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3D/4D Image Registration and Fusion Techniques : A Survey

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***Abstract*— Registration is a process of estimating transformations between two images. It is a process of aligning two images, the reference and the input image. It is very difficult to accurately and repeatable correspond the images of physical structures (particularly those images taken of soft tissue) with one another. Aligning non-rigid medical images is another major challenge that needs to be addressed. Registration of 3D/4D images is another emerging domain. Registration of 4D images in real time is one of the major challenges that need to be addressed, in this paper; review of 3D image registration techniques using wavelets is presented. Review of various techniques for registrations of non-rigid images using wavelets is emphasized in this work. Based on the review, recommendations and discussions are presented for algorithm development and implementation.**

***Keywords*— 3D/4D images, wavelets, image registration, non-rigid images, medical imaging**

I. INTRODUCTION

Image representation of data captured by image sensors provides visual interpretation of information. Images captured at different instants of time, due to movements in the non-rigid objects in the image provide distinct information. Image registration is a process of aligning digital images captured at different time intervals [1]-[2]. Registration is also a process where images captured using various sensors is aligned [3]. Medical image registration is the process of aligning digital medical images so that corresponding features can be compared. By registering these images, a doctor can observe changes in a patient's condition over time (e.g. intra-subject) or compare a healthy patient to a diseased patient (e.g. inter-subject). Image registration has evolved from the mid-1980s from a minor niche into a major sub-discipline. Registration of image requires two inputs, a reference image and an image to be registered. Registration process produces one out, which is termed as registered image. Image registration consists of four steps: Feature extraction, feature matching, transform estimation and resampling and transformation. Remote sensing, hyperspectral imaging, whether forecasting, medical image processing, object tracking are some of the applications where image registration plays a pivotal role [4]. Image registration is a process of registering two images that are of the, same scene taken at different instants of time, taken from different viewpoints and or different sensors. Image registration is also defined as a transform T that will map one image onto another image of the same object such that some image quality criterion is maximized. Fig 1 presents the block diagram of image registration [5].

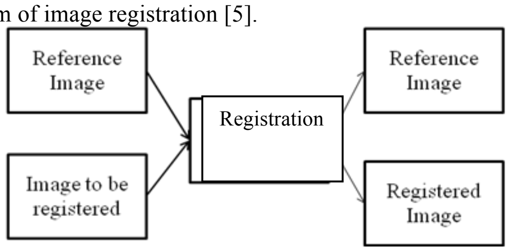


Fig 1 Image registration process

Image to be registered is compared with reference image and the registration process performs image registration and generates a registered image. The registered image is also compared with reference image for validation. Fig 2 illustrates the image registration process. As shown in Fig 2, the general image registration problem is, given two *N*-dimensional sensor readings, fi nd the function *F* that best maps the reading from sensor 2, $S2(x1, \ldots, xn)$ onto the reading from sensor 1, $S1(x1, \ldots, xn)$. Ideally, $F(S2(x1, \ldots, xn)) = S1(x1, \ldots, xn)$. Because all sensor readings contain some amount of measurement error or noise, the ideal case rarely occurs. Many processes require that data from one image, called the *observed image*, be compared with or mapped to another image, called the *reference image* [4]. Hence, a wide range of critical applications depends on image registration.

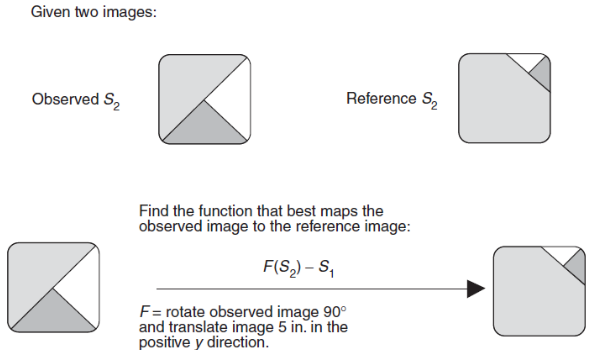


Fig 2 image registration method [4]

Medical image is the technique and process used to create images of the human body for medical science or clinical purposes, including medical procedures seeking to reveal, diagnose or examine disease. In the last 100 years, medical imaging technology has grown rapidly and drastically changed the medical profession. Now, physicians can use the images obtained by different medical imaging technologies to both diagnose and track the progress of illnesses and injuries. In the field of medical imaging, proper integration of the information derived from various scanning techniques like MRI scan, CT scan, SPECT scan etc. is of paramount importance. Before integrating this information obtained from various modalities we need to align them properly and this process is called as image registration. The entire procedure of image registration makes sense if the participant images have been taken well and contain the relevant information. The images of different modalities are obtained using different prevalent methods are the MRI scan and the CT scan [6]-[8]. In this work review of medical image registration techniques using wavelets is presented.

II A BACKGROUND OF MEDICAL IMAGES

Medical Image Registration generally refers to the process of identifying and subsequently aligning corresponding structures or objects from two medical images. To register two images, correspondence and a transformation (spatial mapping) must be found so that each location in one image can be mapped to a new location in the second. This mapping should "optimally" align the two images wherein the optimality criterion itself depends on the actual structures or objects in the two images that are required to be matched. Different types of medical images are discussed[9].

a) CT SCAN

CT (Computer Tomography) is used to obtain image data from different angles around the body using special X-ray equipment. This data is processed in the computer to show a cross section of body tissues and organs. The Radiologists can easily diagnose cardiovascular disease, infectious diseases, cancer, trauma and musculoskeletal disorders. This is possible because we get good clarity in different types of tissue-lung, bone, soft tissue, small muscles , blood vessels and gives detailed cross-sectional views of all types of tissues. These characteristics make CT scan best suited for studying the chest and abdomen. It is also used to measure bone mineral density for the detection of osteoporosis and to quickly identify injuries to the liver, spleen, kidneys and other internal organs.

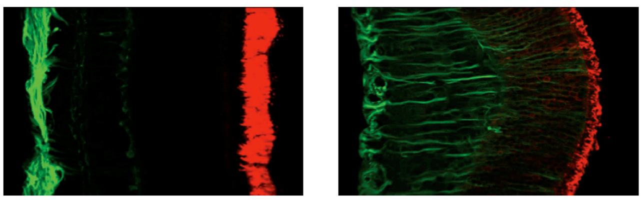
b) MRI SCAN

MRI (Magnetic Resonance Imaging) uses magnetic and radio waves to get the detailed picture of the inside of the body and hence it is free from X-rays or damaging forms of radiation. The rays from MRI equipment forces the nuclei of the human atom into a different position, and when these nuclei moves back into place they send out radio waves of their own back into the scanner which is used to create the image by the computer. These images are based on the location and strength of the incoming signal. The nuclei of hydrogen atoms are used to create MRI scan because our body consists of water, and water contains hydrogen atoms. The part (like bones) have the least number of hydrogen atoms and appears dark where as the tissue with many hydrogen atoms (like fatty acids) looks brighter, hence it is best suited for finding tumors in brain and for examining spinal cord. There are two types of MRI scan images. T1 weighted images provide excellent anatomic detail but do not show good contrast between normal and abnormal tissues, but T2 weighted images provide excellent contrast between normal and abnormal tissues, but has less anatomical details.

c) SPECT SCAN

SPECT (Single Photon Emission Computed Tomography) provides high functional information about a patient's specific organ or body system, where as the CT and MRI scanning methods primarily give the anatomical (structural) information. The principle of nuclear medicine which facilitates both diagnostic and therapeutic procedures is used in SPECT. A pharmaceutical labeled with a radioactive isotope administers the internal radiation. The radioactive isotope emits gamma rays and eventually decays. This gamma rays are collected by the gamma camera which gives a picture of what is happening inside the patient's body. SPECT is one of the best tools used for diagnosis of the brain, heart, kidneys etc and also for detecting tumors in the body because it provides information about blood flow, temperature of the body etc.

