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Comparative study of Image Registration and Image Fusion Techniques

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Abstract: In this paper a survey on image registration and image fusion techniques are presented which are related to medical imaging. Image registration geometrically aligns different images of same scene into one coordinate system, where these images are taken from different viewpoints, at different times and from different sensors. Different classifications of image registration algorithms are reviewed. Prior to image fusion, the images must be registered in order to obtain better fused image. Image fusion combines the information from images to provide high spatial and high spectral resolution in single fused image. Various techniques for image fusion are also addressed in this paper. Survey on image registration and image fusion techniques provides a better insight for further research and application areas.

Keywords: Image registration, image fusion, image domains, imaging modalities, medical imaging

1. INTRODUCTION

Image registration technique is used regularly in medical imaging applications. Image registration determines point-by-point correspondence between two images of a scene. Fusion of multimodality information becomes possible with the aid of registering two images along with depth map of the scene can be determined, changes can be detected in the scene and also objects can be identified [1]. The applications of medical image registration include aligning images from different modalities [2], alignment of pre- and post-contrast images [3-5], comparing follow-up scans with base-line scan [3], in updating surgery and radiotherapy treatment plans [6,7], atlas-based segmentation [8-13], creating anatomy models [14], and aligning images for classification in training phase [15,16].

The modalities in medical imaging can be divided into two global categories – anatomical and functional. Anatomical modalities depicts morphology which include CT (computed tomography), X-ray, US (ultrasound), MRI (magnetic resonance imaging), video sequences and portal images obtained by various catheter 'scopes', such as laparoscopy or laryngoscopy. Certain derivative techniques of anatomical modalities are MRA (magnetic resonance angiography), CTA (computed tomography angiography), DSA (digital subtraction angiography), and Doppler (derived from US). Functional modalities which are depicting information on the metabolism of the underlying anatomy, includes scintigraphy, PET (positron emission tomography), SPECT (single-photon emission computed tomography). These functional modalities combined make up nuclear medical imaging modalities and fMRI (functional MRI). Spatially sparse techniques such as MEG (magneto-encephalography) and EEG (electro-encephalography) are also included in functional imaging modality techniques [17].

To perform image fusion, the images which are to be fused must be registered in order to obtain better information of images in a single fused image. Image fusion improves quality of information in both spectral and spatial domain by joining two images into one single image which have maximum data content without providing details regarding non-existent information in the given images.

Image fusion techniques provide us more accurate medical diagnosis and evaluation information for physicians, so for this to happen, multimodality medical images are required. These multimodality images can be X-ray, CT, MRI, MRA and PET images [18]. These medical images more often provide complementary and occasionally conflicting information. For example, MR image provide normal and pathological soft tissue information, but it doesn't provide bones information, while CT image provide dense structures like bones and implants with less exaggeration, but it does not detect physiological changes. From the above example it is clear that only one type of image is not adequate to provide precise clinical requirement for the physicians. Therefore fusion of medical images is essential in medical imaging applications [19, 20]. To name a few, application areas of image fusion in medical imaging include oncology (data level fusion), microscopy, ultrasound imaging (decision level and feature level fusion) and lesion placement in pallidotomy (data level fusion) [21].

A survey on image registration and image fusion methods with respect to medical imaging are presented in sections II and III respectively followed by concluding the prominence of image registration and fusion techniques in conclusion section.

2. IMAGE REGISTRATION TECHNIQUES

In image registration technique, one image which is called moving image [22] or source image or reference image [1], which is warped to fit with other image called fixed image or target image or sensed image. Provided both source image and target image, common steps involved in image registration are preprocessing, any image registration algorithm, determination of a transformation function and resampling. Preprocessing steps include image smoothing, deblurring, intensity thresholding and boundary detection [1]. Transformation functions include linear transformations such as scaling, rotation, affine transformation and translation [23]. Rigid and non-rigid transformations are also categorized in transformation model function. Nearest neighbor bilinear interpolation, cubic convolution, cubic spline, radially symmetric kernels are categorized under resampling methods [1].

