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N. HARSHA VARDHAN

Department of ECE, Annamacharya Institute of Technologies and Sciences, Rajampet, A.P, India,
n.harshavardhan@gmail.com

S. ASIF HUSSAIN

Department of ECE, Annamacharya Institute of Technologies and Sciences, Rajampet, A.P, India,
sa_hussain@yahoo.co.in

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A NOVEL FEATURE EXPANSION ALGORITHM FOR NONRIGID CT/MRI BRAIN IMAGE REGISTRATION.

HARSHA VARDHAN.N.¹, S.ASIF HUSSAIN²

¹Research Scholar, ²Assistant professor, Department of ECE, Annamacharya Institute of Technologies and Sciences, Rajampet, A.P, India

Abstract- Image registration is one of the challenging tasks in medical image analysis. While coming to non rigid image registration there are mainly two issues to consider. They are i) intensity similarity and ii) gray level transformation. The issue with intensity similarity is it is not necessarily equivalent to anatomical similarity when the anatomical correspondences between source and target images are established. Another issue is choosing an appropriate registration algorithm. It should be robust against monotonic gray-level transformation when aligning anatomical structures in the presence of bias fields. Here new feature- intensity based registration method developed for nonrigid brain image registration to overcome the above stated issues named as Anatomical Region Descriptor (ARD). This method is developed on image feature, it encodes geometric properties of anatomical structures and pixel wise interaction details. It is efficient and theoretically monotonic gray level transformation invariant. This method is integrated with intensity based registration algorithm named as residual complexity for Registration purpose. This proposed method is compared with three other non rigid image registration algorithms. Experimental results of the proposed method show that it achieves the highest accuracy rate among the compared methods.

Keywords- Component; formatting; style; styling; insert (key words)

I. INTRODUCTION

Image registration is one of the challenging tasks in medical image analysis. It has many applications in navigation, clinical diagnosis etc.... Registration is a process of aligning two images into a common coordinate system thus aligning them in order to monitor the changes between them. There are number of registration algorithms for compute transformations to set the correspondences between the images. Image registration is about determining geometrical transformation that aligns points in one view of an object, with corresponding points in another view of that object or another object. In other words, image registration can be seen as a process where we try to find a mapping (transformation) between two images, both spatially and with respect to intensity.

Both rigid and nonrigid image registration plays a vital role in clinical diagnosis. Nonrigid image registration plays a crucial role in medical image analysis and processing. Imaging modalities like computed tomography (CT), magnetic resonance imaging (MRI) or positron emission tomography (PET) are widely used and literally provide physicians with invaluable insight. The amount of data generated by medical imaging devices exceeds the available time and concentration potential of practitioners. In a way, there is a need of computerized technology therefore requires other new digital aids that assist humans in evaluating acquired data. There are many applications of nonrigid image registration including anatomical analysis, image data mining, brain disease diagnosis. Nonrigid image registration is classified mainly into three types. They are i) landmark based,

ii) intensity based and iii) feature based registration methods. In landmark based registration method first select a set of reliable landmark from input images. This landmark selection can be manually semi automatically or even fully automatically performed. Features are extracted from those landmark points. The optimal transformations are then estimated based on these extracted features.

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

Feature-based approaches attempt to find the correspondence and transformation using distinct anatomical features that are extracted from images. These features include points, curves or a surface model of anatomical structures. Feature-based

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

Landmark based registration methods are usually computationally efficient and includes priory known points extracted from the selected landmarks. However, to obtain maximum and accurate registration results, a number of reliable landmarks are needed, and this can bring a lot of computational burdens additionally. Intensity based registration methods are usually fully automatic. However, intensity similarities may not be necessarily equivalent to anatomical similarities. Feature-based approaches drive the registration process based on the adopted features. After adopting the features of images then calculate the features in the edgeless domain. The images registered in the edgeless domain are then forwarded to further alignment to be performed in intensity domain. Then intensity standardization process is to be done to remove the effect of intensity gray-level differences.

In non rigid image registration there are two major challenges are there one is intensity similarity. Intensity distributions are not fully characterize lonely. It leads to anatomical differences between different tissues, so there is a need of designing an anatomical region descriptor for defining signature for each voxel. Another challenge is volume rotation and monotonic gray level bias fields. It generally exists during the imaging acquisition process. So, there is need of a registration algorithm that should be robust against such invariants. For feature based registration methods rotation invariance one of its property and this algorithm may prefer to align the bias fields between the source and target images, instead of aligning their anatomical structures if the registration algorithm is not robust against bias fields. There is a chance of degradation of the performance of registration algorithms due to noise in the input images. The effect of noise is overcome by using different filtering techniques during the registration procedure to remove the noise information from the input images.

