead to new uses of medical images in various healthcare and bio-medical applications including diagnosis, research, treatment and education etc. Different modalities of medical images reflect different information of human organs and tissues, and have their respective application ranges. For instance, structural images like magnetic resonance imaging (MRI), computed tomography (CT), ultrasonography (USG) and magnetic resonance angiography (MRA) etc., provide high-resolution images with excellent anatomical detail and precise localization capability. Whereas, functional images such as position emission tomography (PET), single-photon emission computed tomography (SPECT) and functional MRI (fMRI) etc., provide low-spatial resolution images with functional information, useful for detecting cancer and related metabolic abnormalities. A single modality of medical image cannot provide comprehensive and accurate information. Therefore, it is necessary to correlate one modality of medical image to another to obtain the relevant information. Moreover, the manual process of integrating several modalities of medical images is rigorous, time consuming, costly, subject to human error, and requires years of experience. Therefore, automatically combining multimodal medical images through image fusion (IF) has become the main research focus in medical image processing [1], [2].

In this paper a survey is carried out over the approaches proposed in earlier for medical image fusion. The complete approaches are categorized into various classes like Morphological methods, knowledge based methods, wavelet based methods, neural network based methods, fuzzy logic based methods, contourlet based methods and the non-subsampled contourlet transform based methods. Rest of the paper is organized as follows: section II outlines the complete details about the literature survey and section III concludes the paper.

II. Literature Survey

Generally, any image fusion method involves two phases such as image registration [6] and image fusion [6]. The registration of the images requires a method to correct the spatial misalignment between the different image data sets that often involve compensation of variability resulting from scale changes, rotations, and translations. The problem of registration becomes complicated in the presence of inter-image noise, missing features and outliers in the images. On the other hand, the fusion of the features involve the identification and selection of the features with a focus on relevance of the features for a given clinical assessment purpose.

A. Morphological Methods

The morphology operators has been explored by image processing community for long, and the concept is used by the medical imaging community to detect spatially relevant information from the medical images. The morphological filtering methods for medical image fusion have been applied, for example, in brain diagnosis [47, 15, 49]. An example of modalities used in morphology based fusion can be seen in the fusion of CT and MR images [15, 16, 17]. In such applications, the morphology operators depend heavily on the structuring operator that defines the opening and closing operations. A calculated sequencing of the operations results in the detection of scale specific features. These features from different modalities can be used in for image fusion. The inaccuracies of detecting the features are high when the images are prone to noise and sensing errors. The operators such as averaging, morphology towers, K-L transforms and morphology pyramids are used for achieving the data fusion. These methods are highly sensitive to the inter-image variability resulting from outliers, noise, size and shape of the features.

B. Knowledge based methods

In medical imaging, there are several instances where the medical practitioner's knowledge can be used in designing segmentation, labeling and registration of the images. Generally, the domain-dependent knowledge is needed to set constraints on region-based segmentation and to make explicit the expectation of the appearance of the anatomy under the imaging modality at the stage of grouping the detected regions of interest. There are a range of applications where the domain-dependent knowledge is useful for image fusion such as for segmentation [18], micro-calcification diagnosis [19], tissue classification [20], brain diagnosis [20], classifier fusion [21], breast cancer tumor detection [21] and delineation & recognition of anatomical brain object [18]. The knowledge based systems can used in combination with other methods such as pixel intensity [19]. These methods place a significant amount of trust in the medical expert in labeling and identifying the domain knowledge relevant to the fusion task. The advantage is the ability to benchmark the images with the known human vision standards, while the drawback is the limitations imposed by human judgment in images that are prone to large pixel intensity variability. The use of preprocessing techniques in images can improve the imaging quality and increase the accuracy of ground truths.

C. Wavelet based methods

The primary concept used by the wavelet based image fusion [26-27], [59, 61-69], [40], [70-84], [29, 30, 32-34] is to extract the detail information from one image and inject it into another. The detail information in images is usually in the high frequency and wavelets would have the ability to select the frequencies in both space and time. The resulting fused image would have the "good" characteristics in terms of the features from both images that improve the quality of the imaging. There are several models for injection, the simplest being substitution. There exist several mathematical models for injection, such as simple addition operation and aggregator functions to more complex mathematical models. Irrespective of the models used, for practical reasons, the image resolution remains same before and after the fusion. In addition, the image resolution of the reference image enforces the required number of multiple levels of decomposition, such that a high resolution image would require more number of decomposition levels than a low resolution image. There are several applications of the wavelets in image fusion such as medical image pseudo coloring [85], super resolution [26], medical diagnosis [27, 28, 29, 30], feature level image fusion [31], lifting scheme [31], segmentation [32], 3D conformal radiotherapy treatment planning [33] and color visualization [34].