Most of the image registration methods are consist of following 4 steps [32], as shown in Fig.1:

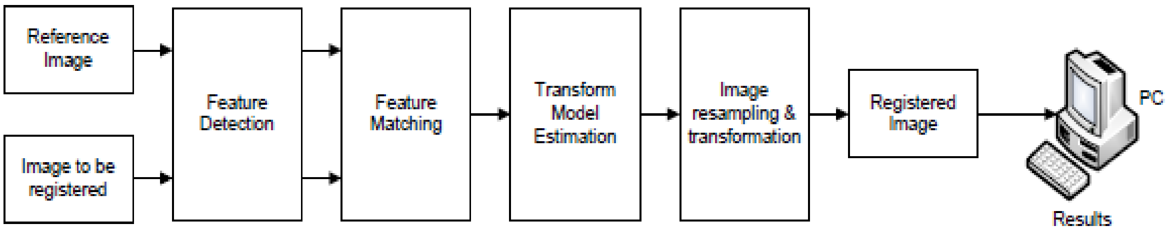

Fig. 1: Steps involved in image registration procedure

2.1 Feature Detection

Detection of important and unique objects such as, closed- boundary regions, line intersections, contours, edges, corners, etc. has to be done manually or preferably, automatically. These features can be presented for further processing by their point representatives such as, line endings, centers of gravity, and distinctive points /control points.

2.2 Feature Matching

This step concerns about establishing the correspondence between the detected features obtained from previous step in source image and as well target image. Different feature descriptors and similarity measures along with spatial accordance are few of the features used for.

2.3 Transform Model Estimation

Estimation of type and parameters of the mapping functions, for aligning the target image with the source image is done in this step. The parameters of the so-called mapping functions are evaluated by means of the traditional feature correspondence.

2.4 Image Resampling and Transformation

The mapping functions are utilized to transform the target image. Appropriate interpolation technique is applied to evaluate image values in non-integer coordinates.

In this section we mainly focus on the types of image registration algorithms. Image registration techniques presented here are based on the concept of aligning the coordinates of source image with target image. Image registration algorithms can be classified as [24]

1. Intensity-based and Feature-based
2. Transformation models
3. Spatial domain and frequency domain methods
4. Single-modality and multi-modality methods
5. Automatic and interactive methods
6. Similarity measures for image registration

A. Intensity-based and feature-based

In general, image registration involves spatially registering the moving image to align/coordinate with the fixed image [1]. Intensity-based image registration look for intensity matching patterns utilizing correlation metrics, where as feature-based image registration technique uses image features such as scale invariant feature transform (SIFT) features, histogram-based features and corner detection features.

The intensity-based registration methods operate directly on the image gray values, without reducing the gray-level image to relatively sparse extracted information. The basic principle of intensity-based techniques is to search, in a certain space of transformations, the one that maximizes (or minimizes) a criterion measuring the intensity similarity of corresponding voxels. Some measures of similarity are sum of squared differences in pixel intensities, regional correction, or mutual information. Mutual information has proved to be an excellent similarity measure for cross-modality registrations, since it assumes only that the statistical dependence of the voxel intensities is maximal when the images are geometrically aligned. The intensity similarity measure, combined with a measure of the structural integrity of the deforming scan, is optimized by adjusting parameters of the deformation field. Such an approach is typically more computationally demanding, but avoids the difficulties of a feature extraction stage.

Feature-based approaches attempt to find the correspondence and transformation using distinct anatomical features that are extracted from images. These features include: points, curves or a surface model of anatomical structures. Feature-based methods are typically applied when the local structure information is more significant than the information carried by the image intensity. They can handle complex between-image distortions and can be faster, since they don't evaluate a matching criterion on every single voxel in the image, but rather rely on a relatively small number of features. The simplest set of anatomical features is a set o f landmarks. However, the selection of landmarks is recognized to be a difficult problem, whether done automatically or manually. For many images, this is a serious drawback because registration accuracy can be no better than what is achieved by the initial selection of landmarks. For practical reasons, the number and precision of landmark locations is usually limited. Hence, spatial coordinates and geometric primitives often oversimplify the data by being too sparse and imprecise.

