Color Image SegmentationAnd Image Registration using Type 2 Fuzzy Sets

Himadri Nath Moulick
Dept-CSE, Aryabhatta Institute of Engg & Management
Durgapur, pin-713148, India
himadri80@gmail.com

Anindita Chatterjee
Dept-IT, Tata Consultancy Services
Kolkata, India
anindita_star24@rediffmail.com

***Abstract*—Optimization of the similarity measure is an essential theme in medical image registration. In this paper, a novel continuous medical image registration approach (CMIR) is proposed. This is our extension work of the previous one where we did a segmentation part of any particular image with a custom algorithm .The CMIR, considering the feedback from users and their preferences on the trade-off between global registration and local registration, extracts the concerned region by user interaction and continuously optimizing the registration result. Experiment results show that CMIR is robust, and more effective compared with the basic optimization algorithm. Image registration, as a precondition of image fusion, has been a critical technique in clinical diagnosis. It can be classified into global registration and local registration. Global registration is used most frequently, which could give a good approximation in most cases and do not need to determine many parameters. Local registration can give detailed information about the concerned regions, which is the critical region in the image. Finding the maximum of the similarity measure is an essential problem in medical image registration. Our work is concentrating on that particular section with the synergy of Tpe-2 fuzzy logic invoked in it.**

Keywords—Multi-model image alignment, Extrinsic method, intrinsic method Introduction.

I. INTRODUCTION

Information systems are often poorly defined, creating difficulty in representing concepts and selecting important features used to solve the problems. Type-1 (T1) fuzzy set (FS) has been around for more than four decades and yet not able to handle all kinds of uncertainties appearing in real life. The above statement sounds paradoxical because the word fuzzy has the connotation of uncertainty. The extension of T1 fuzzy systems, in particular type-2 (T2) accommodates the system uncertainties and minimizes its effect considerably in decision making. However, T2 FS is difficult to understand and explain.

Application of T1 fuzzy logic to rule-based systems is most significant that demonstrates its importance as a powerful design methodology to tackle uncertainties. A fuzzy logic system (FLS) is described completely in terms of T1 fuzzy sets, called type-1 fuzzy logic system (T1FLS), whereas a FLS with at least one T2 fuzzy set is called T2 fuzzy logic system (T2FLS). T1FLSs cannot directly handle rule uncertainties because T1 fuzzy sets are certain. On the other hand, T2FLS is very useful in circumstances where it is difficult to determine an exact membership function of a fuzzy set. Such cases are handled by rule uncertainties and measurement uncertainties. Like T1FLS, T2 has wide applications and the potential of T2 systems outperforms T1 in most of the cases. The aim of the paper is to describe T2 fuzzy systems for managing uncertainties, identifying the frontier research areas where T2 fuzzy logic is applied and proposes an algorithm on application of type-2 fuzzy sets in color image segmentation.

A. Modelling uncertainty using of fuzzy logic

Uncertainty appears in many forms and independent of the kind of fuzzy logic (FL) or any kind of methodology one uses to handle it . Uncertainty involves in real life, due to deficiency of information in various forms. One of the best sources for general discussions about uncertainty is found in. Two types of uncertainties, randomness and fuzziness exist, where probability theory is associated with the former and FS with the latter. Fuzziness (or vagueness) generally recognizes uncertainty resulting from the imprecise boundaries of fuzzy sets, nonspecificity connected with sizes (cardinalities) of relevant sets and strife (or discord), which expresses conflicts among the various sets of alternatives. T1 fuzzy sets are certain and not able to handle all kinds of uncertainties using a single membership value, which is crisp. A FLS needs some measure to capture uncertainties than just a single number. The extended FL, named as T2FL able to handle uncertainties by modeling and subsequently minimizing their effects. T2 fuzzy logic provides the measure of dispersion, fundamental to the design of systems that includes linguistic or numerical uncertainties translating into rules. T2 fuzzy set is a natural framework for handling both randomness and fuzziness. It is the third dimension of T2 membership function (MF) that allows us to evaluate the model uncertainties. A T2FLS has more design degrees of freedom than a T1FLS because T2 fuzzy sets are described by more parameters compare to T1 fuzzy sets. Linguistic and random uncertainties are evaluated using the defuzzified and type-reduced outputs of the T2FLS. The type-reduced output can be interpreted as a measure of dispersion about the defuzzified output.

B. scope of work

Image segmentation is one of the most difficult image processing tasks because the segmented images are not always precise rather vague. In earlier works, image segmentation was applied in monochrome color images, later applied on red, green, blue (RGB) color space. Two main image segmentation techniques are described in the literature; region reconstruction where image plane is analyzed using region growing process

ISBN: 978-81-923777-9-7

and color space analysis where the color of each pixel is represented in the designated color space. Many authors have tried to determine the best color space for some specific color image segmentation problems, however, there does not exist a unique color space for all segmentation problems. Computational complexity may increase significantly with reference to C(Cyan), M(Magenta),Y(Yellow), K(contrast) (CMYK) color space in comparison with gray scale image segmentation. Classically, the RGB color space has been chosen for color image segmentation where a point in the image is defined by the color component levels of the corresponding R, G and B pixels. However, while the region growing techniques tend to over-segment the images, on the other hand the color space analysis methods are not robust enough to significance appearance changes because of not including any spatial information. Fuzzy logic is considered to be an appropriate tool for image analysis, applicable in CMYK and particularly for gray scale segmentation. Recently, fuzzy region oriented techniques and fuzzy entropy based techniques are applied for color image segmentation. The major concern of these techniques is spatial ambiguity among the pixels, representing inherent vagueness. However, there still remain some sources of uncertainties with the meanings of the words used for noisy measurements and the data used to tune the parameters of T1 fuzzy sets may be noisy too. The new concept of evidence theory allows to tackling imprecision in model uncertainty used in pattern classification, and produces good results in segmentation, although this technique based on CMYK model is not often used.