Medical images of two types based on the dimension, 2D and 3D images. As this work focuses on 3D images, introduction to 3D images are presented in this section. Given a large collection of biomedical images of several conditions and treatments, how to describe the important regions in the images, or the differences between different experimental conditions [10]. Fig 3 presents a 3D image, which is compared with 2D image.



(a) Normal (b) 3d

Fig 3 (a) a normal retina and (b) a retina after 3 days of detachment. The retinas were labeled with antibodies to rhodopsin (red) and glial fibrillary acidic protein (GFAP, green)

IV NEED FOR IMAGE REGISTRATION

Better registration techniques could give physicians new and more effective ways of monitoring and treating the millions of patients suffering from cancer. Image registration would be useful for more precise targeting of radiation therapy against tumors. Better image registration could also lead to improvements in image-guided surgery – a surgical procedure where the surgeon uses indirect visualization to operate. Global fig s are imaging market for the US is approximate US$9 billion. According to BCC Research, the 2011 CT market is approximately US$4.3 billion with MRI scanners roughly US$1.7 billion and is growing at 10% a year. Table 1 presents the details of cancer disease that is affecting human [11] [12].

TABLE 1 STATISTICS OF CANCER DISEASE IN HUMAN BEINGS

Cancer	Male	Female
Lung and bronchus	1,108,731	440,390
Prostate	782,647	----
Stomach	691,432	375,111
Colon & rectum	630,358	536,662
Breast	----	1,301,867
Cervix uteri	----	555,094
Liver	502,571	208,557
Oral cavity	200,774	----
Leukemia	188,394	142,569
Urinary bladder	314,256	----
Corpus uteri	----	226,787
Esophagus	361,931	167,352

It is very difficult, if not impossible, to accurately and repeatable correspond the images of physical structures (particularly those images taken of soft tissue) with one another. This challenge is compounded in corresponding images taken over multiple time periods and images taken with multiple modalities. Out of the two main types of structures rigid and non-rigid, algorithms for registering non-rigid images are inaccurate and generate poorly repeatable results. The ability to accurately register these images is critical for the development of medical imaging as a diagnostic tool, especially a collaborative diagnostic tool for cases involving multiple physicians in different places. Hence, this work concentrates on the efficient methods of 4D medical image registration. Challenges in image registration are [13][14]:

- Medical images are 4D in nature
- Non-rigid images are to be registered
- Feature extraction of non rigid images requires efficient transformation techniques
- Online registration algorithms are required for noninvasive surgery
- Fast and efficient algorithms for 3D and 4D image registration

VI TYPES OF IR (IMAGE REGISTRATION) TECHNIQUES

Medical images can come from a variety of imaging modalities (e.g., CT, MRI, X-ray, PET, ultrasound, etc.). Medical imaging establishes shape, structure, size, and spatial relationships of anatomical structures within a patient along with information about function in some cases. Often, it is necessary to compare images from the same patient over time or to compare images from one patient to another. Medical images are of two types rigid and non-rigid. Rigid structures are features held in rigid confines such as the skull or other bony structures and, thus, are more easily registered. Non-rigid structures are features such as soft tissue (e.g., a tumor) that can change over time for a given patient, also known as tissue deformation. For example, a tumor can grow in size or shrink. Algorithms for registering non-rigid images are inaccurate and generate poorly repeatable results. The ability to accurately register these images is critical for the development of medical imaging as a diagnostic tool – especially a collaborative diagnostic tool for cases involving multiple physicians in different places. Non-invasive surgery is a process in which the doctors visually see the internal parts of the body using vision based systems, thus avoiding the destruction of undesirable tissue in the human body without physically penetrating the body. Video recorder penetrating the human body captures images and is presented in a video format to the doctor, this termed as 3D images. 3D models of image sequences are key components in medical image processing. Different three dimensional (3-D) imaging modalities usually provide complementary medical information about patient anatomy or physiology. Four-dimensional (4-D) medical imaging is an emerging technology that aims to represent a patient's movements over time. Image registration has become increasingly important in combining these 3-D/4-D images and providing comprehensive patient information for radiological diagnosis and treatment. Accounting for involuntary movements such as those related to respiration, heartbeat, and digestion could aid many surgeries, such as small cell and non-small cell lung carcinoma, spinal surgeries, and colon cancer surgeries.

The IR methods are classified depending on various factors as detailed below:

1. ID (Image Dimensionality): Refers to the number of geometrical dimensions of the image spaces involved like 2 dimensional or 3 / 4 dimensional.
2. RB (Registration Basis) : This deals with the different aspects of two views used to affect the registration and is divided into three sub categories. Extrinsic or Prospective which is based on foreign reference points / surface attached to the anatomy, Intrinsic or Retrospective based on anatomic features only and non image based where imaging coordinates of the two devices are matched.
3. NT (Nature of Transformation) : This can be either rigid or non rigid transformation. The rigid transformation preserves all distances, straightness of lines, surface planarity non zero angles between straight lines. Non rigid transformation can be further classified as scaling, affine, projective, perspective and curved. Each transformation is closely related to each other and is very close to rigid transformation.
4. DT (Domain of Transformation): This domain may be global where the whole image undergoes registration or local where only a part of the image under goes registration.
5. I (Interaction) : The degree of interaction refers to the control exerted by a human operator over the registration algorithm like initialization of certain parameters (Semi automatic), adjustment through the registration process in response to the visual alignment or other measures of intermediate registration success (Interactive). Fully automatic algorithm is ideal which requires no interaction.
6. OP (Optimization Procedure): This can be either direct parameter computation or search for the parameters. The former case is algorithmic registration in which the quality of registration is estimated continuously during registration process in terms of some function of image and the mapping between them. In the latter case the global extremism is found among the local ones by means of iterative search, forming a closed form solution.
7. MI (Modalities Involved): This refers to the means of acquiring the images to be registered like CT (Computer Tomography), SPECT (Single Photon Emission Computer tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography). Monomodal or intramodal refers to the registration between like modalities like MRI-MRI, CT-CT. Multimodal or intermodal refers to the registration between differing modalities like CT-MRI, MRI-PET. This also can be modality to model (computer representation of a scene) or patient to a modality.
8. S (Subject) : Refer to the patient's involvement. Intrasubject refers to the registration of images within the same patient, intersubject is registration of images of one patient to another, Atlas is registration between patients and atlas derived from patient's images.
9. O (Object): This is particular region of anatomy to be registered like head, liver brain etc..

Fig 4 summarizes the types of image registration process.

The different steps in IR are listed as follows:

1) Feature detection: Detection of features in acquired image like points edges /lines/intersections or corners manually or automatically (Barbara Zitova, Jan Flusser and J. B. Maintz). Medical images are not so rich in distinctive and easily detectable objects and therefore this method had limited application in medical IR. There are numerous feature extraction techniques available in the literature (P. Bas, J. M. Chassery, Jignesh. N. Sarvaiya). Wavelet based methods are found to produce remarkable results in the feature extraction process even when applied to medical images.
2) Feature Matching: Matching of the detected features from the acquired image with the reference image. Spatial relation and feature description s are used depending on the application (R. J. Althof, M. G. I. Wind). The limitations in feature matching methods are that corresponding features may be hard to detect and / or the features may be unstable with respect to time.

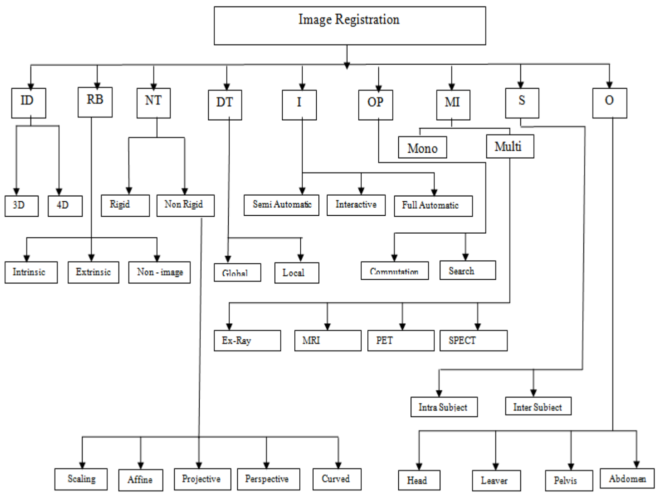


Fig 4. Summarizes the classification techniques for image registration.

