Biomedical Image Registration Using Fuzzy Logic

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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

Fuzzy logic is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than accurate. In contrast with "crisp logic", where binary sets have binary logic, fuzzy logic variables may have a truth value that ranges between 0 and 1 and is not constrained to the two truth values of classic propositional logic. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions.

II. FUZZY LOGIC

Fuzzy logic emerged as a consequence of the 1965 proposal of fuzzy set theory by Lotfi Zadeh. Though fuzzy logic has been applied to many fields, from control theory to artificial intelligence, it still remains controversial among most statisticians, who prefer Bayesian logic, and some control engineers, who prefer traditional two-valued logic.

A. Degrees of truth

Fuzzy logic and probabilistic logic are mathematically similar – both have truth values ranging between 0 and 1 – but conceptually distinct, due to different interpretations—see interpretations of probability theory. Fuzzy logic corresponds to "degrees of truth", while probabilistic logic corresponds to "probability, likelihood"; as these differ, fuzzy logic and probabilistic logic yield different models of the same real-world situations. Both degrees of truth and probabilities range between 0 and 1 and hence may seem similar at first. For example, let a 100 ml glass contain 30 ml of water. Then we may consider two concepts: Empty and Full. The meaning of each of them can be represented by a certain fuzzy set. Then one might define the glass as being 0.7 empty and 0.3 full. Note that the concept of emptiness would be subjective and thus would depend on the observer or designer. Another designer might equally well design a set membership function where the glass would be considered full for all values down to 50 ml. It is essential to realize that fuzzy logic uses truth degrees as a mathematical model of the vagueness phenomenon while probability is a mathematical model of ignorance. The same could be achieved using probabilistic methods, by defining a binary variable "full" that depends on a continuous variable that describes how full the glass is. There is no consensus on which method should be preferred in a specific situation.

B. Applying truth values

A basic application might characterize sub ranges of a continuous variable. For instance, a temperature measurement for anti-lock brakes might have several separate membership functions defining particular temperature ranges needed to control the brakes properly. Each function maps the same temperature value to a truth value in the 0 to 1 range. These truth values can then be used to determine how the brakes should be controlled.
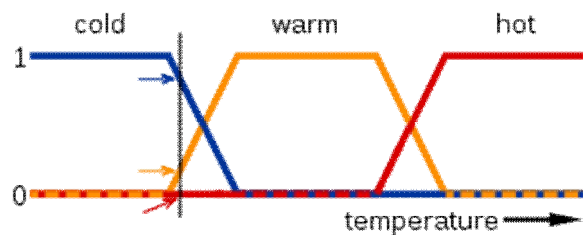

Fig. 1 Fuzzy logic temperature

Fig. 1 shows the meaning of the expressions cold, warm, and hot is represented by functions mapping a temperature scale. A point on that scale has three "truth values"—one for each of the three functions. The vertical line in the image represents a particular temperature that the three arrows (truth values) gauge. Since the red arrow points to zero, this temperature may be interpreted as "not hot". The orange arrow

(pointing at 0.2) may describe it as "slightly warm" and the blue arrow (pointing at 0.8) "fairly cold".

C. Linguistic variables

While variables in mathematics usually take numerical values, in fuzzy logic applications, the non-numeric linguistic variables are often used to facilitate the expression of rules and facts.A linguistic variable such as age may have a value such as young or its antonym old. However, the great utility of linguistic variables is that they can be modified via linguistic hedges applied to primary terms. The linguistic hedges can be associated with certain functions. For example, L. A. Zadeh proposed to take the square of the membership function. This model, however, does not work properly. For more details, see the references. Examples: Fuzzy set theory defines fuzzy operators on fuzzy sets. The problem in applying this is that the appropriate fuzzy operator may not be known. For this reason, fuzzy logic usually uses IF-THEN rules, or constructs that are equivalent, such as fuzzy associative matrices. Rules are usually expressed in the form:IF variable IS property THEN action. For example, a simple temperature regulator that uses a fan might look like this:

IF temperature IS very cold THEN stop fan
IF temperature IS cold THEN turn down fan
IF temperature IS normal THEN maintain level
IF temperature IS hot THEN speed up fan.