The amount of uncertainty is evaluated using the approach proposed by Klir where he generalizes the Shannon entropy to belief functions using two uncertainty measures, mainly the non-specificity and the discord. The robust method using T2 fuzzy set is another approach for handling uncertainty in image analysis. It can take into account three kinds of uncertainty, namely fuzziness, discord and nonspecificity. T2 fuzzy sets have grade of membership value, which are themselves fuzzy. Hence, the membership function of a T2 fuzzy set has three dimensions and it is the new third dimension that

C. *Prelimirers of type-2 fuzzy system*

The term "fuzzy set" is general that include T1 and T2 fuzzy sets (and even higher-type fuzzy sets). All fuzzy sets are characterized by MFs. A T1 fuzzy set is characterized by a two-dimensional MF, whereas a T2 fuzzy set is characterized by a three-dimensional MF. Let us take an example of linguistic variable "speed". Different values of the variable like "very high speed" , "high speed" , "low speed" signify the crisp value. One approach to using the 100 sets of two endpoints is to average the endpoint data and use the average values for the interval associated with "speed". A triangular (or other shape) MF has been constructed whose base endpoints (on the x-axis) are at the two average values and whose apex is midway between the two endpoints. The T1 triangular MF has been represented in two dimensions and expressed mathematically in equation (1)

$$\{(x, \mathrm{MF}(x)) | \; x \in X\} \; \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

However, the MF completely ignores the uncertainties associated with the two endpoints. A second approach calculates the average values and the standard deviations for the two endpoints. The approach blurs the location in between the two endpoints along the *x*-axis. Now the triangles are located in such a way so that their base endpoints can be anywhere in the intervals along the *x*-axis associated with the blurred average endpoints, which leads to a continuum of triangular MFs on the *x*-axis. Thus whole bunch of triangles, all having the same apex point but different base points are obtained as shown in figure 5. Suppose, there are exactly N such triangles, and at each value of x, MFs are: $\mathrm{MF}_1(x)$, $\mathrm{MF}_2(x)$, …, $\mathrm{MF}_N(x)$. Weight is assigned to each membership value, say w_{x1}, w_{x2}, …, w_{xN}, representing the possibilities associated with each triangle at a particular value of x.

The resulting T2 MF is expressed using (2)

$$(x, \{(MF_i(x), w_{xi}) | \; i = 1, \ldots, N\} | \; x \in X\} \; \ldots.. (2)$$

Another way to represent the membership value: {(x, MF(x, w)| x∈X and w∈Jx} where MF(x, w) is the three-dimensional T2 MF, shown in figure 1.

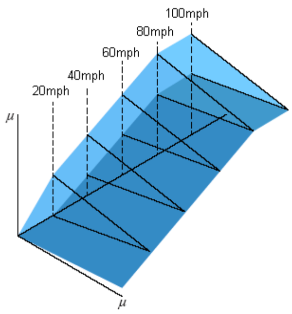

Fig. 1 3-D Representation of T2 FS "Speed"

Another way to visualize T2 fuzzy sets is to plot their footprint of uncertainty (FOU).

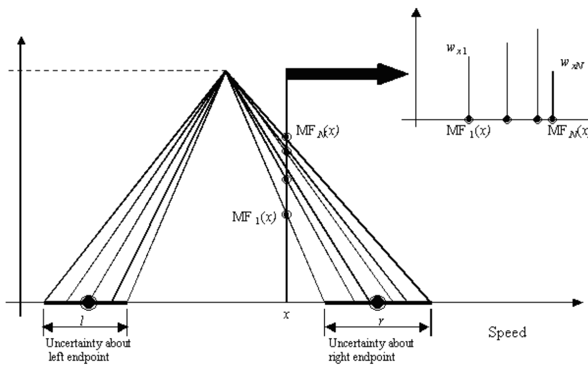

Fig. 2 Triangular MFs (base endpoints l and r) with Uncertain Intervals

D. *Footprint of Uncertainty*

In T2, MF(x, w) can be represented in a two-dimensional *x*-*w* plane, consisting of only the permissible (sometimes called "admissible") values of x and w. It implies that x is defined over a range of values (its domain), say, X while w is defined over its range of values (its domain), say, W. An example of FOU for a Gaussian MF is shown. The standard deviation of the MF is certain while mean, m, is uncertain and varies anywhere in the interval from $m1$ to $m2$. Uncertainty in the primary memberships of a T2 fuzzy set, Ã, consists of a bounded region, called the footprint of uncertainty (FOU).

ISBN: 978-81-923777-9-7

FOU is the union of all primary memberships (Jx), given in (3).

$$FOU(\tilde{A}) = \bigcup_{x \in X} Jx \quad \ldots\ldots\ldots\ldots\ldots..(3)$$

FOU focuses our attention on the uncertainties inherent in a specific T2 membership function, whose shape is a direct consequence of the nature of the uncertainty. The region of FOU indicates that there is a distribution that sits on top of it—the new third dimension of T2 fuzzy sets. Shape of the distribution depends on the specific choice made for the secondary grades. When the secondary grade is equal to one, the resulting T2 fuzzy set is called interval T2 fuzzy sets (IT2FS), representing uniform weighting (possibilities).

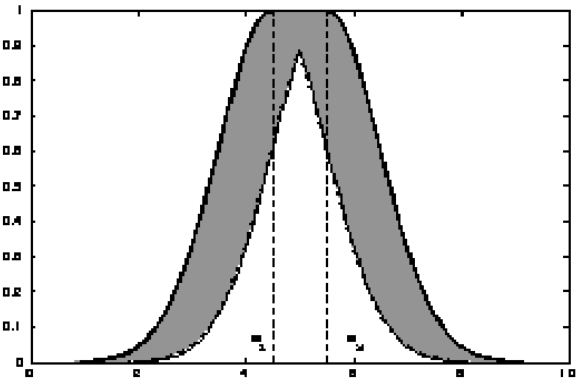

Fig. 3 OU of Gaussian (primary) MF with Uncertain mean

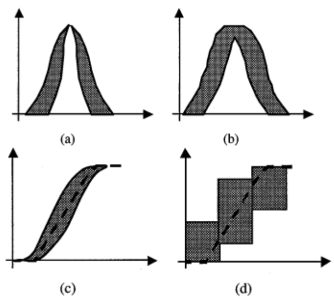

Fig. 4 OU: (a) Gaussian MF with Uncertain Standard Deviation (b) Gaussian MF with uncertain mean (c) Sigmoidal MF with Inflection Uncertainties (d) Granulated Sigmoidal MF with Granulation Uncertainties.

