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Improved Approach for Removing the Motion Artifacts Using Particle Swarm optimization Technique

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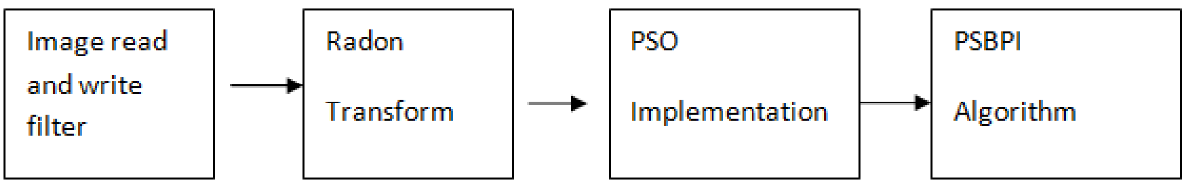
Abstract: *Medical image processing has became a real time expansion, and has been an interdisciplinary research field attracting many research people from applied mathematics, computer sciences, engineering, statistics, physics, biology and medicine. This paper presents the new approach for removal of motion artifacts of medical images. Organs such as heart, lung, brain etc in human body cause motion artifacts during the scans. This artifacts should be removed while reconstruction of the scanned data using the PSBP(pixel specific back projection). The proposed system uses the PSO (particle swarm optimization) for the back projection. The Particle based back projection uses projection data of the particles during back-projection that corresponds to the location at which each angle resided at the time each projection was measured.*
Keywords: *back projection, PSBP ,PSO, Reconstruction*

I. Introduction

Over the past few decades use of medical images in the diagnosis is very common irrespective of the image data type. Clinicians, doctors and surgeons are looking forward for new time efficient ways to observe the data. The registration of the images becomes very tedious and inaccurate for multimodality medical images. In these cases approach of directly comparing the gray levels fails. Recent developments in technology lead us to acquire and process data more efficiently. In clinical diagnosis observation of patient's data and planning for future procedures on the patient is first priority of the doctors, clinicians and surgeons. The better observation is achieved after aligning the images in correct way.. The image can be obtained using different acquiring techniques such as MRI, CT, PET, etc. In image the spatial transform is obtained between this images Over the past years, scientists and researchers developed so many ways to perform image segmentation of medical images. Particle swarm optimisation technique is used for thresholding based segmentation. In this research further improvement of the algorithm is done. We are using Pixel-specific back-projection algorithm which implements time-varying magnification motion model on a pixel by pixel basis. The Particle based-BPI algorithm reduces motion artifacts by performing the back-projection in a frame of reference that moves with the particle characteristics. The motion during scanning is modelled as a shift and as a magnification about some origin point. The Particle based back projection uses projection data of the particles during back-projection that corresponds to the location at which each angle resided at the time each projection was measured. The particle is having moving around in the different directions that are provided by the angle or thetas of rotation. The path is specified by providing the parallel path of the projecting particles, which is determined based on the mid index position of the path between the particles and the projection end of the particles.

Block diagram:



In this paper we discuss all the stages involved in the architecture in following sections.

II. Particle Swarm Optimization

Particle Swarm Optimization proposed by James Kennedy & Russell Eberhart (1995) Combines self-experiences with social experiences. PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO applies the concept of social interaction to problem solving. . The algorithm of PSO is easy to implement and has been successfully applied to solve a wide range of optimization problems in many fields such as image processing fields including image segmentation and projection. Image segmentation is a low-level image processing task aiming at partitioning an image into homogeneous regions. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. All of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Image segmentation methods have been classified into numerous categories of which region and thresholding based segmentations.

Thresholding based segmentation is definitely one of the most popular and effective approaches used in image segmentation. Over the years a wide range of thresholding techniques has been developed and considerable research continues nowadays. All the thresholding techniques involve a bi-level thresholding and a multilevel thresholding. The main objective of thresholding is to determine a threshold for bi-level thresholding or several thresholds for multilevel thresholding giving a suitable classification for pixels in an image. The simplest problem will be a bi-level thresholding one, where only one threshold, which separates the pixels into only two classes, is selected and the image able to be segmented by thresholding it at this value. This can facilitate to generate a binary image where all pixels having gray levels higher than the threshold are assigned to one class and pixels having gray levels lower than the threshold are assigned to another class. However the problem gets more and more complex when we try to achieve segmentation with greater detail by multilevel thresholding. Then the image segmentation problem becomes a multi-class classification problem where, based on the determined thresholds, pixels having gray levels within a specified range are grouped into one class. Determination of appropriate threshold values, that can segment the image efficiently, is the most important task involved in thresholding techniques. Over the years many method has been developed to solve this problem . The determination of appropriate thresholds is still the most difficult task in the thresholding techniques and it is still a challenge and a hot research topic for the researchers.