The feature level improvements on the images by combining wavelets with other techniques have proved to be useful for wavelet based image fusion. The most prominent approach of wavelet image fusion is with neural network [27, 28, 40], where the neural network often takes the roles of feature processing and wavelets take the role of a fusion operator. Similar to neural network, the kernel based operators such as support vector machines (SVM) can be used along with wavelets to achieve image fusion at feature levels [66]. Considering wavelets as a fusion operator, several feature processing methods can be combined such as wavelet-SVM [66], wavelet-texture measure [29], wavelet-MRA [30, 67], wavelet-self adaptive operator [69], wavelet-resolution-entropy [70, 72], nonlinear wavelet-shift invariant imaging [71], ICA-wavelet [86], wavelet-edge feature [75], wavelet-genetic [59], wavelet-contourlet transform [81], neuro-fuzzy-wavelet [82] and wavelet-entropy [84].

D. Neural Network based methods

Artificial neural networks (ANN) are inspired from the idea of biological neural network having the ability to learn from inputs for processing features and for making global decisions. The artificial neural network models require an input training set to identify the set of parameters of the network referred to as weights. The ability of the neural network models to predict, analyze and infer information from a given data without going through a rigorous mathematical solution is often seen as an advantage. This makes the neural network attractive to image fusion as the nature of variability between the images is subjected to change every time a new modality is used. The ability to train the neural network to adopt to these changes enable several applications for medical image fusion such as solving the problems of feature generation [36], classification [36], data fusion [36, 19, 27], image fusion [37, 38, 27, 39, 40, 41, 42, 43], micro-calcification diagnosis [19], breast cancer detection [38, 44, 45], medical diagnosis [27, 28, 42], cancer diagnosis [46], natural computing methods [87] and classifier fusion [45]. Although ANN offers generality in terms of having the ability to apply the concept of training, the robustness of ANN methods is limited by the quality of the training data and the accuracy of convergence of the training algorithm. In order to improve the quality of the features and thereby to improve the robustness of the ANN, hybrids of neural networks and sequential processing with other fusion techniques can be employed. Some of examples of these are wavelet-neural network [27, 28, 40], neural-fuzzy [41, 43], fuzzy-genetic-neural network-rough set [87] and SVM-ANN-GMM [45]. It is practically very difficult to prove the effectiveness of these combinations across all the different imaging modalities as these approaches are skewed towards the quality of the images selected for training that can vary significantly from one imaging condition to another.

E. Fuzzy Logic based Methods

The conjunctive, disjunctive and compromise properties of the fuzzy logic have been widely explored in image processing and have proved to be useful in image fusion. The fuzzy logic is applied both as a feature transform operator or a decision operator for image fusion [47-60], [87-92], [82]. There are several applications of fuzzy logic base image fusion such as brain diagnosis [47, 48, 49, 50], cancer treatment [51], image segmentation and integration [51-52], maximization mutual information [53], deep brain stimulation [54], brain tumor segmentation [55], image retrieval [56-57], spatial weighted entropy [56], feature fusion [56], multimodal image fusion [41, 58, 59], ovarian cancer diagnosis [60], sensor fusion [88], natural computing methods [87] and gene expression [89, 90].

The selection of membership functions and fuzzy sets that result in the optimal image fusion is an open problem. The improvements of feature processing and analysis can be improved to fit the fuzzy space better when combined with probabilistic approaches such as fuzzy-neural network [41, 43], fuzzy-genetic-neural network-rough set [87], fuzzy-probability [89] and neuro-fuzzy-wavelet [82].

