A Review on Medical Image Fusion

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Abstract: Image fusion is an adaptable and multidisciplinary area under study. From satellite imaging to human body system, where the different modalities are required to fuse the two image in order to have orientation details along with descriptive details, image fusion is mostly preferred.Therefore, image fusion review in and recent developments in the area of fusion are discussed in this paper. The present paper focuses on a review of data fusion process, its benefits, existing methodologies, performance evaluation methods and parameters and a few state of the art fusion schemes. The paper provides a literature review on various frequency domain fusion techniques such as wavelet transform, hybrid (Wavelet and curvelet) scheme, non-subsampled contourlet transform, framelet transform and non-subsampled shearlet transform.

***IndexTerms* - Fusion process, Fusion advantage, Fusion review, Image registration.**

I. INTRODUCTION

With the rapid development in high-tech and advanced instrumentation, medical imaging has become an important component in a large number of applications, including diagnosis, treatment and research. This rift development has enabled medical experts to quickly acquire the images of human body [1]. Ultimate goal of image analysis is to extract useful underlying information contained in the processed images with effective resolution and realism [2]. Therefore, a number of processes can take place such as image registration and image fusion. The importance of image fusion in current image processing systems is increasing, primarily because of the increased number and variety of image acquisition techniques to address medical issues represented through images of human body, organs and cells [2].The use of multisensory [1] and multisource image fusion methods can reveal information that is otherwise invisible to human eye. The additional information obtained using fusion can be well utilized for more precise localization of region of interest. Image fusion produces valuable help in many application areas such as remote sensing, biomedical engineering and machine vision applications [3]. The ISI knowledge of web indexing service database was searched with keyword as medical image fusion. The number of papers (including both conference and regular journal papers) published from 1980 to 2016 are given in Fig. 1. The bar plot clearly illustrates an increasing trend of publications for data fusion papers.

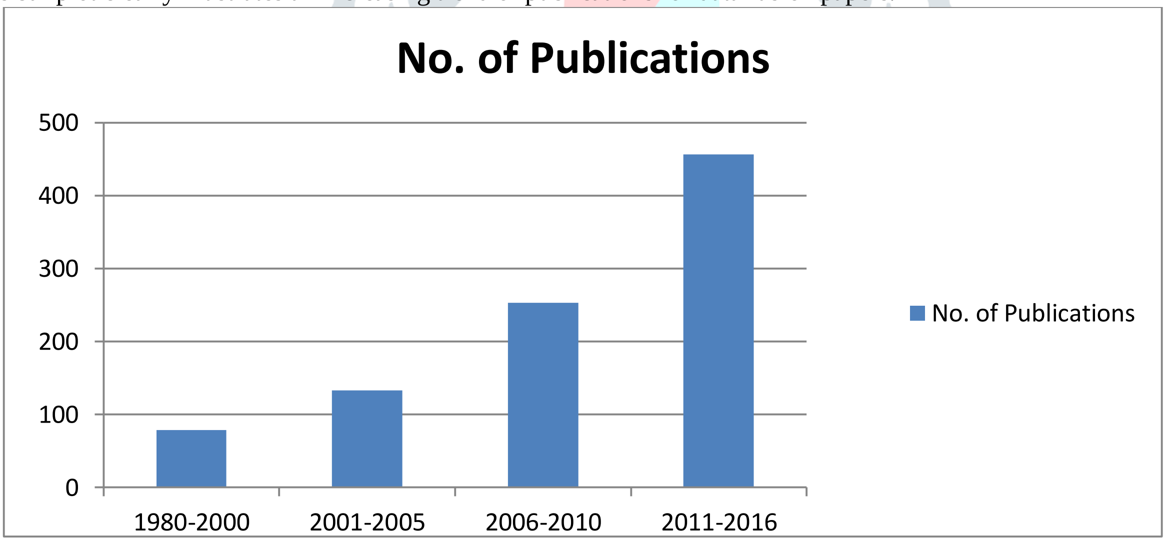

Fig.1 No. of research publications each year on image fusion

II. IMAGE FUSION

Two images taken at different angles of the same scene, or different times from different sensors, or from different viewpoints sometimes causes distortion. So before fusing the images, we have to make sure that both the images are spatially aligned and have the same dimensions. The basic steps used in image fusion are, given in Fig.2 below.