E. Type-2 Fuzzy Set Entropy

The process of obtaining necessary information to perform segmentation leads to the correct selection of the regions of interest of the color image. The proposed work applied theory of fuzzy set to evaluate the regions of interest with fixed accuracy. Fuzziness index [12] and entropy [13] provide the measurement of degree of uncertainty [14] of the segmentation process. To measure the fuzziness of images, a few formal definitions are discussed below. An ordinary fuzzy set A of the universe of discourse X is classically defined by its membership function $\mu_A(x)$: $X \rightarrow [0, 1]$, $x \in X$.

A point x for which $\mu_A(x) = 0.5$ is said a crossover point of fuzzy set $A \subseteq X$. The uncertainty is represented by the "α-cut" of fuzzy set A, whose membership function $\mu^{\alpha}_A(x)$: $X \rightarrow \{0,1\}$ is defined in (4).

$$\mu^{\alpha}_A(x) = 1 \text{ if } \forall x \geq \alpha$$
$$= 0 \text{ if } \forall x < \alpha \quad \ldots. (4)$$

where $\alpha \in [0, 1]$ and $x \in X$

The fuzziness index $\gamma(A)$ of a fuzzy set A reflects the degree of ambiguity by measuring the distance $d(A, A^{0.5})$ between A and its nearest set $A^{0.5}$ (α=0.5) as described in (5).

$$\gamma(A) = 2 \times d(A, A^{0.5}) / n^{1/p} \quad \ldots. (5)$$

A positive scalar p is introduced to keep $\gamma(A)$ in between zero and one depending on the type of distance function used. In the proposed algorithm with the help "α-cut" "n-cut" fuzzy set is described, where n is the number of elements of n-cut vector. This measure represents the area between two membership functions $\mu_A(x)$ and $\mu^{\alpha}_A(x)$, described in (6).

$$\gamma(A) = \lim_{\Omega \to X} \left(\frac{1}{\|\Omega\|} * \int_{\Omega} | \mu_A(x) - \mu_A^{0.5}(x) | \, dx \right) \quad \ldots. (6)$$

where $\|\Omega\|$ represents the size of the set Ω (linear index values) and in practice we can use the discrete formula, given in (7)

$$\gamma_A^p = \left[\frac{1}{\|X\|} * \sum_{x \in X} | \mu_A(x) - \mu_A^{0.5}(x) |^p \right]^{\frac{1}{p}} \quad \ldots. (7)$$

γ^p_A is a monotonic function, where $p \in [1, +\infty]$ and $\|X\|$ represents the cardinality of the set X.

The term entropy of fuzzy set A, denoted by $H(A)$ (monotonic increasing function) was first introduced by De Luca and Termini, expressed in (8).

$$H(A) = \left(\sum S_n(\mu_A(x))\right) / n.\ln 2 \quad \ldots. (8)$$

Where $S_n(\mu_A(x)) = -\mu_A(x)ln(\mu_A(x))-(1-(\mu_A(x))ln(1-\mu_A(x)))$

In this work, we use the extension of the "De Luca and Termini" measure to discrete images, proposed by Pal [53]. The (linear) index of fuzziness of an $M \times N$ image subset $A \subseteq X$ with L gray levels $g \in [0, L-1]$ is defined in (9) and shown in figure 5.

$$\gamma(A) = \frac{1}{MN} \sum_{g=0}^{L-1} h(g) * [\mu_u(g) - \mu_l(g)] \quad \ldots. (9)$$

Where $h(g)$ represents the histogram of the image and $\mu_X(g)$, the membership function consists of $\mu_u(g)$ and $\mu_l(g)$. Entropies are used in with T2 fuzzy sets in gray scale image segmentation by extending the works proposed by Tizhoosh . Tizhoosh applied T2 fuzzy sets for gray scale image thresholding and obtained good results even in case of very noisy images. As proposed in , he used interval T2 fuzzy sets with the FOU, described below:

Upper Limit: $\mu_u(x)$: $\mu_u(x) = [\mu(x)]^{0.5}$

Lower Limit: $\mu_l(x)$: $\mu_l(x) = [\mu(x)]^2$

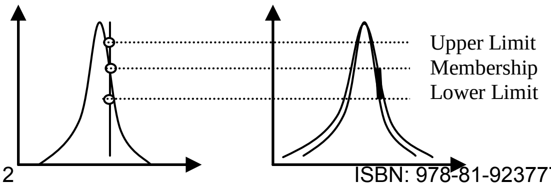

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Fig. 5 Membership functions representing FOU

Here for the CMYK color model, the same functions are used for image segmentation. To overcome the drawback of gray scale imaging, various correctional measures are considered in the proposed algorithm.