There is no "ELSE" – all of the rules are evaluated, because the temperature might be "cold" and "normal" at the same time to different degrees. The AND, OR, and NOT operators of boolean logic exist in fuzzy logic, usually defined as the minimum, maximum, and complement; when they are defined this way, they are called the Zadeh operators. So for the fuzzy variables x and y:

NOT x = (1 - truth(x))
x AND y = minimum(truth(x), truth(y))
x OR y = maximum(truth(x), truth(y)). There are also other operators, more linguistic in nature, called hedges that can be applied. These are generally adverbs such as "very", or "somewhat", which modify the meaning of a set using a mathematical formula.

D. Logical analysis

In mathematical logic, there are several formal systems of "fuzzy logic"; most of them belong among so-called t-norm fuzzy logics.

E. Propositional fuzzy logics

The most important propositional fuzzy logics are:
- Monoidal t-norm-based propositional fuzzy logic MTL is an axiomatization of logic where conjunction is defined by a left continuous t-norm, and implication is defined as the residuum of the t-norm. Its models correspond to MTL-algebras that are prelinear commutative bounded integral residuated lattices.
- Basic propositional fuzzy logic BL is an extension of MTL logic where conjunction is defined by a continuous t-norm, and implication is also defined as the residuum of the t-norm. Its models correspond to BL-algebras.
- Łukasiewicz fuzzy logic is the extension of basic fuzzy logic BL where standard conjunction is the Łukasiewicz t-norm. It has the axioms of basic fuzzy logic plus an axiom of double negation, and its models correspond to MV-algebras.
- Gödel fuzzy logic is the extension of basic fuzzy logic BL where conjunction is Gödel t-norm. It has the axioms of BL plus an axiom of idempotence of conjunction, and its models are called G-algebras.
- Product fuzzy logic is the extension of basic fuzzy logic BL where conjunction is product t-norm. It has the axioms of BL plus another axiom for cancellativity of conjunction, and its models are called product algebras.
- Fuzzy logic with evaluated syntax (sometimes also called Pavelka's logic), denoted by EVŁ, is a further generalization of mathematical fuzzy logic. While the above kinds of fuzzy logic have traditional syntax and many-valued semantics, in EVŁ is evaluated also syntax. This means that each formula has an evaluation. Axiomatization of EVŁ stems from Łukasziewicz fuzzy logic. A generalization of classical Gödel completeness theorem is provable in EVŁ.

F. Predicate fuzzy logics

These extend the above-mentioned fuzzy logics by adding universal and existential quantifiers in a manner similar to the way that predicate logic is created from propositional logic. The semantics of the universal (resp. existential) quantifier in t-norm fuzzy logics is the infimum (resp. supremum) of the truth degrees of the instances of the quantified subformula.

G. Decidability issues for fuzzy logic

The notions of a "decidable subset" and "recursively enumerable subset" are basic ones for classical mathematics and classical logic. Then, the question of a suitable extension of such concepts to fuzzy set theory arises. A first proposal in such a direction was made by E.S. Santos by the notions of fuzzy Turing machine, Markov normal fuzzy algorithm and fuzzy program (see Santos 1970). Successively, L. Biacino and G. Gerla showed that such a definition is not adequate and therefore proposed the following one. Ü denotes the set of rational numbers in [0,1]. A fuzzy subset $s : S \longrightarrow [0,1]$ of a set S is recursively enumerable if a recursive map $h : S \times N \longrightarrow Ü$ exists such that, for every x in S, the function $h(x,n)$ is increasing with respect to n and $s(x) = \lim h(x,n)$. We say that s is decidable if both s and its complement –s are recursively enumerable. An extension of such a theory to the general case of the L-subsets is proposed in Gerla 2006. The proposed definitions are well related with fuzzy logic. Indeed, the following theorem holds true (provided that the deduction apparatus of the fuzzy logic satisfies some obvious effectiveness property). Theorem. Any axiomatizable fuzzy theory is recursively enumerable. In particular, the fuzzy set of logically true formulas is recursively enumerable in spite of the fact that the crisp set of valid formulas is not recursively

enumerable, in general. Moreover, any axiomatizable and complete theory is decidable. It is an open question to give supports for a Church thesis for fuzzy logic claiming that the proposed notion of recursive enumerability for fuzzy subsets is the adequate one. To this aim, further investigations on the notions of fuzzy grammar and fuzzy Turing machine should be necessary (see for example Wiedermann's paper). Another open question is to start from this notion to find an extension of Gödel's theorems to fuzzy logic.