3) Transform model Estimation: Estimation of transformed model , i.e. Parameters of mapping functions aligned with reference image type is estimated (J. Flusser). Global mapping models is based on the assumed CP (Control Points) , slight variation in the assumptions mode will lead to higher order polynomial models (3 or more) . This increase in the order leads to warping of the sensed image in the areas away from the CPs when aligning with the reference image. Radial basis function method using thin plate splins gives rise to high computations time if the number of control points is high. As per R. Bajcsy, the elastic registration method does't yield good result in case of localized image deformation. M. Bro. Neilson, C. Gramkow, H. Lester found the fluid registration method has a blurring effect introduced during the registration process and can be best used in medical IR to find the correspondence to CPs and transform the same using CPs.
4) Resampling and transformation of image: The transformation of the sensed image is done in a forward or backward manner. Every pixel from the sensed image can be directly transformed by the use of the mapping functions estimated in

the above step. As per E. H. W. Meijering, J. P .Thirion , the forward method produces overlaps and / or holes in the output due to rounding descretization. Hence it is complicated to implement. The backward method overcomes the above disadvantage; however the computation cost is high since interpolation is involved. Many other methods were tried and only marginal improvements were found. Nearest neighbour interpolation introduces artifacts in the images which are resampled. Higher order Bilinear interpolation methods give higher accuracy with higher computational complexity.

Fig 5 summarizes processing steps in image registration.

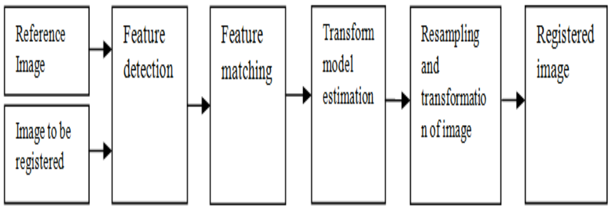


Fig 5 Processing steps in image registration

J.V.Chapnick, M.E.Noz, G.Q. Maguire, E.L.Kramer, J.J.Sanger, B.A.Birnbaum, A.J.Megibow [10] have mentioned the following approaches of image registration way back in 1993.

- Transformations using Fourier Analysis
- Cross correlation approach using Fourier Analysis
- Sum of squares search technique
- Eigen Value Decomposition
- Moment matching techniques
- Warping Techniques
- Procedural approach
- Anatomic Atlas
- Internal landmarks

Wavelet based approaches are gaining popularity for image registration. Several novel approaches of efficient image registration are proposed. These algorithms utilize different techniques spanning on various scientific fields as information theory, optimization and search statistics, image processing and signal processing (wavelets), artificial intelligence techniques. Each has its own advantages and disadvantages over the others. A Fast Algorithm for Image Registration without Predetermining Correspondences was proposed in the year 1996 that applied wavelet transforms to extract a number of feature points as the basis for registrations. The multi-resolution analysis of DWT enables us to obtain good localized time/frequency characteristics, such as abrupt changes, spikes, drifts and trends. Therefore, WT has been widely used to extract features for signal classification. Next section review wavelet transforms for image registration.

VII WAVELET BASED IMAGE REGISTRATION TECHNIQUES

1) Background theory of wavelets

Wavelet analysis is a windowing technique with variable sized regions, which allows the use of long time intervals where precise low frequency information is required and short regions where we want high frequency information.

The wavelet transform is the convolution of a wavelet function Ψ(t) with a signal x(t) :

$$T(a,b) = \int_{-\infty}^{+\infty} x(t)\, \Psi^*_{a,b}(t)\, dt \qquad (1)$$

Where x(t) is a one dimensional continuous signal, Ψ(t) is a wavelet function and T(a,b) represents wavelet coefficients of signal x(t).

At many locations, b and scales a:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\, c\left(\frac{t-b}{a}\right) \qquad (2)$$

Where b represents time shift and a denotes the scaling of the wavelets.

The wavelet function Ψ(t) should satisfy the conditions of zero mean and the existence of the inverse transform. The equation 1 can be implemented by using discrete wavelet transforms using dyadic scale as shown below:

$$T_{m,n} = \frac{1}{\sqrt{2^m}} \int_{-\infty}^{\infty} x(t)\, \Psi^*\left(\frac{t-n2^m}{2^m}\right) dt. \qquad (3)$$

Where n is the number of data points in the signal, $n2^m$ represents the size of the steps between locations (time shift) and 2^m is the scale.

$$\Phi_{m,n}(t) = \frac{1}{\sqrt{2^m}}\, \emptyset\left(\frac{t-n2^m}{2^m}\right), \qquad (4)$$

$\Phi_{m,n}(t)$ represents the scaling function of dyadic discrete wavelet transform, the mean of which is equal to one.

The convolution of above scaling function with the signal produces smoothed or averaged version of the signal represented as S_{mn} as shown below:

$$S_{m,n} = \int_{-\infty}^{\omega} x(t)\, \emptyset_{m,n}(t)\, dt. \qquad (5)$$

The wavelet coefficient $T_{m,n}$ from equation 3 provide the details to obtain the original signal from the smoothed signal. Higher dimensional wavelets like separable and non separable wavelets designed in multiple dimensions and use non rectangular grids.

Yinpeng Jin, Elsa Angelini disucss about wavelet transforms for image registration. Consider f(n), a one dimensional signal of length N. The discrete orthogonal wavelet transform can be organized as a sequence of discrete functions,

$L_m(f) = Lf(n2^m, n2^m)$ and $W_m(f) = Wf(n2^m, n2^m)$ (6)

according to the scale parameter, s= 2^m . A pair of CMF(conjugate mirror filters) are used for fast implementation of filter bank algorithms , h and g are constructed from scaling function Φ and wavelet function Ψ as given below:

$h(n) = \frac{1}{\sqrt{2}}\emptyset\left(\frac{t}{2}\right), \emptyset(t-n)$ and $g(n) = \frac{1}{\sqrt{2}}\Psi\left(\frac{t}{2}\right), \Psi(t-n)$ (7)

where h is a low pass filter and g is a high pass filter. (Jin Daubechies -1992). The discrete orthogonal wavelet decomposition in equation (6) implemented by applying these two filters to the input signal, and recursively decomposing the low frequency band as shown in Fig 6. The same pair of filters can be used to get back the original signal as shown in Fig 7.

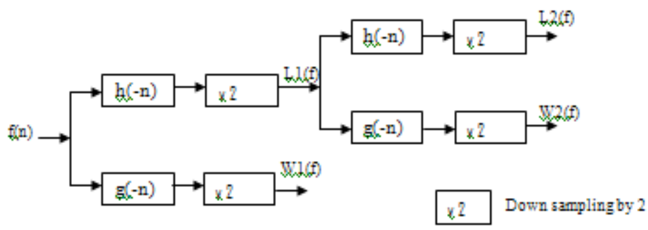


Fig. 6: Illustration of orthogonal wavelet transform of a discrete signal f(n) with CMF (Conjugate mirror filters), a two level expansion. (Yinpeng Jin et.al)

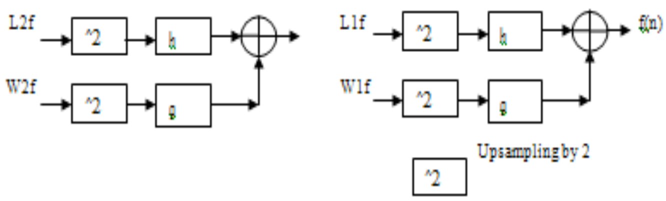


Fig. 7: Illustration of inverse wavelet transform implemented with CMF , a two level expansion. (Yinpeng Jin et.al)

The discrete dyadic wavelet transform , both decomposition and reconstruction can be implemented with a fast filter bank scheme using a pair of decomposition filters H,G and a reconstruction filter K (Jin_Mallat_1992b) as shown in Fig 8.