II. ANATOMICAL REGION DESCRIPTOR

This proposed Region descriptor is extension work from [1] [2]. This method is a 2-D joint histogram consisting features of Uniform Spherical Structure Pattern (USSP) and Uniform Gradient Spherical Pattern (UGSP). Both ussp and ugsp encodes the voxel information of first order and second order voxels.

Methodology diagram to produce an ARD Signed Image:-

Fig.1

Fig.1 shows process of generating an ARD signature image.

A. USSP

USSP is developed from local binary points introduced in [3]. The USSP is a 2-D region descriptor that encodes voxel interaction of the first-order image voxel interaction information. USSP computes and preserves the rotation and monotonic gray-level transformation invariant properties of Local Binary Points (LBP)s. This USSP has some key physical meanings with respect to the fundamental image structures.

Let consider input image as I_m , for each voxel v belongs to I_m , spherical neighborhood S_v centered at v with radius R is defined. N_v samples are taken on the surface of S_v . Here the deterministic incremental grid sequence sampling method proposed in [4] is adopted as the sampling method, which is uniform and computationally efficient.

For each sample v_i on the surface of S_v , it is converted to binary number B_i by comparing its intensities to the intensities of voxel v , which is expressed by

$$B_i = \begin{cases} 0, & \text{If } I_i < I_v \\ 1, & \text{If } I_i > I_v \end{cases} \dots (1)$$

where I_i denotes the intensity of sample v_i , and I_v denotes the intensity of the centred voxel v of S_v .

Based on equation (1), BSSP defined as follows:

Definition 1: The BSSPs are the binary threshold spherical surfaces obtained by (1) for each voxel v belongs to S_v .

The BSSP is monotonic gray-level transformation invariant as monotonic gray-level transformation does not alter the relative intensity differences between the central pixel and the neighbouring pixels. Therefore, the binary label assigned to each neighbouring pixel remains the same before and after the monotonic gray-level transformation; thus, the BSSP remains the same. Therefore, we have the following property of the BSSP.

Property 1: BSSPs are monotonic gray-level transformation invariant.

Therefore, the BSSP is robust against the monotonic gray level bias fields, which commonly exist in brain MRI images; its occurrence of histogram can be treated as the signature for each voxel. However, there are many types of BSSPs that can make the histogram of BSSPs too sparse to reliably reflect the anatomical properties of input images. Therefore, only a subset of BSSPs is considered, namely, the USSP, which represents fundamental image structures. The USSP is definition as follows.

Definition 2: The USSPs are BSSPs that have at most two continuous regions of "0"s and "1"s.

The USSP has some important physical meanings with respect to the fundamental image structures. USSPs have the dominant proportions among all the BSSPs.

While performing ARD it includes five computational algorithms. First of all the input image is read and converted into BSSP. Then checks that BSSP image is either USSP or not. USSP is a subset of BSSP, so USSP is termed as monotonic gray-level

transformation invariant. Then check that acquired USSP is either monotonic gray-level transformation invariant or not. After that an ID is determined from USSP based on number of '0's on surface of USSP. It makes USSP as rotation invariant. Then checks this USSP is feature rotation invariant. To know the extract rotation and monotonic gray-level transformation invariant USSP features as signatures for each voxel using following algorithm.

Algorithm 1

Input: Input image(im), local cubic square window for each voxel(w), radius(r), and the number of neighbouring samples(N).

Output: Vector image, each voxel is represented by a USSP signature.

```

1. w=8;
2. r=4;
3. n=3;
4. k=zeros(r,c);
5. for v1=0:size(im1,1)/w
6.     for v2=0:size(im1,2)/w
7.         sub=im1(v1+1:v1+8,v2+1:v2+8);
8.
9.         H=zeros(1,w);
10.        N=numel(H);
11.        bi1=im2bw(sub);
12.        [q1,num]=bwlabel(bi1,r);
13.        For pr=1:numel(bi1)
14.            pattid=0;
15.            if bi1(pr)==0
16.                pattid=pattid+1;
17.                H(pattid)=H(pattid)+1;
18.            else
19.                H(N)=H(N)+1
20.            end
21.        end
22.        h=norm(H);
23.    end
24. end

```

The multi resolution analysis can be achieved in above algorithm by using different values of radius(r) to calculate the USSP features.