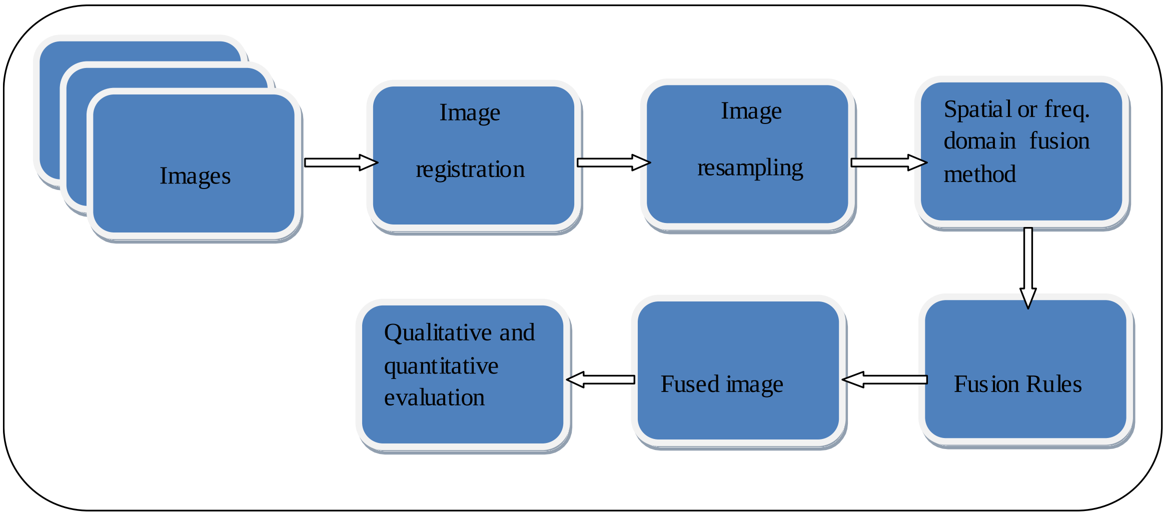

Fig. 2. Block Diagram of Image fusion Process

2.1 Image registration

Image registration algorithms transforms different set of data into single coordinate system. Image registration or image alignment techniques are grouped into two types (i) intensity-based (ii) feature-based registration. The images to be registered are called as source image and target image. Intensity-based registration makes use of the correlation metrics to compare intensity patterns in the images. Feature-based algorithms find the features such as points, lines, and contours in the images. These features are compared in the source and target images to be registered.

2.2 Image resampling

Image resampling is the process of changing the pixel dimension of an image. For performing image fusion images should have same pixel dimensions. Resampling changes the image dimension, so that the images to be fused will be of same dimension. Down-sampling an image means that information is deleted from the image. Similarly up-sampling an image means that new pixels are added based on color and intensity values of existing pixels. Image resampling can be performed by using the methods such as nearest neighbour, bilinear, and bi-cubic (cubic convolution).

2.3 Spatial/ Frequency Domain Fusion

Fusion can be performed in spatial domain or in frequency domain. Spatial domain methods directly manipulate the intensity values. Frequency domain techniques make use of multi-scale decomposition (MSD) transforms. There are many MSD transforms available in the literature such such as Laplacian pyramid, ratio pyramid, wavelet transform, ridgelet transform, curvelet transform, contourlet transform, non-subsampled contourlet transform and framelet transform etc. Using these transforms fusion can be performed at different scales and orientations, independently.