F. Algorithm for Color Image Segmentation

Begin

Step1: Read the JPEG file to be segmented

Step2: Select the proper shape of the interval base T2 fuzzy set MF as

$$A = \int_{x \in X} \int_{u \in Jx} \mu_A(x, u) / (x, u) \; J_x \subseteq [0, 1]$$

Step3: Fix the image size of $M \times N$ matrix;

Step4: Calculate h(g) for each color component of the color space;

//For linear index calculation

Step5: Calculate n – cut of the total image **//for color pattern possibility matching with CMYK;**

Step6: Initialize the position of the T2 MF;

Step7: Shift the MF with gray level ranges;

Step8: Mapping the picture colors into gray scale format;**//For contour detection**

Step 9: calculate the values of MF $\mu_u(g)$ and $\mu_l(g)$ (where $\mu_u(g)$, $\mu_l(g) \subseteq \mu_X(g)$);

Step10: Compute edge of the image based on contour formation;

Step11: Compute similarity matrix say 'W' based on inverting contours;

Step12: Find mid, max and min of fuzzy index;

Step13: Compute the n – cut eigenvectors;**//possible combination of colors for the input picture**

Step14: Threshold the image with γ_{max} value; **//Unwanted pixel elimination based on Median filter**

Step15: Masking of segmented image using msk matrix is defined by

$$msk = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Step16: Median filtering on the segmented image to remove noise;

Step17: Apply the region merging process using the obtained classes of **pixels**;

//Segmented portion of images are merged.

Step18: Smoothing of image to reduce the number of connected components;

Step19: Calculate the connected components;**//n-Cut Eigen vector**

Step20: Calculate the number of pixels in the final image;

End.

G. Experimental Results

In order to test the performance of the algorithm, the samples (figure 6, 10) are taken in JPEG image format having a size of 163×147 pixels in RGB color mode. Results of execution of the algorithm are shown from figure 6.

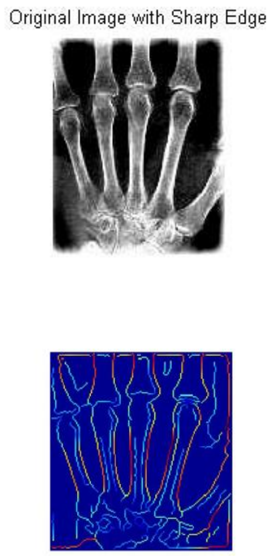


Fig. 6 Original image

Fig. 7 Segmented Image

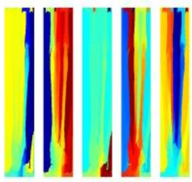


Fig. 8 Contour Detection

ISBN: 978-81-923777-9-7

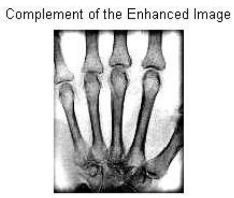


Fig. 9 n-cut eigenvectors

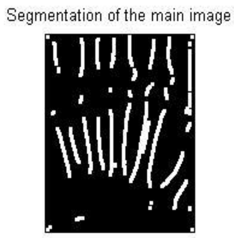
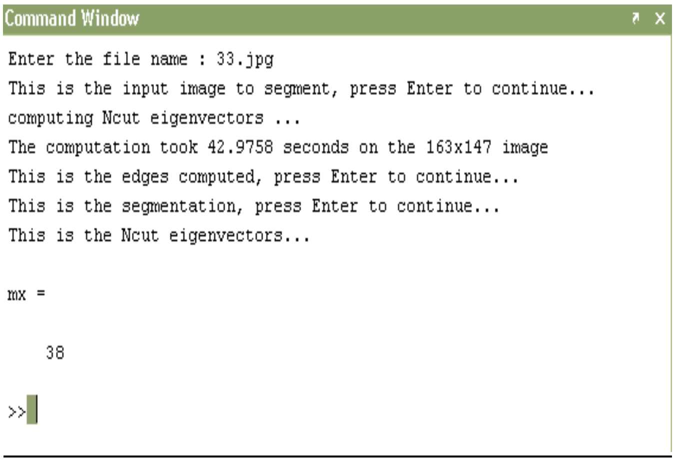


Fig. 10 Complement of the Enhanced Image

H. *Screenshot of matlab*



II. IMAGE REGISTRATION

Image registration is the process of transforming different sets of data into one coordinate system. Data may be multiple photographs, data from different sensors, from different times, or from different viewpoints. It is used in computer vision, medical imaging, military automatic target recognition, and compiling and analyzing images and data from satellites. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurements.

I. *Intensity-based vs feature-based*

Image registration or image alignment algorithms can be classified into intensity-based and feature-based. One of the images is referred to as the *reference* or *source* and the second image is referred to as the *target* or *sensed*. Image registration involves spatially transforming the target image to align with the reference image. Intensity-based methods compare intensity patterns in images via correlation metrics, while feature-based methods find correspondence between image features such as points, lines, and contours. Intensity-based methods register entire images or subimages. If subimages are registered, centers of corresponding subimages are treated as corresponding feature points. Feature-based method established correspondence between a numbers of points in images. Knowing the correspondence between a number of points in images, a transformation is then determined to map the target image to the reference images, thereby establishing point-by-point correspondence between the reference and target images.

J. *Transformation models*

Image registration algorithms can also be classified according to the transformation models they use to relate the target image space to the reference image space. The first broad category of transformation models includes linear transformations, which include translation, rotation, scaling, and other affine transforms. Linear transformations are global in nature, thus, they cannot model local geometric differences between images. The second category of transformations allows 'elastic' or 'nonrigid' transformations. These transformations are capable of locally warping the target image to align with the reference image. Nonrigid transformations include radial basis functions (thin-plate or surface splines, multiquadrics, and compactly-supported transformations), physical continuum models (viscous fluids), and large deformation models (diffeomorphisms).

K. *Spatial vs. frequency domain methods*

Spatial methods operate in the image domain, matching intensity patterns or features in images. Some of the feature matching algorithms are outgrowths of traditional techniques for performing manual image registration, in which an operator chooses corresponding control points (CPs) in images. When the number of control points exceeds the minimum required to define the appropriate transformation model, iterative algorithms like RANSAC can be used to robustly estimate the parameters of a particular transformation type (e.g. affine) for registration of the images. Frequency-domain methods find the transformation parameters for registration of the images while working in the transform domain. Such methods work for simple transformations, such as translation, rotation, and scaling. Applying the Phase correlation method to a pair of images produces a third image which contains a single peak. The location of this peak corresponds to the relative translation between the 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 rotation and scaling differences 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.