B. UGSP

Then we go for UGSP to representing second order voxel wise interaction information. Which is compliment of USSP. The UGSP considers the gradient orientations of the neighbouring voxels of the USSP features.

Let consider input image as I_m , for each voxel V belongs to I_m , spherical neighborhood S_v centered at V with radius R is defined. N_v samples are taken on the surface of S_v . Let D_{vi} denote the image gradient of the i th sample V_i ($i=1,2,\dots,N_v$) on the surface of S_v . Then a rotation invariant measure δv_i is defined for each neighboring voxel V_i , which is the angle

between the orientation of τ_{vi} , and the direction of $V - V_i$. δ_{vi} can be calculated by Eq(1) shown below.

$$\delta_{vi} = \arccos \frac{(\tau_{vi} \cdot (V - V_i))}{(|\tau_{vi}| \cdot |V - V_i|)} \quad \dots(1)$$

where $|\tau_{vi}|$ and $|V - V_i|$ denote the magnitudes of τ_{vi} and $V - V_i$, respectively.

The measure of δ_{vi} is invariant to image rotation because no matter how the images rotate, the relative angle between τ_{vi} and $V - V_i$ the direction of remains the same.

After calculating δ_{vi} for each neighbouring voxel V_i , δ_{vi} is assigned with a label by uniformly partitioning the angle space into four subspace regions. Such operation can be expressed by equation 2

$$L(vi) = \begin{cases} 1, & \text{if } \delta_{vi} \in [0, \frac{\pi}{4}] \\ 2, & \text{if } \delta_{vi} \in [\frac{\pi}{4}, \frac{\pi}{2}] \\ 3, & \text{if } \delta_{vi} \in [\frac{\pi}{2}, \frac{3\pi}{4}] \\ 4, & \text{if } \delta_{vi} \in [\frac{3\pi}{4}, \pi] \end{cases} \quad \dots(2)$$

Then the basic gradient spherical pattern (BGSP) is introduced. BGSP is defined as the labelled spherical surface obtained from the original spherical neighborhood centered at the reference voxel. UGSP subset of BGSP. BGSP having the property of monotonic gray level transformation invariant. This property affects the absolute gradient magnitude of each neighbouring voxel, the gradient orientation remains the same.

The UGSP is defined as:- UGSPs are BGSPs whose surfaces can be covered by at most two uniform regions. These uniform regions are the areas on the surfaces of the corresponding BGSP where all the voxels belongs to the area having the same label.

The UGSP feature will be more sensitive to noise, and the histogram of the UGSP features will become more sparse as it is more difficult for a BGSP to be a UGSP when the number of possible labels to represent the angle space is increased.

Following algorithm describes the procedure of determining whether a BGSP is a UGSP or not.

Algorithm 2

Input: Input image(im), local cubic square window for each voxel(w), radius(r), and the number of neighbouring samples(N).

Output: Vector image, each voxel is represented by a UGSP signature.

```

1.  unf=gradient(double(im1));
2.  n1=numel(find(c>100));
3.  if n1>1
4.    disp('input BGSP does not have gradient
      information')
5.  else
6.    end
7.  [q1,num]=bwlabel(im1,r);
8.
9.  for h2=1:numel(q1)-1
10.   if q1(h2)==q1(h2+1);
11.     cou=cou+1;
12.   Disp ('voxels are flagged')
13.   else
14.     end
15. End

```

Using this algorithm we not only determine the BGSP and also two neighbouring voxels are considered to be connected if and only if they have the same label calculated by equation (2). Then the ID assignment for the UGSP is based on the size of the largest connected component of the UGSP.

Then we go for a new anatomical region descriptor by combining both USSP and UGSP.

C. ARD

In anatomical region descriptor both USSP and UGSP features are combined and this ARD stands as a 2D joint histogram of the both methods.

As stated in earlier sections, the USSP and the UGSP represent the first- order and second-order voxel-wise interaction information, respectively. Therefore, intuitively these both can provide complementary information individually. This leads us to design a new anatomical region descriptor (ARD) feature. The procedure of extracting the ARD feature as signatures for each voxel is stated in following algorithm.

Algorithm 3

Input: Input image (im), local cubic square window for each voxel(w), radius(r), and the number of neighbouring samples(N).