With Φ(x) as the scaling function, Ψ (x) as the wavelet function, X(w) as the reconstruction function, we have :

$$\Phi(2w) = e^{-jws} H(w)\Phi(w) \quad (8)$$

$$\Psi(2w) = e^{-jws} G(w)\Psi(w) \quad (9)$$

$$X(2w) = e^{-jws} K(w)X(w) \quad (10)$$

Where s is a Ψ (x) dependent sampling shift. The three filters H, G, K satisfy :

$$\mathrm{Mod}(H(w))^2 + G(w)H(w) = 1 \quad (11)$$

The filter implementation of discrete dyadic wavelet transform shown in fig. 5 is constructed by defining :

$F_s(w) = e^{-jws}$ F(w) and Fis either G or H or K.

This implementation has a complexity that increases linearly with the number of analysis levels. (Jin_holschneider_1989; Jin_shensa_1992).

In Image processing applications, we often deal with two, three or even higher dimensional data. This extension to higher dimension is quite straight forward.

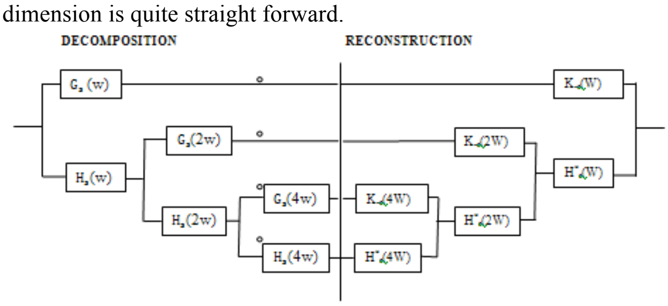


Fig. 8: Filter bank implementation of a one-dimensional discrete dyadic wavelet transform decomposition and reconstruction for three levels of analysis. (Yinpeng Jin et.al) ($H^*_s(W)$ denotes the complex conjugate of $H_s(W)$).

VII TRANSLATION AND ROTATION INVARIANCE

The variation in discrete wavelet transform is large with rotation and translation because a small change in location of an object can result in great variation of corresponding wavelet coefficient. Hence it is required to overcome rotation variance to make the wavelet co efficient useful in registration. The translation variance is caused by down sampling of data at each level of wavelet decomposition. The significant variation in the wavelet co efficient is significantly found for signals that differ only by translation. In the tensor product wavelets, the rotation variance is due to the strong coupling of the wavelets with the orientation of the axes, and the features aligned with axes and at diagonals are highlighted. The features will align with different axes and be high lightened in different sub-band of the transform when an object is rotated. Non separable wavelets also vary with rotation because they are not symmetrical. Hill. P. R, et. al. have made efforts to develop invariant versions of the discrete wavelet transform, but were not very successful as either shift or rotational invariance were solved, while otherwise produced redundant representations.

Registration of 3D images is finding prominence in most of the medical processing applications, due to the additional information present in the registered image that improves doctors to diagnose the diseases and develop report, thus assisting accuracy in detecting diseases. Next section discusses 3D image registration techniques.

VIII 3D IMAGE REGISTRATION TECHNIQUES

Geometric feature based IR and voxel comparison based IR are the two methods for 3D object registration. Voxel based method is slow but is accurate, geometric based method is faster but may not be accurate. In geometric based method, features of images such as points, curvatures, ridges or segments are used as features for aligning objects. These algorithms and methods cannot be applied to polyhedral or voxelized models, as they do not have mathematical representation. In voxel based methods, alignment is based on voxel representations of objects, color, intensity, illumination and reflectance. The computation time in this method is large due to selection of all possible discrete features to perform registration.

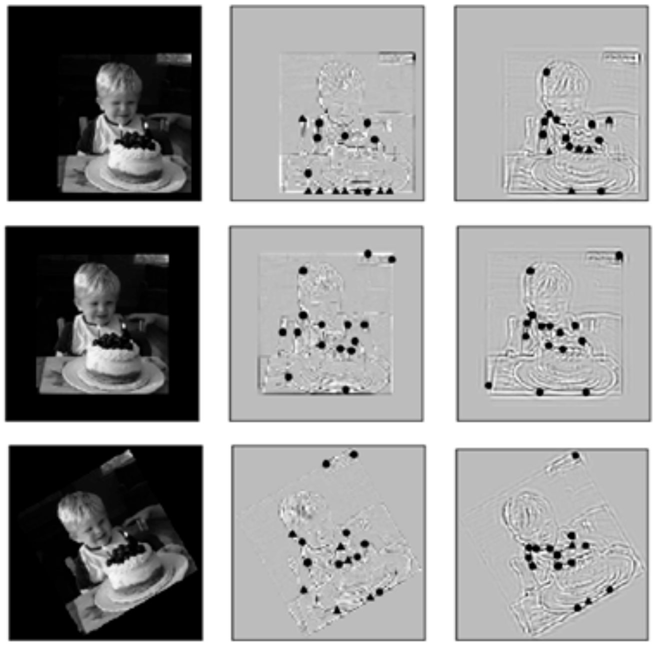


Fig 9 Comparison of DWT and DTCWT extrema in rotation and translation.

TABLE 2 SPEED OF THE WAVELET REGISTRATION ALGORITHM

Model	n	Time 1	m	$\binom{m}{3}^2$	Time 2
Knee MRI	7,077,888	14.4	30	16,483,600	18.2
Shrek Solid Model	3,932,160	12.8	30	16,483,600	33.1
Large Brain MRI	25,186,304	108.9	30	16,483,600	42.1
Brain MRI	7,614,464	7.0	15	207,025	1.9
Brain MRI	7,614,464	7.0	20	1,299,600	4.9
Brain MRI	7,614,464	7.0	25	5,290,000	13.6
Brain MRI	7,614,464	7.0	30	16,483,600	56.5
Brain MRI	7,614,464	7.0	35	42,837,025	374.2

TABLE 3 REGISTRATION RESULTS FOR VARIOUS EXAMPLES

Model		Rotation			Δ_r	Translation			Δ_t
		θ	ϕ	ψ		i	j	k	
Knee	Induced	20	-4	-41		-13	-8	-11	
	Algorithm	20	-4	-40	1	-12	-9	-10	2
Brain	Induced	-28	-37	34		14	-12	3	
	Algorithm	-27	-36	33	4	14	-13	2	2
Full Shrek	Induced	-12	-15	14		-11	3	-11	
	Algorithm	-12	-14	14	1	-12	3	-10	2
Cropped Shrek	Induced	-10	-20	-30		-14	6	-3	
	Algorithm	-10	-21	-30	1	13	-7	4	4
Noise SNR 4.74	Induced	-10	-20	-30		-3	7	0	
	Algorithm	-10	-21	-30	1	-3	8	0	2
Noise SNR 0.67	Induced	-10	-20	-30		-3	7	0	
	Algorithm	-10	-20	-30	1	-3	8	0	1
Clutter	Induced	-6	-8	7		5	-3	2	
	Algorithm	-6	-6	6	3	5	-3	1	2
Gooch Brain 1	Induced	-5	-5	-70		0	0	0	
	Algorithm	1	-3	-73	10	8	4	-2	14
Gooch Brain 2	Induced	0	0	0		0	0	0	
	Algorithm	3	2	-3	8	7	-4	0	11

VIII 3D IMAGE REGISTRATION USING WAVELETS

The wavelet decomposition of signal to a hierarchy of sub-bands with sequential decrease in resolution is very useful when multi-resolution is needed. Hence it is very useful in Image registration. Further a signal can be analyzed with a multi-resolution frame work into a spatial frequency framework. Distinct noise components can be separated easily from a noisy signal based on spatial-frequency characteristics by carefully selecting the wavelet function and space-frequency plane tilting of the transforms. Wavelet domain provides more effective registration algorithms because it's feature characteristics were proven to be potentially more efficient and reliable compared to spatial analysis only (Yinpeng Jin, Elsa Angelini, and Andrew Laine**).**

The Image Registration method using two different similarity measures, MI(Mutual Information) and SAD(Sum of Absolute Differences) in one multi resolution scheme , the wavelet pyramid has proved to perform better compared to the conventional MI methods. But SAD is not effective in multi-modal registration because even when perfectly registered, images from different modalities are different in intensity. Hence MI is used at high resolution levels to ensure accuracy. However, SAD works well in lower resolution registration because only the global features are preserved.