L. *Single- vs. multi-modality methods*

Another classification can be made between single-modality and multi-modality methods. Single-modality methods tend to register images in the same modality acquired by the same scanner/sensor type, while multi-modality registration methods tended to register images acquired by different scanner/sensor types. Multi-modality registration methods are often used in medical imaging as images of a subject are frequently obtained from different scanners. 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.

ISBN: 978-81-923777-9-7

M. Automatic vs. 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.

N. Similarity measures for image registration

Image similarities are broadly used in medical imaging. An image similarity measure quantifies the degree of similarity between intensity patterns in two images. The choice of an image similarity measure depends on the modality of the images to be registered. Common examples of image similarity measures include cross-correlation, mutual information, sum of squared intensity differences, and ratio image uniformity. Mutual information and normalized mutual information are the most popular image similarity measures for registration of multimodality images. Cross-correlation, sum of squared intensity differences and ratio image uniformity are commonly used for registration of images in the same modality.

O. Uncertainty

There is a level of uncertainty associated with registering images that have any spatio-temporal differences. A confident registration with a measure of uncertainty is critical for many change detection applications such as medical diagnostics. In remote sensing applications where a digital image pixel may represent several kilometers of spatial distance (such as NASA's LANDSAT imagery), an uncertain image registration can mean that a solution could be several kilometers from ground truth. Several notable papers have attempted to quantify uncertainty in image registration in order to compare results. However, many approaches to quantifying uncertainty or estimating deformations are computationally intensive or are only applicable to limited sets of spatial transformations.

P. Applications

Image registration has applications in remote sensing (cartography updating), and computer vision. Due to the vast applications to which image registration can be applied, it is impossible to develop a general method that is optimized for all uses. Medical image registration (for data of the same patient taken at different points in time such as change detection or tumor monitoring)) often additionally involves *elastic* (also known as *nonrigid*) registration to cope with deformation of the subject (due to breathing, anatomical changes, and so forth). Nonrigid registration of medical images can also be used to register a patient's data to an anatomical atlas, such as the Talairach atlas for neuroimaging. It is also used in astrophotography to align images taken of space. Using control points (automatically or manually entered), the computer performs transformations on one image to make major features align with a second image. 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.

III. .PROPOSED METHOD

Registration of medical image is the problem of identifying a set of fuzzy transformations which map the coordinate system of one data set to that of the others. Depending on the nature of the input linguistic modalities, distinguishing between uni-modal and multi-modal cases, according to whether the images being registered are of the same type. The multimodal registration scenario is more challenging as corresponding anatomical structures will have differing intensity properties. In all analysis, we focus on the fuzzy–modal case. When designing a registration framework, one needs to decide on the nature of the transformations that will be used to bring images into agreement. For example, rigid transformations are generally sufficient in the case of bony structures while non-rigid mappings are mainly utilized for soft tissue matching. One must also evaluate the quality of alignment given an estimate of the aligning transformation. Objective functions or similarity measures are special-purpose functions that are designed to provide these essential numerical scores. The goal of a registration problem can then be interpreted as the optimization of such functions over the set of possible transformations. In general, these problems correspond to multidimensional non-convex optimization problems where we cannot automatically bracket the solution (as we would in case of a 1D line-search). In the past few decades there have been numerous types of objective functions proposed for solving the registration problem. Among these, there exist a variety of methods that are based on sound statistical principles. These include various maximum likelihood [ ], maximum mutual information [ ], minimum Kullback-Leibler divergence [ ], minimum joint entropy [ ] and maximum correlation ratio [ ] methods. We explore the relative strengths and weaknesses of the selected methods, we clarify the type of explicit and implicit assumptions they make and demonstrate their use of prior information. By such an analysis and some graphical representations of the solution manifold for each method, we hope to facilitate a deeper and more intuitive understanding of these formulations. In the past, similar or more detailed overview studies of the registration problem have been reported. Roche et al. [ ], for example, have described the modeling assumptions in uni-modal registration applications and a general maximum likelihood framework for a certain set of multi-modal registration approaches, and we have described a unified information theoretic framework for analyzing multi-modal registration algorithms [ ]. Within the current clinical setting, medical imaging is a vital component of a large number of applications. Such applications occur throughout the clinical track of events; not only within clinical diagnostic settings, but prominently so in the area of planning, consummation, and evaluation of surgical and radiotherapeutical procedures. Since information gained from two images acquired in the clinical track of events is usually of a complementary nature, proper integration of useful data obtained from the separate images is often desired. A first step in this integration process is to bring the modalities involved into spatial alignment, a procedure referred to as registration. After registration, a fusion step is required for the integrated display of the data involved. An example of the use of registering different modalities can be found in radiotherapy treatment planning, where currently CT is used almost exclusively. However, the use of MR and CT combined would be beneficial, as the former is better suited for delineation of tumor tissue (and has in general better soft tissue contrast), while the latter is needed for accurate computation of the radiation dose. Another eminent example is in the area of epilepsy surgery. Patients may undergo variousMR, CT, and DSA studies for anatomical reference; ictal and interictal SPECT studies;MEG and extra and/or intra-cranial (subdural or depth) EEG, as well as 18FDG and/or 11C-Flumazenil PET studies. Registration of the images from practically any

ISBN: 978-81-923777-9-7

combination will benefit the surgeon. In this paper, our aim is to discuss the merits and the demerits of different registration methods, and give an overview of current techniques.