Output: Feature image , each voxel is represented by a ARD signature.

```

1.  for v11=0:size(im1,1)/w
2.    for v22=0:size(im1,2)/w
3.  sub=im1(v11+1:v11+8,v22+1:v22+8);
4.    H=zeros(1,n+2,1,n-(n/2)+1);
5.    N=numel(H);
6.    bi1=im2bw(sub);
7.    [q1,num]=bwlabel(bi1,r);
8.    pattid=0;

```

```

9.      for pr=1:numel(bi1)
10.     if bi1(pr)==0
11.         num=num+1;
12.     else
13.         num=n+1;
14.     end
15.     end
16.     for pr=1:numel(bi1)-1
17.     if q1(pr)==q1(pr+1)
18.         s=max(max(q1));
19.         id=s-(n/2);
20.     else
21.         id=n-(n/2)+1;
22.     end

```

The robustness of the ARD is demonstrated in fig 2.(a) and fig 2.(b) where Fig 2.(a) is a slice image obtained from Connell university database without any field bias distortion. Fig 2.(b) is ARD signature image. Which is generated after applying the above stated algorithms on fig 2(a). If u take a keen observation on fig2.(b) the intensity of image is slightly varied. All the parameters like CSF, Gray value and White values of both input and signed images are tabulated in table 1.

Fig.2.(a). Input image

Fig.2.(b). Binary converted image

Fig.2.(c). Gradient image

Fig.2.(d). ARD image

Fig.2.(e).Histogram for Input image

Fig.2.(f).Histogram for Signed image

Fig 2.(a) shows the original image and its characteristics are plotted by using a histogram shown in fig 2.(e) Fig 2.(d) shows the ARD signature image and its characteristics are plotted by using a histogram shown in fig 2.(f).

Table I

	IMAGE VALUES		
Parameter	Input	USSP	ARD
CSF volume	5.9985	6.8842	8.3886
Gray volume	5.3870	3.2184	4.1684
White volume	0.6115	3.6658	4.2202
CSF & gray	0.8981	0.5746	0.4969
CSF & white	0.1019	0.3387	0.5031

Table 1. shows the Parameter variations of both USSP signature image and ARD signature image along with input image for a corresponding image shown in Fig 2.(a)

III. REGISTRATION PROCESS

The overall flow chart of the registration algorithm is follows as shown below:-

Fig. 3 shows the flow chart of a registration process.

Where fixed image is source image and float image is target image. That means the features of the source image is transferred to the target image to achieve registration.

Here in this paper ARD signature image is used as a fixed image, and transform its features on to the float image to produce a new image with features of fixed image.

Let consider two images I_m and $Refim$ to be aligned, assuming the following intensity relationship:

$$I = J(\tau) + S + \mu \quad ..(4)$$

Where S is an intensity correction field and μ is zero mean Gaussian noise (note that for any two images there always exists a correction field S). τ is the geometric transformation that aligns I_m and $Refim$. The maximum a posterior (MAP) approach to estimate S and τ is to maximize the probability

$$P(T, S | I_m, Refim) \propto P(I, J | \tau, S) P(\tau) P(S) \dots(5)$$

where we assume the independence of τ and S . The first term is a joint likelihood of the images, which leads to the familiar similarity measure. $P(\tau)$ is a prior used to regularize the transformation and $P(S)$ is a prior on S that reflects our assumption on spatial intensity interactions. Now, we also assume that pixel-wise probabilities are i.i.d., but only given the correction field. MAP estimation in Equation (2) is equivalent to minimization of the following objective function:

$$E(S) = \| I_m - Refim - S \|^2 + \delta \| PS \|^2 \quad ..(6)$$

where images and correction field are in column-vector form, $\|.\|$ is Euclidean norm and P is a regularization operator for S . For now we omit the transformation τ and its regularization term, to make the derivation of S clear.

To get S let the gradient as zero.

$$S = (Id + \delta P^T \tau^* P)^{-1} (I_m - Refim) \quad ..(7)$$

Where Id is nothing but an identity matrix, $P^T \tau^* P$ is a square, symmetric and positive semi defined matrix. Substitute S along with $P^T \tau^* P$ in Eq(3).