The complex wavelets outperforms on wavelets in the field of medical imaging. It gives very good alignment results. Medical images have lot of phase information, curves and textured information for which the complex wavelet is ideal. Also it retains the good qualities of wavelets like robustness, accuracy and multimodality. A new technique for multimodal automatic Image registration is presented by Milad Ghantous and group which proves that this technique has superior accuracy compared to the discrete wavelet transform method. High speed is achieved due to the application of algorithm in pyramidal fashion based on Dual tree complex wavelet transform. Matching in the lowest level is based on cross correlation and at higher levels the search interval is then refined using MI as the matching criteria due to it's ability to register multimodal images and as well as uni-modal cases.

Hala. S. Own introduced an Image registration algorithm based on Q-shift Complex wavelet transform and proved that Complex wavelet transform is potentially good domain for registration. The shift invariant property of the Complex wavelet transform is used to invert geometric distortion.

Sukriti and others developed an algorithm for medical image registration based on Genetic algorithm using complex wavelets and demonstrated that the complex wavelets, which are called the next generation wavelets gave robust and accurate solution in different applications.

Surface based methods are extensively used in image registration and voxel based methods are almost absent because it is relatively easy to obtain a surface from the patient through, either using laser scanning, probes, 2D imagery etc., while obtaining reliable image information for voxel property based methods is more difficult. Also the surface based methods are, on the average , still faster than voxel property based methods.

The main drawback of surface based methods is that they cannot cope with shift of relevant anatomy relative to the surface used in registration. This may be severely restraining to intra-operative application. Here the voxel based method can be used.

Julie S. Chalfant and others developed an algorithm for three dimensional Object Registration using wavelet features. This algorithm is used to conduct rigid registration of voxelised three dimensional objects using wavelet transform for the objects grossly misaligned and brings them close into alignment. Global alignment is achieved without the need for initial alignment and fine registration may be conducted using elastic registration methods. This method is faster than other geometric feature registration methods and significantly faster than the voxel intensity methods. Hence this method has become a pre-processing step for voxel intensity methods feasible.

Image Registration has become very successful in the last two decades with variety of applications. Most obvious reason is the fast and convenient access of data due to the development in data digital data archiving and communication. This has provided platform for registration of multimodal images in various disciplines. Image Registration has become a component of image analysis.

Further segmentation is an important process in image analysis to determine the areas of interest and accurate demarcation of objects yield valuable information. In medical application quantification is often the ultimate goal. The physician needs a quantified data after diagnosis to determine the extent of progression of a disease. Hence the progress in Image Registration should go hand in hand with other areas.

With development in technology, and growth of sophistication in the field of medicine, it is required to adopt technology to meet the requirements of common man. Thus there is convergence of medical image techniques and communication systems that lead to telemedicine and remote facility. In a primary health centre, with the availability of medical equipments, capturing real time images of patients, it is required to transmit the data to remote locations on the doctor's mobile devices for diagnosis. Thus it is required to develop a hardware based module that can capture images and compress images and transmit the same to remote locations. In this scenario, it is required to develop dedicated hardware for compression and registration using System on Chip platforms. Image registration is always followed by image fusion. As the registered images have to be fused to extract appropriate information, fusion is an integral part of registration process. Next section discusses various fusion techniques.

IX IMAGE FUSION

Image fusion utilizes information obtained from a number of different sensors surveying an environment to achieve refined information for decision making. Information fusion can be performed at any level of the image information representation. Corresponding to other forms of information fusion, image fusion is usually performed at one of the three different processing levels:

1. Signal
2. Feature
3. Decision level.

The Fig 10 shows the image fusion processing levels which consist of N image sequence as input .coe file, single image process which does the feature extraction of the input image and fusion process are carried out by three levels in image fusion domain.

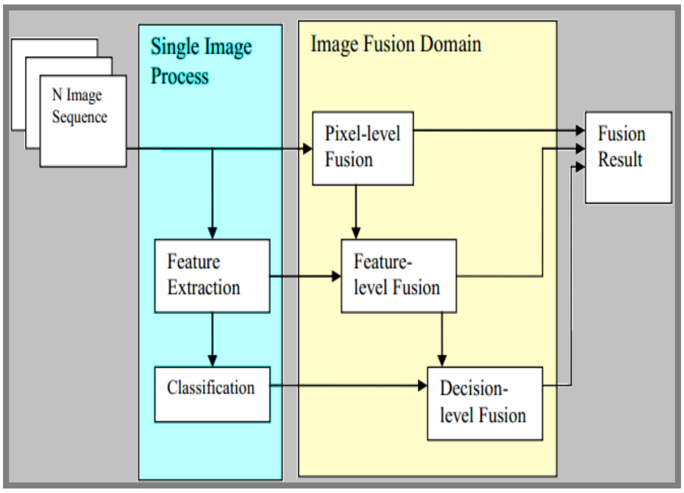


Fig 10 Image fusion processing levels

Signal level image fusion is also known as pixel-level image fusion which represents fusion at the lowest processing level, where a number of raw input image signals are combined to produce a single fused image signal (Vladimir 2001). Feature level image fusion is also known as object level image fusion where it fuses feature and object labels and property descriptor information that have already been extracted from individual input images. Decision level is also known as symbol level. Decision level is the highest level, where it represents fusion of probabilistic decision information obtained by local decision makers operating on the results of feature level processing on image data produced from individual sensors (Vladimir 2001). There are many image fusion methods like averaging, principle component analysis and various types of Pyramid Transforms, Discrete cosine transform, Discrete Wavelet Transform special frequency and so on, are available and are classified according to processing level.

X GENERAL APPLICATION LEVEL BLOCK DIAGRAM OF IMAGE FUSION

The Fig 11 shows the top level application block diagram of image fusion using wavelet transform which consists of two registered images, discrete wavelet transform block, fusion block and inverse wavelet transform block

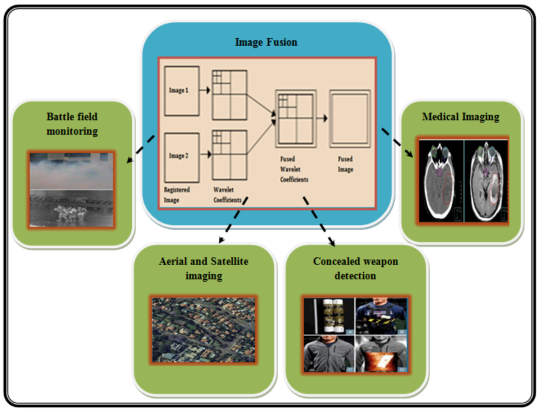


Fig 11 Top level application block diagram of image fusion

The requirement for the successful image fusion is that images have to be correctly aligned on a pixel-by-pixel basis. In this project, the images to be combined are assumed to be already perfectly registered. Image fusion is applicable in different fields such a medical imaging, battle field monitoring, aerial and satellite imaging and concealed weapon detection.

