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AN INNOVATIVE APPROACH FOR MULTIMODALITY REGISTRATION OF BRAIN IMAGES USING PARTICLE SWARM OPTIMIZATION

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Abstract: Modern developments in imaging with its unique capability of extracting quantitative information have developed in to a new era for scientific and biomedical research. Registration is nothing but a geometrical transformation that aligns points in one angle of an object with related points in another angle .The basic elements of multimodality registration are interpolation, similarity measure, optimization etc. 2D medical images are acquired by tomographic modalities, such as magnetic resonance (MR) imaging, computed tomography (CT, single-photon emission computed tomography (SPECT), and positron emission tomography (PET). The general measure used in this process is the normalized mutual information, which is briefly explained in this work by iterative improvisation of this function value, a transformation will be determined. The rigid transformation with translational and rotational parameters has been applied to the moving image. For this, improved PSO algorithm is used for searching the registration parameters. Simulation results reveal the potency of the implemented multimodality registration method.

Keywords: PSO, CT, MRI, rigid transform, multimodality registration.

I INTRODUCTION:

Image registration, generally referred as matching or warping which involves aligning two or more images. Image registration is a pivotal step for image analysis in which desired information results in innumerable images.In each of these modalities, some set of 2D slices provides a 3D array of image intensity values. Mostly 2D images are x-ray projections grabbed from a film or from a digital radiograph or projections of visible light grabbed like a photograph or from a video frame. In medical applications, the object in each view will be some anatomical region of the body.

Fast and authentic image registration has driven the innovation force in the medical imaging process. It also has enhanced the diagnoses of patients and change accounts in structures of morphology over time. Multimodality image registration has the tendency to fuse the images and it also has registered 2D/3D images between the many different modalities. Multiple images have represented the same anatomy using the different modalities of imaging and this process is nothing but the multi-modality registration of images. The algorithms of multimodality image registration have linked to the algorithms of image transformation.Multi-modality metrics of similarity function have used to drive registration. The metrics of multimodality are acceptable for registering the images which have different characteristics of intensity. These are also based on determining the province of function between many images. The metrics of multimodality has generally based on establishing statistical and functional dependencies.

Particle swarm optimization:

PSO is a potent speculative optimization technique depending on the movement and intelligence of particles used to analyze the search space of a given problem in order to get the set of particles desired to acquire a precise objective. This approach was introduced by James Kennedy and Russell C. Eberhart in 1995 [1], .PSO specifies a comparatively new concept of algorithms that may be used to find ideal solutions to arithmetic and subjective problems. It can be implemented in recent developing programming languages and has proven very advantageous and fast when enforced to a various set of optimization problems [2]. PSO has evolved through simulation of a interpreted bird flocking model. Combines self-experience with social experience .Population-based optimization. Algorithm generally need the particles to establish a group and move around the work space to get the best possible solution. The particle elaborated in the group to search for its own properties and other particles properties also. The best solution received by a particle is also known as pbest and another best value attained by neighborhood of the particle is known as gbest. Iterative measure is followed in each time step with random weight age values to find pbest and gbest values for each particle .The following figure gives the information of theory of the particle swarm optimization pi is current position and pi+1 is updated position of a particles, and vpbest and vgbest are the best values attained by particle and best value attained by its neighbor respectively.

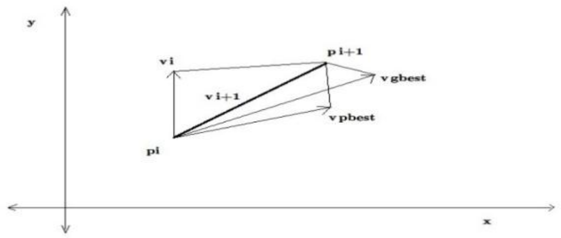


Fig:1 Concept of searching a particle in space

The components involved in particle swarm optimization are particle, velocity, fitness, pbest and gbest. Particle is just simply basic solution to an optimization problem, during PSO particles change their position. Velocity is rate of change of position of the particles. Fitness is the best solution obtained by the particle. P best is the best solution resulted in previous particle, and gbest is best value by any particle in the swarm.