2.4 Fusion rule

The images are mixed by the schemes which are called fusion rules to form the single fused image. Fusion rules can be implemented directly or by using activity measure which represent the importance of a transform coefficient. Examples of direct fusion rules are maximum selection, averaging, and weighted averaging. Examples of activity measures are spatial frequency, entropy, sum modified Laplacian regional energy etc. The fused image is reconstructed using corresponding inverse transform

III. Literature Survey

This section provides a literature review on some latest state of the art fusion schemes. R. Singh and A. Khare [4] performed image fusion on two pairs of CT and MR images collected from internet repository. In the developed methodology, the authors applied Daubechies complex wavelets and utilized maximum selection rule. The method outperformed spatial domain and other wavelet domain methods visually and quantitatively. Agarwal and S. S.Bedi [5] fused CT and MRI images using hybrid image fusion technique .The images were segmented into bands using wavelet transform. The segmented images were then fused into sub bands using curvelet transform which broke the bands into overlapping tiles and efficiently converted the curves in images using straight lines. These tiles were integrated together using inverse wavelet transform to produce a highly informative fused image. They used the dataset of CT and MRI images for their experiments. Entropy, Correlation Co-efficient(CC),Root mean Square error(RMSE),Peak signal to noise ratio(PSNR),Mutual Information (MI),Edge association (QAB/F) were the performance parameters to be evaluated. It was found that Entropy , RMSE, Peak signal to noise ratio(PSNR),Mutual Information (MI),Edge association(QAB/F) were better to principle component analysis (PCA), Laplacian Pyramid, Wavelet transform and curvelet transform fusion method but CC was poor as compared to other transforms in comparison. Proposed hybrid scheme compensated all the shortcomings of wavelet and curvelet transform. It removed ringing effect and produced smooth corners and edges in fused image however Correlation coefficient (CC) was poor as compared to other transforms. Gaurav Bhatnagar et al [1] experimented on human visual system(HVS) inspired medical image fusion of multimodal images. The authors used framelet transform to decompose all the source images because the transform overcomes the drawbacks of existing wavelet and related transforms and is easy to use. They used HVS inspired fusion rules .For low frequency band visibility measure based fusion rule was used. For high frequency texture information based rule was used. For this smallest univariate segment assimilating nucleus (SUSAN) feature extraction algorithm was used which used local finalisation of gray values. The dataset used was MRI, CT and PET images. The proposed method was compared with principle component analysis (PCA), contrast pyramid, gradient pyramid, wavelet transform and contourlet transform. Performance parameters used were Mean, standard deviation, entropy, spatial frequency, Mutual Information, structural similarity, saliency based similarity measure QsAB/F, Edge based similarity measure QAB/F.From visual and mathematical analysis it was clear that the proposed method preserved spectral information and also improved spatial details compared to other methods in comparison. Except one or two cases this method gave best results than other algorithms. Padma Ganasala & Vinod Kumar [6] performed multimodality medical image fusion based on new features in non-subsampled shearlet transform (NSST) domain .Images were decomposed by using NSST. Saliency metric of LF subband coefficient was formulated as the sum of variation in the squares of the coefficients. Two activity level measurement parameters: absolute maximum within a 3×3 neighbourhood and the sum of absolute differences of successive rows and columns within a 3×3 neighbourhood are utilised in the high frequency fusion rule.Nine sets of CT-MRI and SPECT-MRI images of different diseases were fused.Mutual Information (MI),Spatial frequency, standard deviation , Edge information based metric (QAB/F),Universal image quality index (UIQI) based quality metrics Q, Qw and Qewere used as performance parameters.MI , standard deviation , Universal image quality index based quality metrics Q, Qw and Qe were found higher in value by above method whileQAB/F and spatial frequency were comparable with other method giving highest values. Proposed method worked better compared to other fusion rules like regional avg. energy based LF fusion rule and contrast based HF fusion rule in NSST, Weighted energy based LF fusion rule and neighbourhood characteristic based HF fusion rule in NSST. Ali et al. [2] used maximum frequency as fusion rule, RMSE and PSNR (peak signal to noise ratio) as performance parameters. Fusion results were compared with DWT. Xu et al. [7] used uniform discrete curvelet transform, feature similarity index based fusion rule for low pass subband coefficients and a complex coefficients feature similarity index based rule for high pass subband coefficients. Entropy(IE), mutual information and edge association QAB/F were used as performance parameters to compare the results with DWT, CNT and NSCT based fusion. Visual and quantitative analysis showed superiority of the proposed methods. Ellmauthaler