In medical imaging, the images that are captured from the Computed Tomography (CT) and Magnetic response imaging (MRI) scanners are fused to enhance the areas of interest such as, Tumour volumes and counters of critical structures. Image fusion technique allows healthcare providers to profit from increased visualization, as well as improved workflow enhancements and better delivery of overall patient care. In Concealed weapon detection, the concealed weapon inside the jacket is detected by thermal or infrared camera and the man features are detected by the visible camera. The images from infrared and visible camera are fused and resultant image presents the clear picture about the concealed weapon.

In the first step, the wavelet transforms of the images are computed. The wavelet transform contains the low-high bands, the high-low bands and high-high bands of the image at different scales (Vladimir 2001). Since larger absolute transform coefficients correspond to sharper brightness changes, a good integration rule is to select, at every points in the transform domain, the coefficients whose absolute values are higher. In this way, the fusion takes place in all the resolution levels and more dominant features at each scale are preserved in the new multi-resolution representation. A new image has been constructed by performing an inverse wavelet transform. Due to compactness, orthogonality and availability of directional information, the wavelet transform can effectively extract the salient features at different scales. The wavelet transform based image fusion technique produces the more naturally fused image even when the images to be combined are very different. An area–based maximum selection rule and a consistency verification step are proposed for feature selection. Better fusion results, both visually and quantitatively can be achieved using wavelet transform when compared to averaging and lapacian pyramid based image fusion.

XI DWT BASED IMAGE FUSION

The requirement for the successful image fusion is that images have to be correctly aligned on a pixel-by-pixel basis. In this research work, the images to be combined are assumed to be already perfectly registered. The Fig 12 shows the top level block diagram of image fusion using wavelet transform. The two input images image1and image 2 that are captured from visible and infrared camera respectively are taken as inputs. The wavelet transform decomposes the image into low-low, low-high, high-low, high-high frequency bands. The wavelet coefficients are generated by applying the wavelet transform on input images. Wavelet coefficients of the input images are fused by taking the average of input images. The resultant fused image is obtained by applying the inverse wavelet transform.

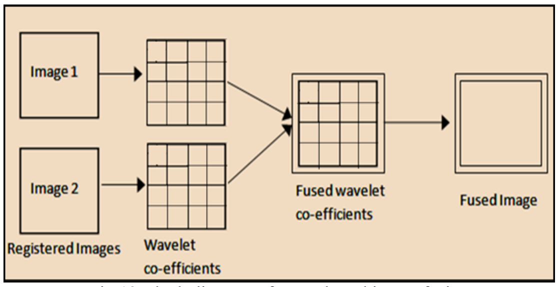


Fig 12 Block diagram of DWT based image fusion

The Fig 13 shows the flow chart to develop the image fusion process. The function developed to perform the image fusion, called wavelet and has four basic blocks:

Step 1: images size checking.
Step 2: transform to wavelet domain.
Step 3: wavelet domain fusion.
Step 4: inverse wavelet transforms.

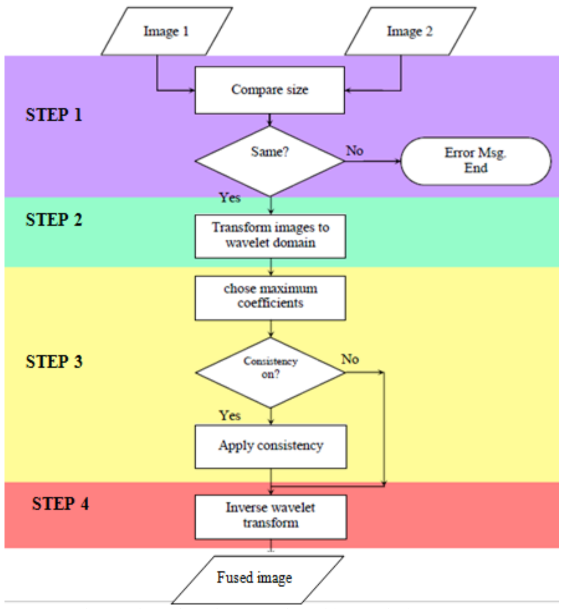


Fig 13 Flow chart for DWT based image fusion process

The most complex and significant step in this algorithm is to carry out the wavelet transformation. The wavelet transforms are applied to images. The wavelet transform consists of low-high, the high-low and high-high frequency bands of the image at different scales (Vladimir 2001). Since larger absolute transform coefficients correspond to sharper brightness changes and a good fusion rule to be selected at every point in the transform domain. The fusion takes place in all the resolution levels and main features at each scale are conserved in the new multi-resolution representation. Finally, a new image is constructed by applying inverse wavelet transform on fused image. Due to compactness, orthogonality and availability of directional information, the DWT can successfully extract the main features at different scales. The wavelet transform based image fusion technique produces the more naturally fused image even when the images to be combined are very different. An area–based maximum selection rule and a consistency verification step are proposed for feature selection. Better fusion results, both visually and quantitatively can be achieved using wavelet transform when compared to averaging and lapacian pyramid based image fusion (Manjunath 2008)

XII PERFORMANCE PARAMETERS

a. Entropy as a Quality Metric

Entropy is defined as amount of information contained in a signal. Shannon was the first person to introduce entropy to quantify the information. The entropy of the image can be evaluated as a.

$$H = -\sum_{i=1}^{G} P(i)\log_2(P(d_i));$$

Where G is the number of possible gray levels,P(d_i) is probability of occurrence of a particular gray level d_i .

Entropy can directly reflect the average information content of an image. The maximum value of entropy can be produced when each gray level of the whole range has the same frequency. If entropy of fused image is higher than parent image then it indicates that the fused image contains more information.

b. Standard Deviation as a Quality Metric

This metric is more efficient in the absence of noise. It measures the contrast in the fused image. An image with high contrast would have a high standard deviation.

$$\sigma = \sqrt{\sum_{i=0}^{L}\left(i-\bar{i}\right)^2 h_{I_f}(i)}, \cdots \bar{i} = \sum_{i=0}^{L} i h_{I_f}$$

Where, h_{i_f}(i) is the normalized histogram of the fused image.

L is number of frequency bins in histogram.

c.Root Mean Square Error (RMSE)

A commonly used reference-based assessment metric is the root mean square error (RMSE) which is defined as follows:

$$RMSE = \sqrt{\frac{1}{\mathrm{MN}}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(\mathrm{R(m,n)} - F(m,n)\right)^2}$$

Where R(m,n) and F(m,n) are reference and fused images, respectively, and M and N are image dimensions.

XIII REVIEW OF IMAGE FUSION ALGORITHMS

The paper titled “Multi-Sensor Image Fusion Using the Wavelet Transform” by Hui Li, B. S. Manjunath and Sanjit K. Mitra, which recommends that the Wavelet transform based image fusion approach produces more naturally fused image even when the images to be combined are very different. Manjunath has stated that by using the simplest method averaging, the contrast of features uniquely presented in either of the images is reduced. To solve this problem, several Laplacian pyramid based fusion schemes has been proposed. But still the laplician pyramid based techniques have certain drawbacks. Often the fused images contain the blocking artifacts in the regions where the multi-sensor data are significantly different.