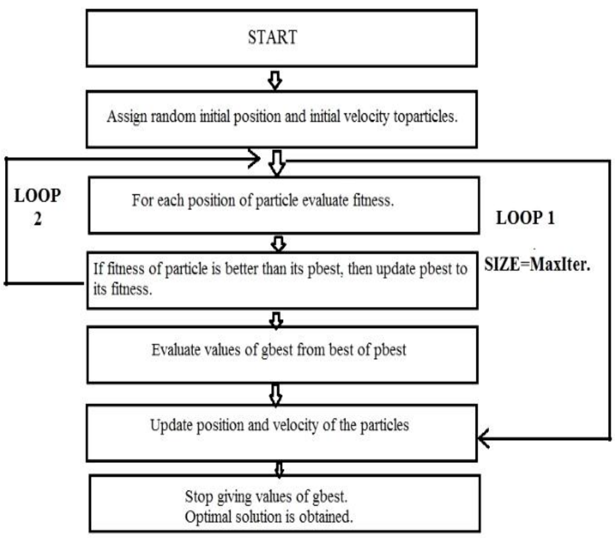


Figure:2 Flow chart for PSO algorithm.

The overall functioning of the algorithm is given below:

Step I: The position and the velocity of the particles are arbitary set within lower and upper boundaries

Step II: During every iteration the velocity of a particle is updated according to mathematical equation:

$$v_i = wv_i + c_2R_2(p_{i,best} - p_i) + c_2R_2(g_{i,best} - p_i)$$

Where p_i is position of the ith particle, and v_i is velocity of ith particle. $p_{i,best}$is the best objective value found by the ith particle and $g_{i,best}$ is the best objective value inaugurated by total swarm.

Step III: After getting the updated velocities the new position of the particle is attained between two consecutive iterations using the equation:

$$p_1 = p_i + v_i t$$

Where t is time between two consecutive iterations. After getting new position the countercheck is done to check if value is in given upper and lower limit.

Step IV: The values of $p_{i,best}$ and $g_{i,best}$ are updated using following conditional statements:

$$p_{i,best} = p_i \;\; if\; f(p_i) > f(p_{i,best})$$

$$g_{i,best} = g_i \;\; if\; f(g_i) > f(g_{i,best})$$

Step V: Iterative procedure is persued to repeat this algorithm until it reaches to a breakpoint. Once it's stopped the values of $g_{i,best}$ and $f(g_{i,best})$ are returned as solution.

II IMPLEMENTATION:

This paper mainly presents the approach for image registration we used particle swarm optimization PSO for optimization of the of similarity metric. Proposed work determines rigid transformation of moving images related to similarity metric of the fixed image. Geometric transformations actually maps the points in one space to points in another: (x',y',z') = f(x,y,z). These transformations are so simple like scaling every coordinate, or complex, like nonlinear twists and bends. Image registration is nothing but the transformation of points on the onfirst image to the homologous points on the second image and spatial transform is determined. This process takes fixed image f(X) and moving image m(X) as input data. Where X is position of pixel. Images are either 2D or 3D. Registration is an optimization problem of finding the spatial mapping of the points from the fixed image to that of the moving image. The transformation component between these images is defined as T(X). In this process the registration intensities at the grid points are evaluated and intensities at the non-grid points are calculated using the interpolation method. The main parameter which is optimized during the process of registration is metric component S (f, m_0).This parameter gives an accuracy to which fixed image is matched with moving image. The images are blurred using Gaussian filter.

The steps eloborated in multimodality registration are explained below:

Step 1: The distinctive objects in the image are identified using image segmentation for both images. This can be edges, contours, regions, etc.

Step 2: The relation across these objects is obtained for both fixed and moving image.

Step 3: The transformation function for mapping both images is obtained by matching both images.

Step 4: After acquiring the final transformation matrix the images are resampled and transformation is applied on the input image.

Rigid registration is generally utilized for image frameworks . The modalities are registered by rigid registration. By this redundancy can be reduced and the information is more clear between modalities.