III.   COLOR MODELS

H. RGB color model

A representation of additive color mixing. Projection of primary color lights on a screen shows secondary colors where two overlap; the combination of all three of red, green, and blue in appropriate intensities makes white. The **RGB color model** is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue. The main purpose of the RGB color model is for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography. Before the electronic age, the RGB color model already had a solid theory behind it, based in human perception of colors. RGB is a *device-dependent* color model: different devices detect or reproduce a given RGB value differently, since the color elements (such as phosphors or dyes) and their response to the individual R, G, and B levels vary from manufacturer to manufacturer, or even in the same device over time. Thus an RGB value does not define the same *color* across devices without some kind of color management. Typical RGB input devices are color TV and video cameras, image scanners, and digital cameras. Typical RGB output devices are TV sets of various technologies (CRT, LCD, plasma, etc.), computer and mobile phone displays, video projectors, multicolor LED displays, and large screens as JumboTron, etc. Color printers, on the other hand, are not RGB devices, but subtractive color devices (typically CMYK color model). This article discusses concepts common to all the different color spaces that use the RGB color model, which are used in one implementation or another in color image-producing technology.
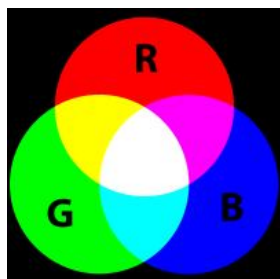

Fig. 2 Additive primary colors

To form a color with RGB, three colored light beams (one red, one green, and one blue) must be superimposed (for example by emission from a black screen, or by reflection from a white screen). Each of the three beams is called a *component* of that color, and each of them can have an arbitrary intensity, from fully off to fully on, in the mixture. The RGB color model is *additive* in the sense that the three light beams are added together, and their light spectra add, wavelength for wavelength, to make the final color's spectrum. Zero intensity for each component gives the darkest color (no light, considered the *black*), and full intensity of each gives a white; the *quality* of this white depends on the nature of the primary light sources, but if they are properly balanced, the result is a neutral white matching the system's white point. When the intensities for all the components are the same, the result is a shade of gray, darker or lighter depending on the intensity. When the intensities are different, the result is a colorized hue, more or less saturated depending on the difference of the strongest and weakest of the intensities of the primary colors employed. When one of the components has the strongest intensity, the color is a hue near this primary color (reddish, greenish, or bluish), and when two components have the same strongest intensity, then the color is a hue of a *secondary* color (a shade of cyan, magenta or yellow). A secondary color is formed by the sum of two primary colors of equal intensity: cyan is green+blue, magenta is red+blue, and yellow is red+green. Every secondary color is the *complement* of one primary color; when a primary and its complementary secondary color are added together, the result is white: cyan complements red, magenta complements green, and yellow complements blue. The RGB color model itself does not define what is meant by *red*, *green*, and *blue* colorimetrically, and so the results of mixing them are not specified as absolute, but relative to the primary colors. When the exact chromaticities of the red, green, and blue primaries are defined, the color model then becomes an absolute color space, such as RGB or Adobe RGB.

Pixel color depth
1-bit   monochrome
8-bit   grayscale
8-bit   color
15/16-bit color (High Color)
24-bit   color   (True   Color)
30/36/48-bit   color   (Deep Color)
Related
Indexed   color Palette
RGB   color   model
Web-safe color

Fig. 3 Digital Representations

The RGB color model is the most common way to encode color in computing, and several different binary digital representations are in use. The main characteristic of all of them is the quantization of the possible values per component (technically a *sample*) by using only integer numbers within some range, usually from 0 to some power of two minus one $(2^n – 1)$ to fit them into some bit groupings. As usual in computing, the values can be represented either in decimal and in hexadecimal notation as well, as is the case of HTML colors text-encoding convention.