An area-based maximum selection rule and a consistency verification step are adopted for feature selection. Better fusion results, both visually and quantitatively have been achieved using Wavelet transform due to its compactness, orthogonality and the availability of the directional information. One important criterion that is recommended by this paper is the stability of the inverse transform from the fused multi-resolution representation. The reconstruction of the laplician pyramid is unstable especially in the regions where two images are significantly different. As a result, artifacts are often visible. However, no such artifacts are observed when wavelet transform is adopted for image fusion. This paper aims at overcoming the drawbacks of lapliacian and averaging image fusion techniques. The paper titled **“Implementation of Image Fusion Techniques Using FPGA”** by **M.A. Mohamed and B.M. El-Den (Mohamed, 2010),** discusses in detail about the generic pre-processing flow of Image fusion and different measures to evaluate the performance of fusion process. The main characteristics of image fusion techniques like averaging, DCT, PCA, DWT, Laplacian pyramid, morphological pyramid, gradient pyramid, spatial frequency and artificial neural networks are discussed in the context of its mathematical formulation. This paper addresses the issues in image fusion: Fused two images by different techniques which present in this research, Quality assessment of fused images with above methods, comparison of different techniques to determine the best approach. The experimental results for above techniques are quantitatively evaluated by calculation of Root Mean Square Error RMSE, Entropy, Mean square error MSE, signal to noise ratio SNR and peak signal to noise ratio PSNR measures for fused images and a comparison is accomplished between these methods to implement the best technique by using FPGA. From the paper, it is concluded that the DWT based image fusion provides the best results among all other discussed techniques.

The paper titled **“A wavelet-based image fusion tutorial” by Gonzalo Pajares and Jesus Manuel de la Cruz (Gonzalo, 2004),** discusses about the different fusion method including multi-resolution analysis and a review on wavelet theory. This paper recommends an image fusion tutorial based on wavelet decomposition, i.e. a multi-resolution image fusion approach. The tutorial performs a synthesis between the multi-scale-decomposition-based image approaches. This paper discusses about the block diagrams of generic fusion schemes where the input images have identical and different resolutions and also how to implement 2-D wavelet transform for multi-resolution decomposition images. This paper illustrates about how to merge the DWT coefficients by using activity-level measurement, coefficient grouping method and coefficient combining methods. For each wavelets family, author obtained the member of the family giving the best results and then stated that this member is selected for a global comparison with all the others. The best results are obtained for the member whose values are closest to the ideal case, i.e. differences in the mean zero, correlation coefficient one and low standard deviations. The paper titled “A VLSI ARCHITECTURE FOR DISCRETE WAVELE:T TRANSFORM” by Xuyun Chen, Ting Zhou(1996*)*, discusses about the DWT and multi-resolution analysis and the architecture of DWT. This paper discusses about a specific VLSI architecture for forward and inverse DWT. The characteristics of the Daubechies filter wavelet coefficient are considered to reduce the total circuit area. In addition, Booth algorithm and balanced pipelines have been adopted and result in a higher throughput for 5 clocks’ pipeline latency and at 2 outputs per clock. In this paper, it is suggested that this architecture is suitable for VLSI implementation and it is described and verified by the hardware description language VLSI. The mismatch of image features in multi-sensor images reduces the similarities between the images and makes it difficult to establish the correspondence between the images. This problem was found in the investigation, when trying to develop a global motion estimation technique based in block matching algorithms without satisfying results. The lower resolution imagery does not adversely affect the higher resolution imagery when used with multi-resolution image representations. Full Search algorithm image registration technique requires $(2d+1)^2$ block comparisons. This high computational complexity makes it often not suitable for real-time implementations. Without any previous image processing, it is not suitable at all for image registration purposes when the two images come from different sensors such as infrared and normal vision cameras or even when they come from the same sensor but with different focus points.

Multi-sensor image fusion application and importance since 1990 are revealed

A multi-sensor image fusion system overcomes the limitations of a single sensor vision system by combining the images from these sensors to form a composite image (Canga 2002). The Wavelet transform based image fusion approach produces more naturally fused image even when the images to be combined are very different (Manjunath 2008). By using the simplest method averaging, the contrast of features uniquely presented in either of the images is reduced (Manjunath 2008). The issues in image fusion is quantitatively evaluated by calculation of Root Mean Square Error RMSE, Entropy, Mean square error MSE, signal to noise ratio SNR and peak signal to noise ratio PSNR measures for fused images (Mohamed 2010). The DWT coefficients can be merged using activity-level measurement, Coefficient grouping method and Coefficient combining methods (Gonzalob2004). By using laplacian and averaging image fusion, often the fused images contain the blocking artifacts in the regions where the multi-sensor data are significantly different(Manjunath 2008). An area-based maximum selection rule and a consistency verification step are adopted for feature selection. Better fusion results, both visually and quantitatively have been achieved using Wavelet transform due to its compactness, orthogonality and the availability of the directional information (Manjunath 2008). Next section discusses various architectures for DWT realization.

XIV VLSI ARCHITECTURES FOR DWT REALIZATION

The paper "Low-Power And High-Speed VLSI Architecture For Lifting-Based Forward And Inverse Wavelet Transform"[1] proposed by Xuguang Lan and Nanning Zheng, presents the low-power, high-speed architecture which performs two-dimension forward and inverse DWT (discrete wavelet transform) for the set of filters in JPEG2000 using line based and lifting scheme. It consists of one row processor and one column processor each of which contains four sub-filters. And the row processor which is time-multiplexed performs in parallel with the column processor. Optimized shift-add operations are substituted for multiplications, and edge extension is implemented by embedded circuit. The whole architecture which is optimized in the pipeline design way to speed up and achieve higher hardware utilization has been demonstrated in FPGA. Two pixels per clock cycle can be encoded at 100MHz. The architecture can be used as a compact and independent IP core for JPEG2000 VLSI implementation and various real-time image/video applications. This architecture can be easily adopted for image registration techniques.

Anirban Das, Anindya Hazra, and Swapna Banerjee have proposed the architecture of the lifting based running 3-D discrete wavelet transform (DWT), which is a powerful image and video compression algorithm in the paper "An Efficient Architecture for 3-D Discrete Wavelet Transform"[2]. The proposed design is one of the first lifting based complete 3-DDWT architectures without group of pictures restriction. The new computing technique based on analysis of lifting signal flow graph minimizes the storage requirement. Proposed architecture reduces memory referencing and related low power consumption, low latency, and high throughput. The proposed architecture has been successfully implemented on Xilinx Virtex-IV series field-programmable gate array, offering a speed of 321 MHz, making it suitable for real time compression even with large frame dimensions. The architecture reported in this work need to be scaled to larger size, so that it can be used to extract features for image registration. Suitable modification to this architecture would enable image registration.

Chin-Fa Hsieh , Tsung-Han Tsai , Neng-Jye Hsu , and Chih-Hung Lai , proposed[3] a novel, efficient VLSI architecture for the implementation of one-dimension, lifting-based discrete wavelet transform (DWT). Both folded and the pipelined schemes are applied in the proposed architecture the former scheme supports higher hardware utilization and the latter scheme speed up the clock rate of the DWT. The architecture has been coded in Verilog HDL, and then verified successfully by the platform of Quartus-II of version 5.0. The proposed architecture effectively shortens the critical path and therefore enhances the clock period, without adding the number of adders and multipliers/shifters. Latency and through put can be further enhanced to meet medical applications.

Jen-Shiun Chiang, and Chih-Hsien Hsia have proposed a highly efficient VLSI architecture for 2-D lifting-based 5/3 filter discrete wavelet transform (DWT) in "An Efficient VLSI Architecture for 2-D DWT using Lifting Scheme"[4]paper. The architecture is based on the pipelined and folding scheme processing to achieve near 100% hardware utilization ratio and reduce the silicon area. Proposed efficient 2-D lifting-based DWT VLSI architecture uses lossless 5/3 filter and pipelined processing. The architecture can have almost 100% hardware utilization. The advantages of the proposed DWT have the characteristics of higher hardware utilization, less memory requirement, and regular data flow. For medical images, the architecture proposed in this paper can be extended to process 4D images.