B. Transformation Models

Image registration algorithms can also be classified according to the transformation model used to relate the reference image space with the target image space. The first broad category of transformation models includes linear transformations, which are a combination of translation, rotation, global scaling, and shear and perspective components. Linear transformations are global in nature, thus not being able to model local deformations. Usually, perspective components are not needed for registration, so that in this case the linear transformation is an affine one. The second category includes 'elastic' or 'nonrigid' transformations. These transformations allow local warping of image features, thus providing support for local deformations. Nonrigid transformation approaches include polynomial wrapping, interpolation of smooth basis functions (thin-plate splines and wavelets), and physical continuum models.

C. Spatial Domain and Frequency Domain

Many image registration methods operate in the spatial domain, using features, structures, and textures as matching criteria. In the spatial domain, images look 'normal' as the human eye might perceive them. Some of the feature matching algorithms are outgrowths of traditional techniques for performing manual image registration, in which operators choose matching sets of control points (CPs) between images. When the number of control points exceeds the minimum required to define the appropriate transformation model, iterative algorithms like RANSAC are used to robustly estimate the best solution.

Other algorithms use the properties of the frequency-domain to directly determine shifts between two images. Applying the phase correlation method to a pair of overlapping images produces a third image which contains a single peak. The location of this peak corresponds to the relative translation between the two images. Unlike many spatial-domain algorithms, the phase correlation method is resilient to noise, occlusions, and other defects typical of medical or satellite images. Additionally, the phase correlation uses the fast Fourier transform to compute the cross-correlation between the two images, generally resulting in large performance gains. The method can be extended to determine affine rotation and scaling between two images by first converting the images to log-polar coordinates. Due to properties of the Fourier transform, the rotation and scaling parameters can be determined in a manner invariant to translation. This single feature makes phase-correlation methods highly attractive vs. typical spatial methods, which must determine rotation, scaling, and translation simultaneously, often at the cost of reduced precision in all three.

D. Single-modality and multi-modality methods

Another useful classification is between single-modality and multi-modality registration algorithms. Single-modality registration algorithms are those intended to register images of the same modality (i.e. acquired using the same kind of imaging device), while multi-modality registration algorithms are those intended to register images acquired using different imaging devices. There are several examples of multi-modality registration algorithms in the medical imaging field. Examples include registration of brain CT/MRI images or whole body PET/CT images for tumor localization, registration of contrast-enhanced CT images against non-contrast-enhanced CT images for segmentation of specific parts of the anatomy and registration of ultrasound and CT images for prostate localization in radiotherapy.

E. Automatic and interactive methods

Registration methods may be classified based on the level of automation they provide. Manual, interactive, semi-automatic, and automatic methods have been developed. Manual methods provide tools to align the images manually. Interactive methods reduce user bias by performing certain key operations automatically while still relying on the user to guide the registration. Semi-automatic methods perform more of the registration steps automatically but depend on the user to verify the correctness of a registration. Automatic methods do not allow any user interaction and perform all registration steps automatically.

F. Similarity measures for image registration

Image similarity-based methods are broadly used in medical imaging. A basic image similarity-based method consists of a transformation model, which is applied to reference image coordinates to locate their corresponding coordinates in the target image space, an image similarity metric, which quantifies the degree of correspondence between features in both image spaces achieved by a given transformation, and an optimization algorithm, which tries to maximize image similarity by changing the transformation parameters. The choice of an image similarity measure depends on the nature of the images to be registered. Common examples of image similarity measures include cross-correlation, mutual information, sum of square differences and ratio image uniformity. Mutual information and its variant, normalized mutual information are the most popular image similarity measures for registration of multimodality images. Cross-correlation, sum of square differences and ratio image uniformity are commonly used for registration of images of the same modality.