III SIMULATION RESULTS:

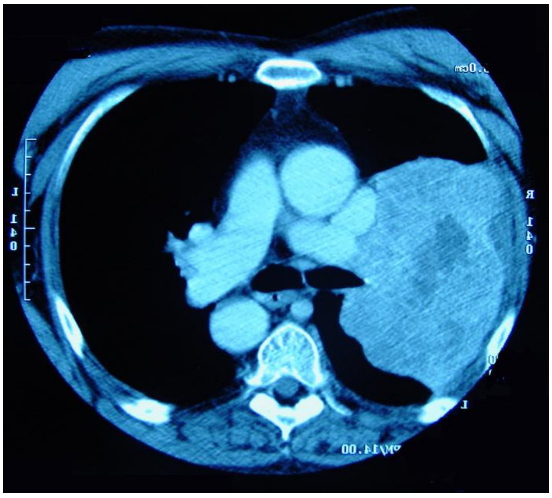
The results of registration revealed in growth after changing the initial radius and maximum iteration properties of optimizer and the settings of optimizer are assigned while using initial conditions trying to refine the further registration. Finally all the images were displayed by executing the mat lab code.The optimizer configures the similarity metric of image to be used during the registration. The useful technique for acquiring improved results of registration is to initiate with much simple type of transformation like rigid and then utilize the resulting change as an initial condition for much complex types of transformation like affine transformation The parameters used for the simulation of multimodal images are given below in the table

Table:1 Initial parameters for Simulation of 300 iterations

S.NO	Properties	Values
1.	Growth factor	1.050000e+00
2.	Epsilon	1.500000e-06
3.	Initial radius	6.250000e-03
4.	Maximum iterations	100

Table 2: Initial parameters for Simulation of 300 iterations

S.No	Properties	Values
1.	Growth factor	1.050000e+00
2.	Epsilon	1.500000e-06
3.	Initial radius	6.250000e-03
4.	Maximum iterations	300