Q. Pre Problem Area

In image processing one is often interested Not only in analyzing one image but in comparing or combining the information given by different images. For this reason, i*mage registration* is one of the fundamental tasks within image processing. The task of image registration is to find an *optimal geometric transformation* between *corresponding* image data. In practice, the concrete type of the *geometric transformation* as well as the Notions of *optimal* and *corresponding* depends on the specific application. Image registration is a problem often encountered in many application areas like, for example, geophysics, computer vision, and medicine. Here, we focus on medical applications. In the last two decades, computerized image registration has played an increasingly important role particularly in medical imaging. Registered images are Now used routinely in a multitude of different applications such as the treatment verification of pre- and post-intervention images and time evolution of an injected agent subject to patient motion. Image registration is also useful to take full advantage of the complementary information coming from multimodal imagery, like, for example, computer tomography (CT) and magnetic resonance imaging (MRI). However, the interpretation of medical images and of the registration result typically requires expert knowledge. For this reason we use the simple test images shown in Fig. 1 where even a Non-expert has an intuitive understanding of the outcome of a registration procedure.

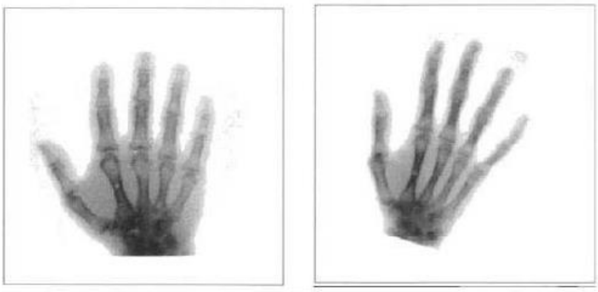


Fig. 10 Two different images of human hands

R. Landmark Based Registration

Parametric Registration: Image registration techniques which are based on a finite set of parameters and/or a finite set of so-called image features. The basic idea is to determine the transformation such that for a finite Number of features, any feature of the template image is mapped onto the corresponding feature of the reference image. Typical features are, for example, "hard" or "soft" landmarks in the images. A landmark is the location of a typically outstanding feature of an image, e.g., the tip of a finger or the point of maximal curvature. Hard landmarks or prospective landmarks are so-called fiducial markers which are positioned before imaging at certain spatial positions on a patient. Typically, the spatial position of these landmarks can be deduced from the images with high accuracy; see, e.g., Maurer & Fitzpatrick (1993) and references therein. However, this type of landmark might be very uncomfortable for the patient. In contrast, soft landmarks or retrospective landmarks are deduced from the images themselves. The spatial location of these "anatomical" landmarks requires expert knowledge and/or sophisticated image analysis tools for automatic detection; see, e.g., Rohr (2001). To make the feature-based registration idea slightly more formal, let F(R, j) and F(T, j) denote the jth feature in the reference image R and the template image T, respectively, j = 1, …, m, where m ∈ N denotes the Number of features. The registration problem reads as follows.

Let m ∈ N and the features F(R, j) and F(T, j), j = 1,…, m, be given. Find a transformation ϕ : Rd → Rd, such that

$$F(R, j) = \phi(F(T, j)),\ j = 1, , m$$

Smooth Registration: Parametric Registration results of approximating some monotonic data a linear and a quadratic polynomial. Although the quadratic polynomial is optimal with respect to the data, it is Not preferable for registration. This is because the quadratic is Not bijective, manifests oscillation, and does Not reflect the monotonicity of the data. Instead of tuning parameters in an expansion of the transformation in terms of some more or less artificial basis functions, we introduce additional smoothness restrictions to the transformation. These restrictions are expressed by a functional *S*. Roughly speaking, smoothness is measured in terms of curvature. It turns out, somewhat surprisingly, that the minimizer of this regularized approach is again parameterized: it is a linear combination of shifts of a *radial basis function* plus some polynomial corrections. In order to provide a detailed insight into the underlying interpolation concepts, we present a general treatment following Light (1995). To begin with, we are looking for an interpolant ψ : R*d* → R which is smooth in a certain sense.

S. Morphological Gradient Method

The registration and hybrid visualization of 3D medical images has received no little attention from researchers in the past few years. The reasons for this may be clear: there are numerous applications in diagnostic as well as treatment settings, from integrating the complementary character of multi-modal images. Notable application fields include neurosurgery and radiation therapy planning. For example, in the latter , dose calculation is done best using a CT image, while often the target area can best be identified in an MR image. A second important reason is the recent availability of computing power and computer architecture that can handle the entire bulk of 3D data (although the images at hand have also grown in size considerably), while older methods often required data reduction to, e.g., a limited point set, surface, or abstract representation. It must be noted though, that the images at hand have also grown in size considerably. Such computing power gives access to a class of so called voxel based methods, that are in most cases preferable to existing methods. Existing 3D rigid (i.e., restricted to translational and rotational transformations) registration methods can be divided into extrinsic (external attachment based) and intrinsic (patient related) approaches. Examples of extrinsic registration methods include methods based on a facial mould or a stereotactic frame. Compared to these methods, voxel based methods[ ] are more patient friendly, and show higher reproducibility. Moreover, they allow for retrospective registration, and extensions for non-rigid registration. Examples of intrinsic registration approaches other than voxel based methods are landmark registration [ ]surface based registration[ ]and hybrids of these techniques. Compared to these methods voxel based methods are better reproducible and less labour intensive. It is not only the voxel mothds but the landmark based method also better representable . Our aim I to find out the difficulties in the current method and try to make a minimization of uncertainties within it . To make a comprehensive study of these methods gives us an idea to

 ISBN: 978-81-923777-9-7

develop the most authenticated method with the help of these ideas.