I. CMYK color model

The **CMYK color model** (**process color**, **four color**) is a subtractive color model, used in color printing, and is also used to describe the printing process itself. **CMYK** refers to the four inks used in some color printing: **c**yan, **m**agenta, **y**ellow, and **k**ey black. Though it varies by print house, press operator, press manufacturer and press run, ink is typically applied in the order of the abbreviation. The "K" in CMYK stands for *key* since in four-color printing cyan, magenta, and yellow printing plates are carefully *keyed* or aligned with the *key* of the black *key plate*. Some sources suggest that the "K" in CMYK comes from the last letter in "blac**k**" and was chosen because B already means blue. However, this explanation, though plausible and useful as a mnemonic, is incorrect. The CMYK model works by partially or entirely masking colors on a lighter, usually white, background. The ink reduces the light that would otherwise be reflected. Such a model is called *subtractive* because inks "subtract" brightness from white.
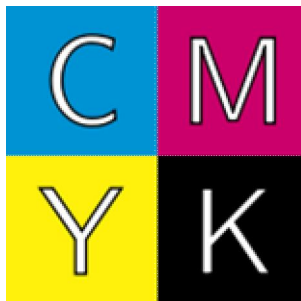

Fig. 4 Cyan, magenta, yellow, and key (black).

Fig. 4 Layers of simulated glass show how semi-transparent layers of color combine on paper into spectrum of CMY colors.

IV. PROPOSED METHOD

J. CMYK model Color Image Segmentation using Type 2 Fuzzy Sets

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.

K. 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.

L. 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 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 dimensions and it is the new third

dimension that provides more design degrees of freedom for handling uncertainty. In the proposed work, color uniformity has been considered a relevant criterion to partition an image into significant regions using fuzzy entropy based approach to take into account simultaneously the color and spatial properties of the pixels. For an image with high resolution, a new scheme has been proposed in the paper based on CMYK color model using T2 fuzzy sets that tackles total uncertainty inherent in the images.

M. 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)

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

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)

$$(x, \{(\mathit{MF}_i(x), w_{xi})| \, i = 1, ..., N\}/ \, x \in X\} \ldots.. (2)$$

Another way to represent the membership value: $\{(x, \mathrm{MF}(x, w)| \, x \in X \text{ and } w \in Jx\}$ where $\mathrm{MF}(x, w)$ is the three-dimensional T2 MF, shown in figure 6.
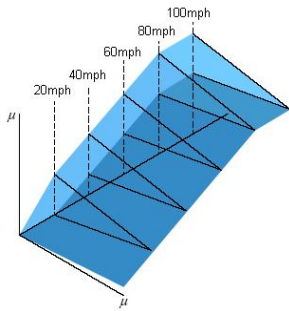
Fig. 5 3-D Representation of T2 FS "Speed"

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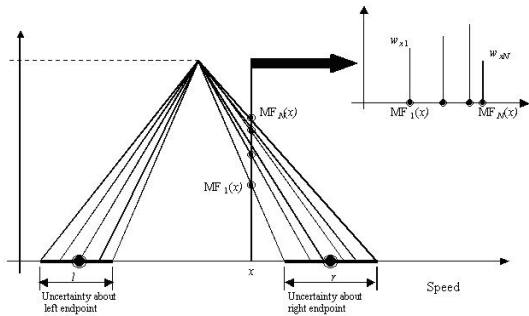

Fig. 6 Triangular MFs (base endpoints l and r) with Uncertain Intervals

N. 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 in figure 3. The standard deviation of the MF is certain while mean, *m*, is uncertain and varies anywhere in the interval from *m*1 to *m*2. Uncertainty in the primary memberships of a T2 fuzzy set, Ã, consists of a bounded region, called the footprint of uncertainty (FOU). FOU is the union of all primary memberships (*Jx*), given in (3).