F. Contourlet Based Methods

Contourlet transform is a new image analysis tool, which is anisotropic and has good directional selectivity. So it can accurately represent the image edges information in different scale and different direction frequency sub-bands, and some fusion algorithms based on the Contourlet transform have been proposed in recent years. 2-D separate wavelet is good at isolating the discontinuities at object edges, but it can only capture limited directional information. Contourlet transform can effectively overcome the disadvantages of wavelet. Contourlet transform is a multi-scale and multi-direction framework of discrete image. In the transform, the multiscale analysis and the multi-direction analysis are separated in a serial way. The Laplacian pyramid is first used to capture the point discontinuities, and then followed by a directional filter bank (DFB) to link point discontinuities into linear structures. The combination of a Laplacian pyramid and a directional filter bank is a double filter bank structure. The basis function of contourlet transform has 2l directions and flexible ratio of length to width. Contourlet can decompose image into 2l directional subbands, which means that the directions of each level are arbitrary and contourlet is anisotropy. So contourlet can achieve the optimal approximation rate for representing any 2-D piecewise smooth contours.

To overcome these shortcomings of the wavelet transform, Do and Vetterli [22] proposed Contourlet transform which can give the asymptotic optimal representation of contours and has been successfully used for image fusion. However, the up- and down-sampling process of Contourlet decomposition and reconstruction results in the Contourlet transformlacking shift-invariance and having pseudo-Gibbs phenomena in the fused image [23]. Ali et al. performed the combination of CT and MRI by the curvelet transforming [3] and Yang et al. proposed a fusion algorithm for multimodal medical images based on contourlet transform (CT) [4].

G. Non-subsampled Contourlet transform based Methods

The contourlet transform is a multidirectional and multiscale transform that is constructed by combining the Laplacian pyramid with the directional filter bank (DFB). The pyramidal filter bank structure of the contourlet transform has very little redundancy. However, designing good filters for the contourlet transform is a difficult task. In addition, due to downsamplers and upsamplers present in both the Laplacian pyramid and the DFB, the contourlet transform is not shift-invariant. An overcomplete transform is proposed that that is called as non-subsampled contourlet transform (NSCT). Transform divided into two shift-invariant parts: 1) a non-subsampled pyramid structure that ensures the multiscale property and 2) a non-subsampled DFB structure that gives directionality. The combinations of these two can preserve more details in source images and further improve the quality of fused image. The multiscale property of the NSCT is obtained from a shift-invariant filtering structure that achieves subband decomposition similar to that of the Laplacian pyramid. This is achieved by using two-channel non-subsampled 2-D filter banks. The directional filter bank of Bamberger and Smith [25] is constructed by combining critically-sampled two-channel fan filter banks and resampling operations. The result is a tree-structured filter bank that splits the 2-D frequency plane into directional edges. A shift-invariant directional expansion is obtained with a non-subsampled DFB (NSDFB). Main motivation is to construct a flexible and efficient transform targeting applications where redundancy is not a major issue .The NSCT is a fully shift-invariant, multiscale, and multi-direction expansion that has a fast implementation. The design problem is much less constrained than that of contourlets. This enables NSCT to design filters with better frequency selectivity there by achieving better sub band decomposition. NSCT provide a framework for filter design that ensures good frequency localization in addition to having a fast implementation through ladders steps. The NSCT has proven to be very efficient. Li and Wang employed the non-subsampled contourlet transform (NSCT) for thecombination ofMRI and SPECT in [5]. Compared with other multiscale decomposition, NSCT proposed by da Cunha et al. [6] is a more prominent tool and it has been successfully used in image denoising [7] and image enhancement [8]. Because of its properties of multiscale, multi-direction, and the full shift-invariance, when it is used for image decomposition, it can capture the higher dimensional singularities such as edges and contours that cannot be effectively represented by the wavelets and avoid pseudo-Gibbs phenomena that presents in the contourlet transform. Specifically, when it is used for image fusion, the impacts of misregistration on the fused results can also be reduced effectively [9] and the correspondence between different subbands is easily found. Therefore, NSCT is more suitable for medical image fusion. Although medical image fusion methods based NSCT have achieved good results [10, 11, 12, 13, 14], most existing fusion methods neglect the dependencies between subband coefficients at the interscale and intrascale. However, the dependencies between decomposition coefficients commonly exist. What's more, the characteristics show non-Gaussian distribution and have the heavy tailed phenomenon. Thus making full use of the statistical dependencies between subband coefficients will effectively improve fusion performance.Cunha et al. [24] proposed the non-subsampled Contourlet transform (NSCT) based on Contourlet transform. This method inherits the advantages of Contourlet transform, while possessing shift-invariance and effectively suppressing pseudo-Gibbs phenomena.