T. Knowledge Based registration

Medical image registration has been an important area of research in the medical application of computer vision's techniques for the past several years. It can be defined as a task of finding the transformation that will optimally superimposes features from one imaging study over those of another study. R.egistration of imagesfrom multiple modalities can provide complementary information for clinical diagnosis, treatment planning and therapy evaluation. This t8aak is often diffcult due to the presence of structural variations and outliers. Structrual variations can result from inter-subject variations, development, pathologies, treatment, or the fact that different imaging modalities manifest distinct tissue properties. Outliers of surface points are obtained when images contain artifacts or high level of noise or as a failure of the contour extraction process. In this article, we describe a new multiple-feature matching technique t1ia.t aims at, addressing this problem. The new method is an extension of Pelizzari's surface-fitting method [l]. Since contour points are used, this technique is not sensitive to intensity variations. Sensitivity to structural variation is minimized by the use of a fuzzy logic system, which incorporates human expert knowledge to evaluate the confidence of a correspondence pair. Structural variations and outliers can thus be identified and excluded

from the ma.tching process; thus minimizes their adverse effect on the registration. In the surface-fitting methods, surface contours of the two images to be registered are extracted to construct a *m.odel* surface and a *target* surface. A cost function, for example sum of the distances between matching points on the two surfaces, is constructed to evaluate the fit between these two surfaces. Registration of the two surfaces is obtained by minimizing the cost function, which is usually achieved by the use of iterative optimization techniques. Each iteration in the registration can be interpreted as a two-step process. First, for each point on the *model* surface, a matching point on the *target* surface is assigned. Second, based on current assignment the cost function is computed and the transformation parameters are updated so as to decrease the cost. Implicit in these methods one has made the assumption that all contour points are of equal reliability and significance and true correspondence points of all *target* surface points exist.

U. Elastic Spline Registration

Longitudinal brain image studies quantify the changes happening over time. Jacobian maps, which characterize the volume change, are based on non-rigid registration techniques and do not always appear to be *clinically* plausible. In particular, extreme values of volume change are not expected to be seen. The Free-Form Deformation (FFD) algorithm suffers from this drawback. Different penalty terms have been proposed in the past. We present in this paper a regularisation of the B-Spline displacements using nonlinear elasticity. Our work links a finite element method with *pseudo-forces* derived from a similarity measure. The presented method has been evaluated on longitudinal T1-weighted MR images of Huntington's disease subjects and controls. Multiple time point consistency, the Jacobian map homogeneity and statistical power for group separation have been used. Our new method performs better than the *classical* FFD, while keeping similar registration accuracy. When studying brain images using non-rigid registration, the determinant of the Jacobian provides a measure of local volume change that is often of interest for quantifying deformations over time or between subjects. However, as each registration method produces a slightly different transformation (and equally importantly, via a different deformation mechanism) the Jacobian determinant maps vary both quantitatively and qualitatively. Moreover, the quality of the map (judged directly by clinicians, or indirectly via results of tensor-based morphometry) is not necessarily correlated with the quantitative accuracy of the registration. For example, using different techniques such as the Free-Form Deformation [1] (FFD), the fluid [2], the diffeomorphic demons algorithm [3] or symmetric normalization (Syn) [4], different Jacobian determinant maps are obtained even though the warped images all match the reference — see Fig. 1. In order to generate smooth and plausible transformation with the FFD method, efforts have been made to impose constraints on the deformations. Rueckert *et al.* [1] proposed a penalty term based on the bending energy. Rolhfing *et al.* [5] presented another based on the logarithm of the Jacobian determinant. The Jacobian determinant was also embedded in a regularizer by Sdika [6]. However, simple constraints or penalty terms are either incapable of modelling large deformations or unable to prevent highly variable (or negative) Jacobians. Considering that the general aim of the above penalty terms is to favour physically plausible deformations, a natural alternative is to directly include a biomechanical regulariser, for example based on equations of continuum mechanics. Linear elastic registration has been used since the 1980s [7,8], however, linearity breaks down for large deformations, limiting the flexibility of such methods. Fluid-mechanical regularisation allows large deformation without discontinuities, but also permits unrealistically severe distortions. This paper argues in favour of a nonlinear elastic regulariser coupled with a spline model, that should handle large but realistic deformations while maintaining an anatomically reasonable Jacobian map. Yanovsky *et al.* [9] also investigated nonlinear elasticity. They developed a variational form which coupled similarity and elasticity functionals, using a linear strain energy function (Saint Venant-Kirchhoff model), and solved the system using finite differences. The development and solution of the coupled system was facilitated by an approximation for the material displacement derivatives. We present a decoupled regularisation of the FFD algorithm using nonlinear elasticity. Solution of the

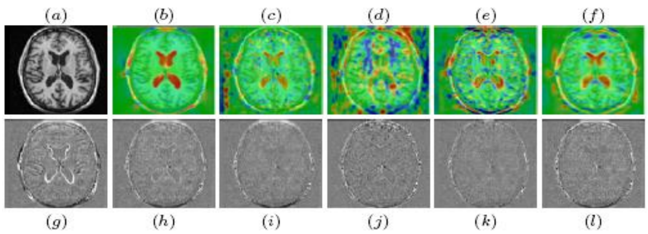


Fig. 11 Variation in volume change distribution with different registration algorithms. A floating image has been registered to a reference image (a) using: fluid (b,h), Syn (c,i), demons (d,j), free-form deformation (e,k) and the proposed method (f,l). It can be appreciated from the difference images (bottom row) that all techniques successfully recovered the initial differences (f). However the Jacobian determinant maps (top row) reveal very different patterns of deformation. (log2(det(J)) is shown with colour range from -0.5 to 0.5).

equations of continuum mechanics is performed using the finite element method, which requires no approximation of the deformation components, and allows for incorporation of elaborate constitutive models. The deformation model is linked to an appropriate similarity metric by so-called *pseudo-forces*

ISBN: 978-81-923777-9-7

derived from the metric's gradient. The scheme is shown to produce both accurate and smooth deformation fields. We emphasize that in employing a continuum mechanics-based model our aim, in this case, is to produce physically consistent smooth transformations, not to model the physiology of the disease process itself; we do not claim, for example, that deformations associated with tissue loss are directly analogous to mechanical compressions.