A low bit rate three dimensional decomposition algorithm for video compression with simple computational complexity is proposed [5] by Awad Kh. Al-Asmari and Abdulaziz Al-Rayes. The algorithm performs the temporal decomposition of a video sequence in a more efficient way by using 4-tap short symmetric kernel filter (Haar filters) with decimation factor of 4:1 instead of 2:1 used in the classical 3D-wavelet algorithms. The pyramid coding decomposition concept is then used for the spatial domain. The main goal is to design a simple encoding algorithm with a very high performance. Local adaptive vector quantization (LAVQ) is used to encode some of the spatial subbands. The codebook of LAVQ is simple and robust to the motion which occurs in the video sequences and which seldom captures from a single training sequence. The other subbands are encoded using the very simple coding algorithm called absolute moment block truncation code (AMBTC). The AMBTC is used for the bands that are highly correlated and with no motion or sparks information. The algorithm proposed in this work, does not perform better on real time images and medical images. Thus preprocessing of the images prior to feature extraction is required.

M.F. L´opez, S.G. Rodr´ýguez, J.P. Ortiz, J.M. Dana, V.G. Ruiz and I. Garc´ýa have proposed "Fully Scalable Video Coding with Packed Stream"[6] where Scalable video coding is a technique which allows a compressed video stream to be decoded in several different ways. This ability allows a user to adaptively recover a specific version of a video depending on its own requirements. Video sequences have temporal, spatial and quality scalabilities. In this work they have introduce a novel fully scalable video codec. It is based on a motion-compensated temporal filtering (MCTF) of the video sequences and it uses some of the basic elements of JPEG 2000. The techniques adopted for video coding can be extended to perform medical image registration.

In the paper [7], "3D Discrete Wavelet Transform VLSI Architecture for Image Processing" Malay Ranjan Tripathy, Kapil Sachdeva, and Rachid Talhi have proposed an improved version of lifting based 3D Discrete Wavelet Transform (DWT) VLSI architecture which uses bi-orthogonal 9/7 filter processing. This is implemented in FPGA by using VHDL codes. The lifting based DWT architecture has the advantage of lower computational complexities transforming signals with extension and regular data flow. This is suitable for VLSI implementation. It uses a cascade combination of three 1-D wavelet transform along with a set of in-chip memory buffers between the stages. These units are simulated, synthesized and optimized for Spartan-II FPGA chips using Active-HDL Version 7.2 design tools. The timing analysis tools of this (Active-HDL), reports the frequency above 100MHz and ensures 100% hardware utilization. The architecture is very slow in terms of latency and throughput, hence suitable modifications to this architecture enhances the throughput and latency. To achieve this, images sequences can be divided into sub images or voxels, processing of individual voxels can improve the processing speed of the architecture.

"An Efficient Architecture For Lifting-Based Forward And Inverse Discrete Wavelet Transform" [8]is proposed by Aroutchelvame, S. M. and K. Raahemifar where architecture performs both forward and inverse lifting-based discrete wavelet transform . The proposed architecture reduces the hardware requirement by exploiting the redundancy in the arithmetic operation involved in DWT computation. The proposed architecture does not require any extra memory to store intermediate results. The proposed architecture consists of predict module, update module, address generation module, control unit and a set of registers to establish data communication between predict and update modules. The symmetrical extension of images at the boundary to reduce distorted images has been incorporated in the proposed architecture as mentioned in JPEG2000. This architecture has been described in VHDL at the RTL level and simulated successfully using ModelSim simulation environment. For real time processing of medical images, the architecture proposed in this work should be extended into 4D space, thus making it suitable for 4D image registration.

XV Applications of IR

Due to the innumerable applications to which Image Registration can be applied, it is impossible to develop a general method that is optimized for all uses. A few applications are listed below.

Remote Sensing using spectral classification, weathering forecasting, environmental monitoring, change detection, image mosaicing, integrating information into GIS (Geographic Information System). It is also used in astrophotography to align images taken of space.

In medicine IR is used in combining data from different modalities like CT, MRI, SPECT etc., monitoring tumor growth, Atlas-based segmentation/brain stripping, Comparison of patient's data with anatomical atlases, map (cartography) updating. Also in *elastic* (also known as *nonrigid*) registration to cope with deformation of the subject (due to breathing, anatomical changes, and so forth). In Computer vision IR is used in target updating, automatic quality control. Image registration is essential part of panoramic image creation. There are many different techniques that can be implemented in real time and run on embedded devices like cameras and camera-phones.

XVI. Conclusion

Wilhelm Conrad Roentgen's discovery of X-rays in 1895 spawned revolutionary advancements in the treatment of human disease. Subsequent imaging modalities such as ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and single photon emission computed tomography (SPECT) have further advanced the state of the art in medicine. However, none of the current imaging modalities are capable of providing adequate, real-time, high resolution images quickly enough to construct real-time 4-D images for non-invasive surgery. For example, tumor sites located in the thorax and abdomen are affected by respiratory motion (and to a lesser degree digestive tract motion and heart beat and gross vascular motion), and existing imaging techniques are generally not fast enough to account for this motion in real time. Respiration is an involuntary' action—patient's cannot be expected to hold their breath during procedures although some clinical techniques help patient's control breathing to restrict motion. Furthermore, breathing patterns differ for each patient. In fact, breathing patterns vary not only from one treatment session to another, but even within a single treatment session. Consequently, one cannot assume a general respiration pattern for patients prior to observation and treatment. One treatment solution for treating tumors subject to unconscious motion is to treat the entire gross potential tumor volume (PTV); that is, the tissue volume covering all possible areas the tumor could conceivably be located. However, irradiating a PTV exposes healthy tissue to high doses of radiation, potentially damaging it. At the same time, conservative treatments that aim to minimize damage to healthy tissue could allow the re-growth and metastasis of tumor tissue.

Another major challenge in image registration is the registration of non rigid objects in a human body. Unlike rigid tissue registration techniques, there is no "gold standard" for evaluating the accuracy and repeatability of the registration of images of non-rigid structures in the body. Organs within the body naturally change shape and move relative to one another between imaging sessions. (For example, rigid tissue registration techniques use skeletal features as a gold standard reference, which allows for more consistent alignment of images with respect to these features.) The lack of a gold standard for assessing and evaluating the success of non-rigid registration algorithms is one of their more significant drawbacks. Solving the challenges posed by registering images of rigid tissue appears to be well advanced; however, there is ample room for innovation in the registration of non-rigid images. New algorithms will need to focus on registering deformed tissue, 4D (i.e. 3D+time) imaging, and ultrasound. Algorithms for deformed tissue will enable better tracking of diseased tissue over time. Algorithms for 4D registrations will allow for better image-guided surgery. This, in conjunction with augmented reality, could improve surgical outcomes. In addition, 4D registration will enable better diagnosis with fMRI and PET. Ultrasound is a ubiquitous modality because of its cost, effectiveness, and portability. Efforts should be made to improve registration algorithms to further the uses of this modality. It is required to develop new algorithms focusing on registering deformed tissue, 4D (i.e. 3D+time) imaging, and ultrasound. Algorithms for deformed tissue will enable the better tracking over time of diseased tissue.

In 4-D imaging technologies, progress has been made combining image registration and classification to provide intrinsic simplification and cross verification. It remains a challenge, however, to develop a fully automated deformable image registration algorithm, reducing the method's applicability in real-time image generation. As the organs in the body are not rigid, they deform, often substantially, between treatments and even during a treatment episode. Deformable image registration is generally a "passive" mapping process. It does not anticipate how patient anatomy might deform. An example is whether superficial 3-D contour information detected by a real time infrared camera can be used to predict the motion of internal organs. Anatomically, the correlation between superficial and internal organ motion should exist, although as a complex relationship. Therefore, an anatomic model based image registration with motion estimation can provide an "active" mapping process.

The primary applications of high resolution, high speed, 4-D imaging; predictive imaging; or other target tissue location technologies for directed energy based surgical therapy. Tissue altering directed energy-based surgical systems are widely used in an array of applications including:

- Aesthetic
- Oncologic
- Cardiovascular
- Gynecologic
- Orthopedic
- Otorhinolaryngologic (ear, nose and throat)
- Urologic surgical procedures

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