After simplifying the objective functions because P is orthogonal, and the majority of multiplications and inversions are only with diagonal matrices within.

$$E = r^T Q d \left(\frac{\beta \lambda}{1 + \beta \lambda} \right) Q^T r = r^T Q L Q^T r = r^T A r \quad ..(8)$$

where $d(\cdot)$ denotes a diagonal matrix. Where $A = QLQ^T$ and eigen values of A are all nonnegative and bounded between $[0, 1]$. Here defined a new

square, symmetric and positive semi definite matrix with eigen values ϵ .

$$E = d([I_1, \dots, I_N]) = d \left(\frac{\beta \lambda}{1 + \beta \lambda} \right), \quad 1 \geq I_i \geq 0 \quad(9)$$

By choosing particular regularization operator P , Then A is known and minimize the equation with respect to the transformation $|\tau$.

$$E(\tau) = r^T A r = (I_m - Refim(\tau)) \quad(10)$$

The matrix A is of size N^2 , where N is a number of image pixels. In above equation A represents a covariance matrix. By ignoring the independent terms of τ a new similarity measure existed as shown below

$$E(\tau) = - \sum_{n=1}^N \log \frac{1}{(q_n^T r)^2 / \alpha + 1}; r = (I_m - Refim(\tau)) \quad(11)$$

IV. IMPLEMENTATION AND RESULTS

By define the basis eigen vectors Q and the transformation τ using the FFD transformation with 3 hierarchical levels of B-spline control points. We use the gradient descent optimization method to iteratively update the transformation parameters τ .

RESULTS

Fig.4.(a). Reference image

Fig.4.(b). Float image

Fig.4.(c). Registered image

Fig 4. 4.(a) is a reference image, Fig 4.(b) is a float image and Fig 4.(c) is a registered image. Where the features of the float image transforms on to the reference image and produced the Registered /Deformed Image.

Here, evaluation of the proposed method by performing nonrigid image registration experiments on the simulate database obtained from Brain web. The proposed method is also compared Fig. 4.(d),

4.(e). Typical deformation field obtained by using the proposed method. It is shown that the generated deformation field is smooth and does not have folding effects, which preserves the topology of the anatomical structures with two registration algorithms. They are 1) SSD and 2) Correlation coefficient. In above mentioned experiments, subvolume is 3 and window size 'w' was set to 5, and the number of neighbouring samples was set to 80 in ARD algorithm. Above experiments were run on a 2-GHz duo core central processing unit 2-GB random access memory computer.

Fig.4.(d). Using CC method

Fig.4.(e). Using SSD method

Fig.4.(f). Using Proposed method

Above figures shows the reconstructed brain images using different methods. Fig 4.(d) is a resultant registered image of the proposed method. Fig 4.(e) is a resultant registered image using Correlation coefficient method. Fig 4.(f) is a resultant registered image using SSD method.

For comparison purpose, the registered image of the proposed method is also shown in Fig.4(f). It is shown that the brain images obtained via the proposed method preserve most of the details of the input images, particularly in the ventricular and cortical regions. In Fig.4.(d), 4.(e), 4.(f), significant differences are highlighted with blue circles.

V. CONCLUSION

In this paper, a new feature expansion algorithm for nonrigid image registration has been proposed. The proposed method is based on image features, namely the ARD. The ARD has two kinds of complementary features, i.e., USSP and UGSP, which encode the

first- and second-order voxel-wise interaction information respectively. The ARD is rotation and monotonic gray-level transformation invariant, which are properties that are analyzed and proved here. This ARD signed images then fed to registration process. By reducing the residual complexities of the images. Experimental results demonstrate that the proposed method has the highest registration accuracy among all the compared methods.

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AUTHORS

Harsha Vardhan N. received B.Tech Degree in Electronics & Communication Engg. from JNTUniversity, Anantapur, India. He is currently pursuing M.Tech Degree in Electronics & Communication Engg. Specialization in Embedded Systems from Annamacharya Institute of Technology & Sciences, Rajampet, A.P. India. His research interests include embedded systems, Networking and Image Processing.

S. ASIF HUSSAIN received B.Tech & M.Tech Degree in Electronics & Communication Engg. from JNTU University, Hyderabad, India. He is currently working towards PhD Degree in Biomedical Engineering at JNTU, Anantapur, India.

Presently he is with Annamacharya Institute of Technology & Sciences, Rajampet, A.P. India working as an Assistant Professor in Dept. of ECE. Currently he is working on a research project sanctioned by AICTE of 11.30 lacs on biomedical engineering. He presented many research papers in National & International Conferences. He is a member of Professional societies like ISTE (India), BMESI (India). His research interests include embedded systems, Time Series Analysis and Image Processing.