V. Comparative framework of Existing model over proposed rule base model

We introduce the use of a variable smoothing kernel, whose width is driven by a fuzzy controller, to regularize a deformation field in the context of image registration. Our ideas show that such a technique outperforms the classical fixed-width regularization, being capable of removing irregularities in the deformation field while maintaining an adequate adaptive behavior for localized deformations, thus preserving fine details. To Define the medical image problem, provide a short introduction to a select group of multi-modal image alignment approaches are necessary. More precisely, we compare widely-used statistical methods applied in medical image problems for analysis and comparison. Clarifying the implicit and explicit assumptions made by each, is to aim to yield a better understanding of their relative strengths and weaknesses. The purpose of this paper is to present an new concept of rule base multiscale modeling of cerebral blood flow picture over the existing medical imaging methods. These methods will be classified according to a model based on salient criteria, the main dichotomy of which is *rulebase and without rulebase* methods. The multiscale model of the human cerebral vasculature has been developed which includes a three-dimensional (3D) CFD model of the circle of Willis (CoW) and fractal tree models of all regions of small cerebral vasculature, namely Anterior, Middle and Posterior Cerebral Arteries (ACA, MCA, PCA). The realistic 3D CoW model was constructed from the medical imaging data with the use of 3D Slicer segmentation which is already been developed . The fuzzy rulebase flow model in the fractal tree models of ACA, MCA and PCA has been developed with the effects of blood vessel structural property, arterial size-dependent blood viscosity and nonparabolic velocity profile incorporated. In this paper we have introduced the rulebase profile to get better result than of previous one. The coupling of the CFD model and the fractal tree models has been already been extended from one-way to fuzzy rulebased method in this work. The hybrid model has been used to predict the transient blood flow in cerebral arteries and study the effect of occlusion on flow distribution in the brain. In this work, a method has been developed to fully couple the CoW and the vascular network flow models. In an iterative procedure, actual pressures at the CoW outlets are used to determine the flow in each vascular network, which is then applied as boundary conditions in the CoW CFD simulation.

*Rulebase :*Let the pulsalite pressure be P_a and the Neutonian velocity be N_v , when capillary pressure is constant then Cp = Constant

Rulebase for ACA

If Pa is low and Nv is low then ACA blood flow is moderate

If Pa is low and Nv is high then ACA blood flow is high

If Pa is high and Nv is low then ACA blood flow is low

If Pa is high and Nv is high then ACA blood flow is very high .

Rulebase for MCA

If Pa is low and Nv is low then MCA blood flow is low

If Pa is low and Nv is high then MCA blood flow is high

If Pa is high and Nv is low then MCA blood flow is low

If Pa is high and Nv is high then MCA blood flow is very high .

Rulebase for PCA

If Pa is low and Nv is low then PCA blood flow is very low

If Pa is low and Nv is high then PCA blood flow is high

If Pa is high and Nv is low then PCA blood flow is low

If Pa is high and Nv is high then PCA blood flow is very high.

Pulsatile pressure ranging 80–125 mmHg with a period of 0.7 s was specified at the CoW inlets internal carotid (ICAs) and vertebrobasilar (VA) arteries [11]. The flow in the cerebral microcirculatory system is characterised by low pulsatility Therefore, a constant capillary pressure of 25 mmHg was assigned at the terminals of the vascular branching networks. The density of the blood was assumed to be 1050 kg/m3, and the blood flow was assumed be Newtonian with viscosity equal to 0.0036 Pa.s. The prediction results are shown in Fig-3 Due to this CoW geometry specifics, the flows in the left and right branches of the brain are significantly different (Fig 12 and the geometry effect is most pronounced in the ICA flow. The difference in the flow predictions resulted from the coupling method is displayed in Fig 3. The one-way coupling approach, which was based on the assumption about uniform distribution of pressure in the CoW, produced significantly higher in- and out- flow predictions. In addition to the prediction of the flow in the normal condition, the computational model was also used to simulate the variation of the flow through the circle of Willis as a result of possible physiological and pathological changes in the network of small cerebral vasculature. Fig 3 demonstrates the variation of the blood flows in the brain when the peripheral resistance of ACAs increased due to an uniform 10% vasoconstriction in ACA networks. Vasoconstriction is the narrowing of the blood vessels, which can be caused by various physiological and/or pathological conditions.

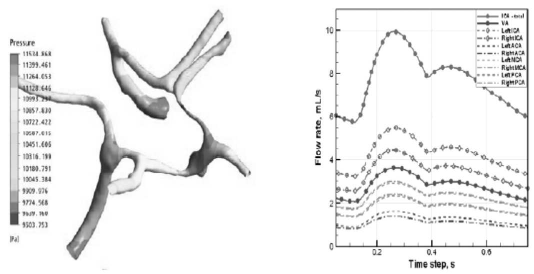


Fig. 12 Flow of bloods in ICA of CoW with ACA , MCA and PCA

IV. CONCLUSION

Medical image registration has been an important area of research in the medical application of computer vision's techniques for the past several years. It can be defined as a task of finding the transformation that will optimally superimposes features from one imaging study over those of another study. The rules were applied to predict the transient flow and

ISBN: 978-81-923777-9-7

pressure distributions in the brain vasculature comprising a patient specific circle of Willis geometry and fractal models of peripheral vascular networks. The rules were shown to be able to efficiently provide detailed descriptions of the flow and pressure distributions at different levels of blood vessel sizes and simulate the variations of the blood flow in the major cerebral arteries when the peripheral vasculatures are subjected to various physiological and pathological conditions. In order to improve the prediction, the mechanisms of active regulation of blood flow need to be defined and implemented in the future model development.

V. FUTURE WORK

In this paper, we propose a continuous medical image registration framework and its implementation algorithm. This approach utilizes users' feedback and optimizes the registration to satisfy the user's requirement in both global registration and local registration. The key contributions are as follows:

• We exploit continuous registration approaches in image registration, and propose CMIR framework and its implementation algorithm, which is to continuously optimize the registration result.

• We integrate global registration and local region registration in CMIR. Multi-objective optimization is implemented through genetic algorithm to provide composite measure that integrates global measure and local measure.

• We apply continuous algorithm CMIR and basic algorithm BMIR to brain image registration. The experiment shows that CMIR and BMIR are both effective in global registration, and CMIR is more effective in local regions concerned by users.

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ISBN: 978-81-923777-9-7