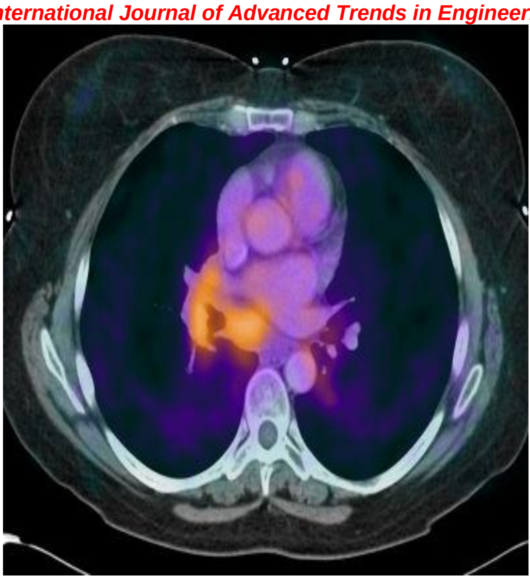


Fig:3 The two input images for multimodality registration

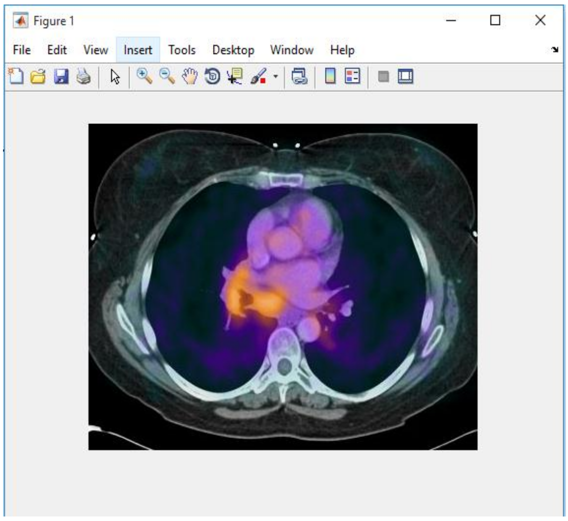


Fig: 4 fetching the raw image

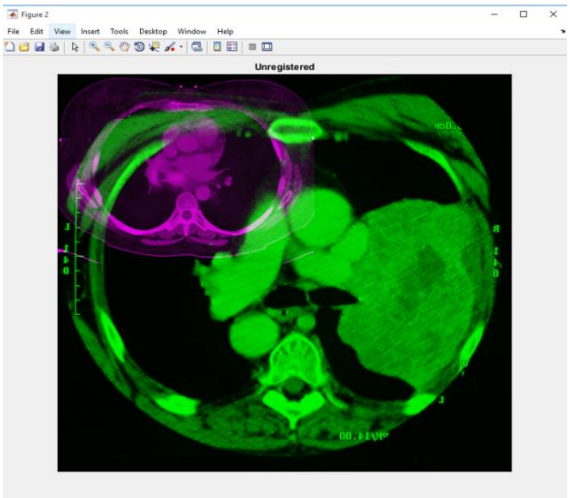


Fig: 5 Output shows unregistered image with image1 top ,image2 bottom

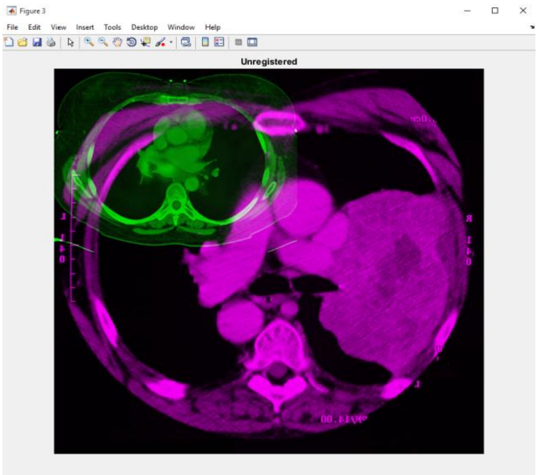


Fig:6 This output shows unregistered image with image2 top bottom, image1.

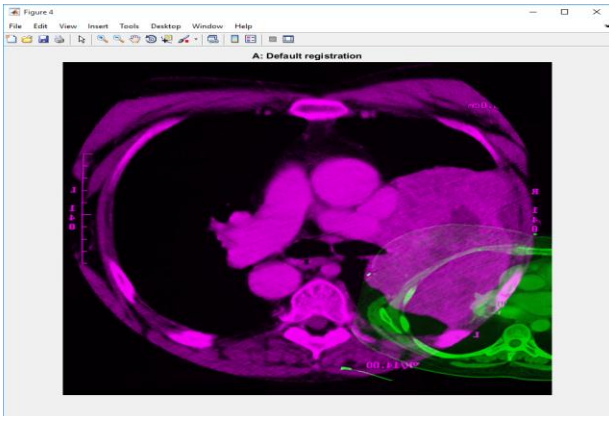


Fig 7 : Default registration

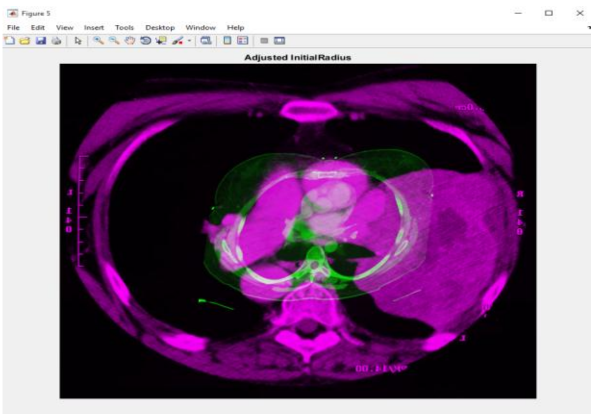


Fig:8 image registration with initial radius optimizer Initial Radius/3.5;

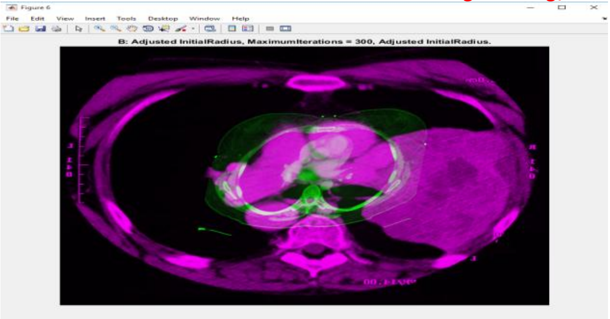


Fig:9 image registration with initial radius optimizerInitialRadius/3.5 and 300 itrations;