et al. [8] used undecimated wavelet transform . They used choose maximum (CM), CM with intra-scale grouping (CM-IS), CM-IS with window based activity measure and fusion rules by Burt and Kolezynski [9]. Mutual information, QAB/F and QP parameters were used for comparison with NSCT, dual tree complex wavelet transform (DTCWT) and undecimated wavelet transform (UWT) without spectral factorization. Y. Yang [3] used edge based scheme and variance based scheme to fuse low frequency and high frequency band coefficients respectively. Information entropy, overall cross entropy and average gradient were used as parameters for comparison with pixel averaging method. F. Xiao [10] worked on translation invariant wavelet transform to fuse multifocus and remote sensing images and used weighted combination of coefficients as fusion rule where weights were computed using local weighted energy with consistency verification. Experimental results were compared with DWT and SWT using RMSE, mutual information and information entropy as parameters. Visual and quantitative analysis showed superiority of their methods. Zheng et al. [11] fused multisource images using support value transform. They used support value using support value transform to represent important features of the image. In support vector machines (SVM) the pixels with large support values are more important for SVM model , this feature was used for their research. Multiscale support value filters were used to do support value analysis. Quality of visual information (QAB/F), conditional entropy (CE) and mutual information (MI) were the parameters used for comparison of the proposed method with Laplacian pyramid, discrete wavelet transform and undecimated "atrous" wavelet transform. R. Li and Y. J. Zhang [12] performed experiment to find out the appropriate no. of decomposition levels for fusion of out of focus images. They used the difference in energy levels from higher bands for decomposition. The level selection was done by minimizing the mean square error (MSE) between fused image and input image. It was observed that MSE decreases with the rise in decomposition level. It reached minimum point at third level of decomposition. The MSE remained low with a rise in decomposition level. The actual best levels and computed best levels by the proposed method were found nearly equal maximum difference being equal to 1. All the results showed the estimated levels were a good estimate of best levels. M. Kumar and S. Dass [13] experimented on pixel level fusion of CT and MR images using a total variation (TV) based algorithm. They used a TV seminorm based approach along with principle component analysis for the estimation of fused image. Fusion was used as an inverse problem. Locally affine model was used as forward model. The input images were split into blocks. The pixels inside each block were arranged lexicographically. These pixels were used to compute correlation matrix . Principal eigenvector of this matrix was computed to find the gain of that block. After computing sensor gains of all blocks local affine transform equation was solved iteratively to find all the fused image pixels. The results were compared with least squares error method (LSE) and similarity index (SI) was taken as performance parameter. The SI for proposed method was found to be equal to 0.62 as compared to LSE method equal to 0.58. Yang et al. [14] performed fusion in two steps. In initial step sum modified Laplacian based rule was used to fuse low frequency coefficients and log Gabor energy rule was used for high frequency coefficients. Morphological opening and closing operations were applied on initial fused image to generate a fusion decision diagram. This diagram was used to select pixels of source image and initial fusion image to produce final fusion image. Experimental results showed superiority of the proposed method when compared with traditional gradient pyramid, DWT, NSCT and bilateral gradient based sharpness criterion. P. Ganasala and V. Kumar [6], [15] performed fusion of CT and MR images using NSST. P. Ganasala and V. Kumar [6] proposed sum of variation in the squares of the coefficients as saliency metric of low frequency (LF) sub band coefficient. Two windows based activity level measurement parameters: absolute maximum and the sum of absolute differences of successive rows and columns were used in the high frequency fusion rule. Mutual information, standard deviation, universal image quality index based quality metrics (Q, Qw and Qe.) were found higher in value while QAB/F and spatial frequency were comparable to other fusion rules as regional average energy based LF and contrast based high frequency (HF) fusion rule, weighted energy based LF and neighborhood characteristic based HF fusion rule. P. Ganasala and V. Kumar [15] fused LF and HF subband coefficients using pulse coupled neural network. Performance parameters as mentioned above in [2] were compared with regional average energy based LF and contrast based HF fusion rule, weighted energy based LF and neighborhood characteristic based HF fusion rule. Visual analysis and quantitative analysis showed that proposed method retained salient information of CT and MRI images with good contrast. Shanthakumar et al. [16] have done performance analysis of classifier for brain tumor detection segmentation and diagnosis. Their method employed an adaptive