H. Other Methods

There are several methods that are based on dimensionality reduction techniques such as independent component analysis (ICA) [86, 93] and principal component analysis (PCA) [94-97]. These dimensionality reduction techniques often find their use as feature processing methods and are used in combination with techniques such as ones based on wavelets [86]. A first order fusion of volumetric medical imagery is presented in [98]. A multimodal image fusion based on PCA using the intensity-hue-saturation (IHS) transform has been shown to preserve spatial features and required functional information without color distortion [97]. There are different mathematical transforms on features that can enhance the performance of the image fusion. For example, combination of complex contourlet transform with wavelet has been shown to result in robust image fusion [95, 96]. Transforms based methods are also applied for liver diagnosis [99], risk factor fusion [100], prediction of multifactorial diseases [100], parametric classification [100], local image analysis [101], multi-modality image fusion [102, 103, 95, 104, 96, 81]. Possibilistic clustering methods show improvement over the fuzzy c-means clustering and have a wide range of application in registration stages of image fusion. Some of the applications of Possibilistic clustering include tissue classification [105], brain diagnosis [48, 106] and automatic segmentation [52]. SVM based techniques are kernel based techniques that are data and parameter driven having a strong control over the feature space. The ability of the SVM to reject the outliers in the data makes it a useful tool in image fusion, and leads to their being used in applications of cancer diagnosis [46, 107], classifier fusion [107, 108, 45], breast cancer tumor [108, 45], image fusion [66, 109], content-based image retrieval [110, 111], tumor segmentation [109], gene classification [112] and feature fusion [111]. Since SVMs can be used in registration as well as fusion stages, they can be combined with other methods to improve the speed of processing and accuracy when processing large image feature space under the influence of noise. Some examples of combined use of SVM with other methods include SVM-wavelet [66], SVM-adaptive similarity [110], SVM-data fusion [109] and SVM-ANN-GMM [45]. A prediction fusion is explained in [113]. Use of quaternionic signals representation for analysis and fusion of multi-components 2D medical images is presented in [114]. The use of ICA for the fusion of brain imaging data is presented in [115]. A Text fusion watermarking in medical image with semi-reversible for secure transfer and authentication is explained in [116]. Fusion of multiple expert annotations for medical image diagnosis is reported [117]. Fast fusion of medical images based on Bayesian risk minimization and pixon map is presented [118].

III. Conclusion

The field of medical diagnostics and monitoring using medical images faces several technological, scientific and societal challenges. The technological advancements in imaging technologies have resulted in improved imaging accuracies. However, every modality of imaging has its own practical limitations, which is further imposed by the underlying nature of the organ and tissue structures. This enforces the need to explore the possibility to newer imaging technologies and to explore the possibility of using multiple imaging modalities. The ability of image fusion techniques to quantitatively and qualitatively improve the quality of imaging features makes multi-modal approaches efficient and accurate relative to uni-modal approaches. The availability of a large number of techniques in feature processing, feature extraction and decision fusion makes the field of image fusion appealing to be used by medical imaging community. The extensive developments in medical image fusion research summarized in this literature review indicate the importance of this research in improving the medical services such as diagnosis, monitoring and analysis. The availability and growth of a wide range of imaging modality has enabled progress in medical image fusion to be useful for clinical deployment. Although, there has been significant progress in the medical image fusion research, the application of the general fusion algorithms is limited by the practical clinical implications as imposed by the medical experts based on the requirements of specific medical studies.

The algorithms used for medical image fusion studies have resulted in the improved imaging quality and have proved to be useful for clinical applications. The prominent approaches include wavelets transforms, neural networks, fuzzy logic, morphology methods, and classifiers such as support vector machines. Combining one or more image fusion methods is also observed to be successful in medical image analysis. The algorithmic approaches to image fusion are also limited by the imaging hardware. The problem is much more significant in developing image fusion algorithms and devices for real-time medical applications such as robotic guided surgery. Since several of these challenges remain open and the image fusion in medical imaging has proved to be useful and the trust in these techniques is on the rise, it is expected that the innovation and practical advancements would continue to grow in the upcoming years.

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