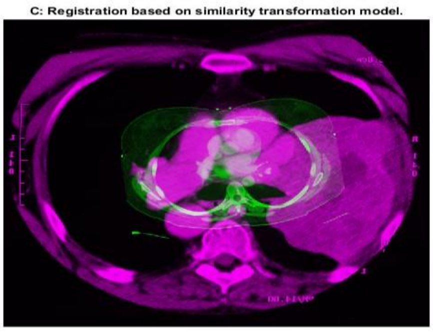


Fig :10 registration based on similarity transformation model

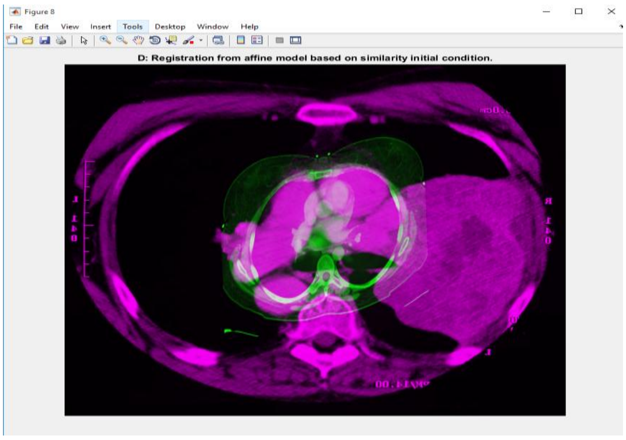


Fig: 11 Registration from affine model based on similarity initial condition

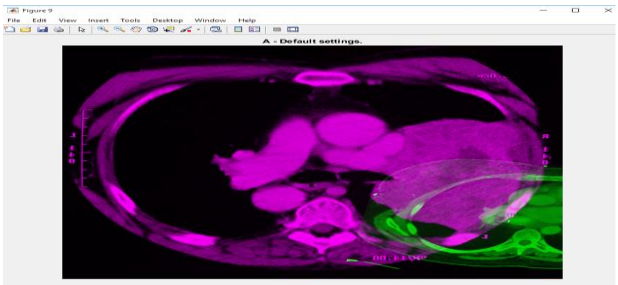


Fig: 12 Default settings

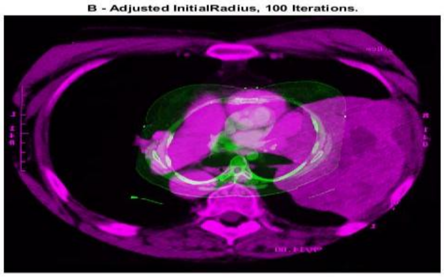


Fig: 13 adjusted initial radius with 100 iterations

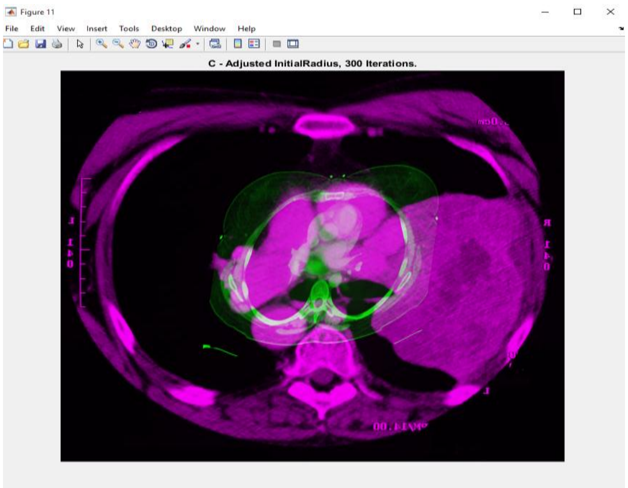


Fig: 14 Adjusted initial radius with 300 iterations

IV CONCLUSION:

The images are displayed and compared along with the moving image and fixed image. When the points in the image of the moving image and the fixed image are made equal, the images are registered. Using the optimizer, the radius is adjusted. The moving image was made rigid and is registered. The image was registered with iterations and the optimization was obtained in the registration. The registration based on optimization performs best when a better initial condition can be provided that associates the fixed and moving image. The optimizer configures the similarity metric of image to be used during the registration. The useful technique for acquiring improved results of registration is to initiate with much simple type of transformation like rigid and then utilize the resulting change as an initial condition for much complex types of transformation like affine transformation. The results of registration revealed in growth after changing the initial radius and maximum iteration properties of optimizer and the settings of optimizer are assigned while using initial conditions trying to refine the further registration. Finally all the images were displayed by executing the mat lab code.

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