3. IMAGE FUSION TECHNIQUES

The problem of preserving the maximum information of any interior body part for clinical visualization within a single image is not possible due to multi modalities available in medical images. Image fusion is a technique, using which maximum information can be achieved in a single image by combining two images. The different types of techniques used to fuse images are presented in detail in this section. The other applications of image fusion excluding medical imaging are microscopic imaging, computer vision, remote sensing and robotics [26].

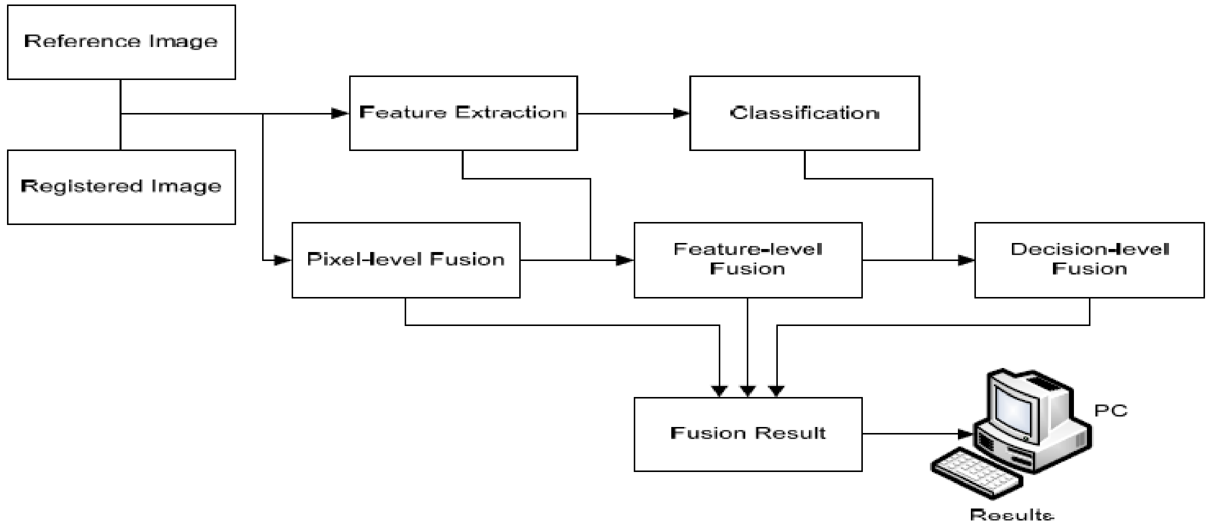

Fig. 2: Levels involved in image fusion processing.

Image data representation at any level can be performed by information fusion. Image fusion is mostly performed at any of these various processing levels, shown in Fig. 2:

1. Pixel-level
2. Feature-level
3. Decision level

Pixel-level image fusion is also known as signal level image fusion which symbolize fusion at lowest processing level, which means a number of coarse input image signals are united to generate a single fused image signal [33]. Feature level image fusion is also called as object level image fusion, where it fuses object and feature labels and property descriptor data, which is already been derived from distinctive input images [34].Decision level fusion is also known as symbol level fusion, which is the highest level that presents fusion of probabilistic decision data extracted by local decision makers performing on the results of feature level processing on image information created from distinctive sensors [33].

There are various methods that have been developed to perform image fusion. Some well-known image fusion methods are listed below [27]:

(1) Intensity-hue-saturation (IHS) transform based fusion

(2) Principal component analysis (PCA) based fusion

(3) Multi scale transform based fusion

(a) High-pass filtering method

(b) Pyramid method

(i) Gaussian pyramid

(ii) Laplacian Pyramid

(iii) Gradient pyramid
(iv) Morphological pyramid

(v) Ratio of low pass pyramid

(c) Wavelet transforms

(i) Discrete wavelet transforms (DWT)

(ii) Stationary wavelet transforms

(iii) Multi-wavelet transforms

(d) Curvelet transforms

A. Image Fusion Algorithms

Pixel-based, region-based and wavelet-based algorithms were implemented to obtain all objects in an image in focus using image fusion technique.