neuro fuzzy inference system (ANFIS) which was based on the automatic seed point selection range. Segmentation results were evaluated using similarity index (SI), overlap fraction (OF), extra fraction (EF) and positive predictive value (PPV) and their values were found to be 0.817%, 0.817%, 0.182%, and 0.817%, respectively. These results indicated that their approach performed better compared to many conventional processes. T. Wang et al. [17] experimented on fluid Vector Flow (FVF) and its applications in brain tumor segmentation to address problems of insufficient capture range and poor convergence for concavities. With the ability to capture a large range and extract concave shapes, FVF demonstrated improvements over techniques like gradient vector flow, boundary vector flow, and magnetostatic active contour on synthetic images, pediatric head MRI images and brain tumor MRI images. Torbati et al. [18] have done segmentation of CT and MR images using a moving average self organizing map as initial step of segmentation in neural network. A merging process was used to connect the objects of a joint cluster together. The DWT was used to build the input features to neural network. Jaccard index and the Rogers and Tanimoto's index were used to compare the results with manual segmented images. Hausdorff distance and mean absolute distance were used to find difference between segmented tumor boundary with manual segmentation. The brain CT and MR images (white matter, gray matter and CSF segmentation) were also segmented in a better way compared to incremental supervised neural network and SOM-based methods. Banerjee et al. [19] performed Single seed demarcation of brain tumor MRI images using multithresholding. A two-stage ROI segmentation was used for detecting glioblastoma multiforme (GBM) tumors. Discrete curve evolution was done to identify multiple intervals around the important visually critical points, using a threshold. A post-processing operation was done using connected-component analysis and flood-fill operation. This operation helped to extract each refined ROI around a single seed inserted by the user. Quantitative analysis was done in terms of Jac and Dice coefficients. Experimental results were compared with manual segmentation, Grow-cut, multi-level Otsu's variance and LLE entropy methods. The segmented ROI was found more accurate against compared methods. Vijayakumar et al. [20] performed segmentation and grading of brain tumors on apparent diffusion coefficient images (ADC). Their method used a mixture of unsupervised artificial neural networks and multiresolution wavelets. The images were decomposed using wavelets which were selectively reconstructed to form wavelet filtered images. These wavelet filtered images along with FLAIR and T2 weighted images were used as the features to unsupervised neural network – self organizing maps (SOM). Segmentation was done between tumor, edema, necrosis, CSF and normal tissue. The results were compared with manually segmented images. Sensitivity and the specificity for the proposed method was found to be 0.86 and 0.93, respectively. N. Nabizadeh and M. Kubat [21] experimented on Brain tumors detection and segmentation of T1 weighted and FLAIR MR Images using Gabor wavelet and statistical features. Gabor wavelets were used for feature extraction. Statistical features extraction method used gray level co-occurrence matrix, gray level run length matrix, histogram of oriented gradient and linear binary pattern for extraction of features. Experiments were performed using several classifiers such as support vector machine (SVM), k-nearest neighbor principle, sparse representation classifier, nearest subspace classifier and k-means clustering. Experimental results demonstrated superiority of statistical feature extraction method compared to Gabor wavelets method for all the types of classifiers in comparison. Abdullah et al. [22] segmented CSF from brain MR images using spatial fuzzy clustering method with evolutionary expectation maximization (EM) method that was improved using genetic algorithm. Comparison was done using EM, fuzzy C means and spatial fuzzy C means method. This method overcome partial volume effect in a better way by including some pixels that were present in ground truth. The mean similarity index of white matter (WM) for the proposed method was .93 as compared to other methods in which it varied from .66 to .87. The mean similarity index for gray matter (GM) was .90 while in above mentioned compared methods it varied from .57 to .81. The mean similarity index for CSF was found to be .87 whereas in other methods it varied from .42 to .75.

IV. CONCLUSIONS

It is observed that though many methods exist for medical image fusion, still the hybrid methods have yet to be explored. wavelets, curvelets, ridgelets and contourlets perform according to the medical image modality. However, many fields such as registration followed by fusion, segmentation followed by fusion and fusion followed by segmentation are yet to be explored due to change in image texture and intensity information. The brief review has provided the insight to various operations which can be performed via image fusion. The future genre can exploit these various existing algorithms along with modifications to achieve better performance indexes for image fusion.

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