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

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, described in figure 4. 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).
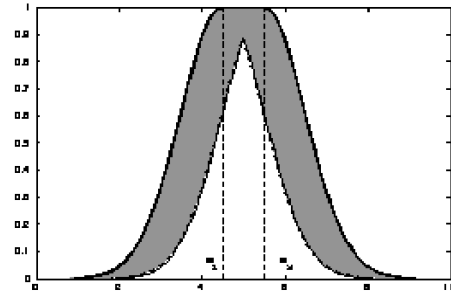

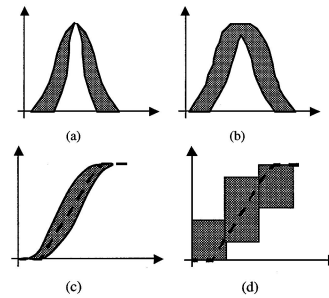Fig. 7 OU of Gaussian (primary) MF with Uncertain mean

Fig. 8 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.

O. 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 $\mu_A(x): X \to [0, 1]$, $x \in X$. 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 $\mu^\alpha_A(x): X \to \{0,1\}$ is defined in (4).

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

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

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).

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

(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)

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

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).

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

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×N* image subset $A \subseteq X$ with *L* gray levels $g \in [0, L-1]$ is defined in (9) and shown in figure 5.

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

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

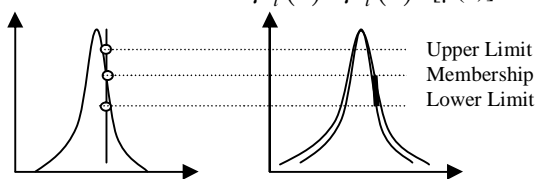Lower Limit: $\mu_l(x)$: $\mu_l(x)=[\mu(x)]^2$

Fig. 9 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.

V. 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.

P. 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.

Q. 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 allow '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).

R. 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.

S. 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.

T. 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.

U. 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.

V. 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.

W. 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.

VI. .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 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.

X. *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.
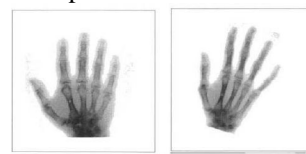

Fig. 10 Two different images of human hands

Y. *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 $\in$ N denotes the Number of features. The registration problem reads as follows.

Let m $\in$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.

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

AA. *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.

BB. *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
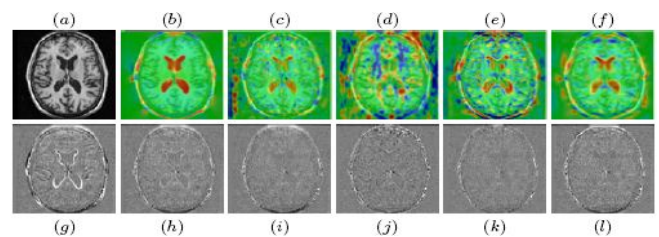

Fig. 11 Variation in volume change distribution with different registration algorithms. A floating image has been registered to a reference image (a) using: fluid (b,h), Syn (c,i), demons (d,j), free-form deformation (e,k) and the proposed method (f,l). It can be appreciated from the difference images (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* 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.

CC. *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.
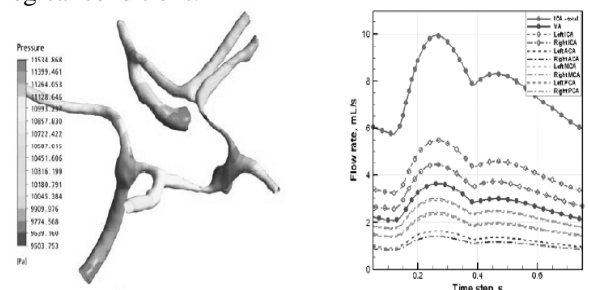

Fig. 12 Flow of bloods in ICA of CoW with ACA , MCA and PCA

VII. 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 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.

VIII. FURURE WORK

In this paper, we proposed 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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