1) Simple Average

The most basic method to combine two images to obtain maximum information in one image is done using average method. Consider two images which are to be fused, pixel values of both these image are obtained and the resulting fused image will have the pixel value after averaging each pixel value of these two input images.

2) Select Maximum

To obtain the image with high focus, there is a need to retain the pixel values of input images with high intensity values. This algorithm results in providing a fused image where the values of
each pixel is the maximum value obtained from either input images. So the output will have the greater information compared to given input images [28, 29].

B. Discrete Wavelet Transform

Wavelet transform is the most common image fusion algorithm which provides accurate results. This method decomposes the image into its low-low, low-high, high-low and high-high frequency bands at different scales. Low-low band is the raw scale variant; again on this frequency band wavelet transform can be applied. This band contains directional information due to spatial orientation. This method provides higher absolute values of wavelet coefficients in the high bands which correspond to edge features and line features [28, 30, 31].

The advantages of wavelet transform algorithm to perform image fusion are different image resolutions can be managed well due to multi-scale and multi-resolution nature of wavelet transform. Secondly, discrete wavelet transform (DWT) preserves image content by decomposing the image into various kinds of coefficient values, so by combining the coefficients again with inverse DWT one can achieve original information of the image. Image fusion is one of the many applications of wavelet transform [27, 28].

C. Principal Component Analysis

PCA is a statistical method which transforms the correlated variables into uncorrelated variables known as principal components. PCA considers the intensity values of images as data. This procedure computes an optimal and compact description of data set. While performing image fusion operation, the pixel values with higher intensity from the input images are considered into a subspace where the redundancy of the values must be optimized in order to obtain better fused image. The first principal component computes accounts for variance of the dataset for as much of the remaining variance as possible. Further this principal component is taken to be along the direction with the maximum variance. Whereas second principal component lie in the subspace perpendicular to the first. Third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. Unlike FFT, DCT, wavelet, etc. PCA basis vectors depend entirely o the dataset [32]. The input images which are to be fused are arranged in two column vectors and their empirical means are calculated to compute Eigen vector and Eigen values for this vector. Eigen vectors corresponding to the larger Eigen value are obtained [32].

4. PRE-PROCESSING FOR IMAGE REGISTRATION

For image registration, transformation between reference image and target image should be found. Before finding transformation, image should be pre-processed in order to improve its quality. Suitable filters are applied to remove and reduce noise and sometimes smoothing is also applied to reduce blur. Filters suppress the high frequencies i.e. smoothens the image or the low frequencies, i.e. enhances the image. The adjustment of brightness and contrast may also require the histogram manipulation for image enhancement.

5. RESULTS COMPARISON OF VARIOUS IMAGE FUSION TECHNIQUES

Results of different image fusion techniques/algorithms are presented in Table 1 [25]. The results are compared with respect to the respective performance analysis parameters. The parameters could be PSNR (Peak Signal-to-Noise Ratio), EN (Entropy), NCC (Normalized Correlation Coefficient), and RMSE (Root Mean Square Error).

TABLE 1. COMPARISON OF DIFFERENT FUSION TECHNIQUES

Sl. No.	Fusion Technique/Algorithm	Parameters measured
1	Simple Average	PSNR-25.48 EN-7.22
2	Simple Maximum	PSNR-26.86 EN-7.20
3	PCA	NCC-0.998 PSNR-76.44
4	DWT	RMSE-2.06 EN-7.42
5	DWT and PCA combined	PSNR-67.08 EN-7.24
6	Combination of Pixel & Energy Fusion rule	PSNR-27.75

6. CONCLUSION

This survey on image registration and image fusion techniques provides us a better insight to choose and develop new techniques to obtain maximal information in an image. Due to multimodalities available in image acquisition, obtaining high spectral and high spatial information in a single image is not possible. In most of the medical imaging applications where the physicians are required to examine the internal body for diagnosing, images with maximum information is mandatory for better diagnosis of diseases. Medical imaging is one of the many applications of image registration and image fusion techniques.

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