Now, the PSO technique has been used to solve the problem of thresholding based segmentation. Zahara et.al, (2005) combined a hybrid Nelder–Mead simplex search method and the PSO technique to solve the objective functions of Gaussian curve fitting and the Otsu's method. This combination is applied to image thresholding with multi-modal histograms. In a multilevel threshold selection based on PSO was proposed. The PSO technique was used to find near-optimal thresholds by minimizing the cross entropy between the original image and its thresholded version. Maitra et al. (2008) proposed a new thresholding algorithm for histogram-based image segmentation using a hybrid cooperative-comprehensive learning based on the PSO algorithm.The proposed system uses the PSO for the back projection. In back projection method, the sinogram is determined by the Radon transform. After the transformation, the sinogram will be used for the back projection. During the projection activity, the particles are initialized. The particles are assumed as parallel particles in which the positions are calculated for the particles to project. The particles are made as the parallel particles and they are moved on to the path as initialized. The rotator paths specify the particles movement in different directions with the angle as thetas. The particle movements are then recorded and initialized. This algorithm uses number of particles to form a group and move around in space to find best possible solution. The particle involved in the group search for its own properties and properties other particles as well. The best solution achieved by a particle is also known as pbest and another best value achieved by neighbourhood of the particle is known as gbest. Iterative procedure is followed in each time step with random weightage values to find pbest and gbest values for each particle.

The following figure explains the concept behind the particle swarm optimisation pi is current position and pi+1 is updated position of a particles in the swarm, and vpbest and vgbest are the best values achieved by particle and best value achieved by its neighbour respectively.

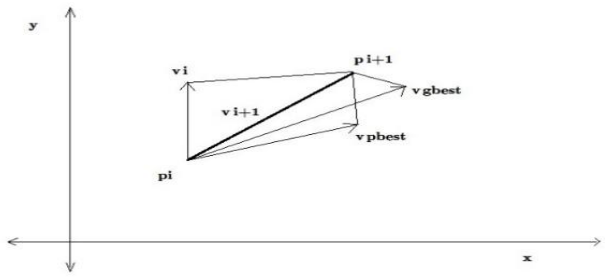


Figure2. Concept behind updating search point in swarm.

III. Algorithm

The parameters involved in particle swarm optimization are particle, velocity, fitness, pbest and gbest. Particle is just simply candidate’s 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 achieved in previous particle, and gbest is best value achieved by any particle in the swarm.

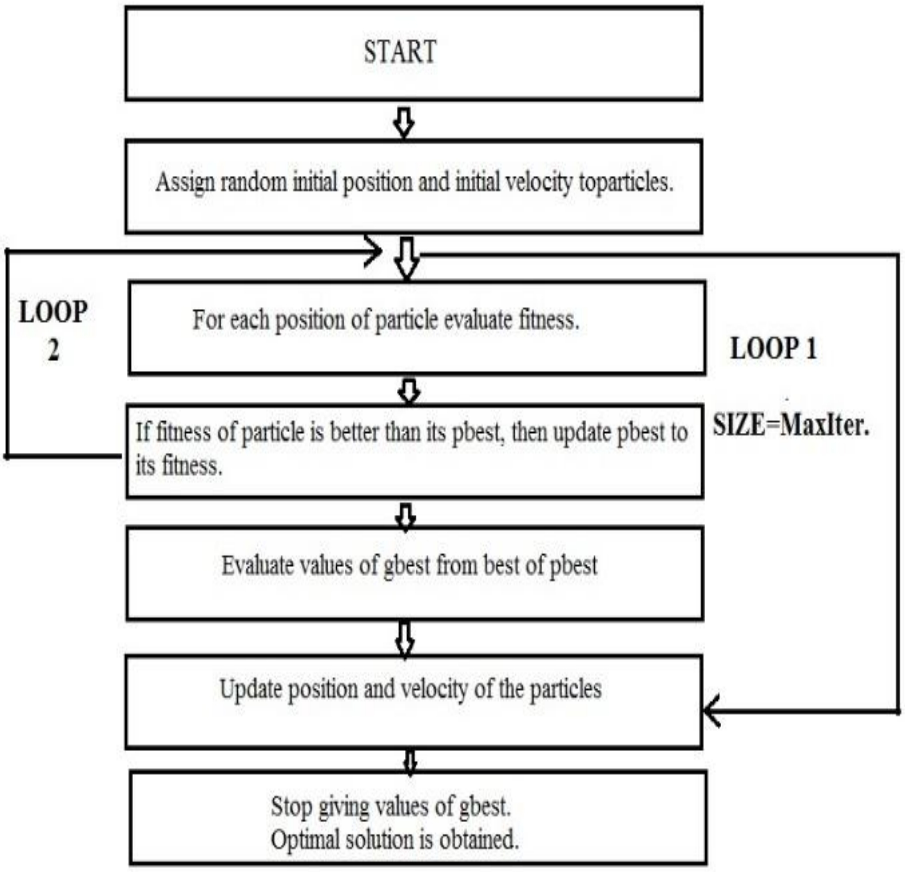


Figure3. Flow chart for PSO algorithm.

The overall functioning of the algorithm is given below:
Step I: The position and the velocity of the particles are randomly set within lower and upper boundaries
Step II: During each iteration velocity of a particle is updated using following 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 found by the entire swarm.
Step III: After getting the updated velocities the new position of the particle is achieved between two successive iterations using the equation:

$$p_1 = p_i + v_i t$$

Where t is time between two successive 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 process is followed to repeat this algorithm until it reaches to a termination. Once it's terminated the values of $g_{i,best}$ and $f(g_{i,best})$ are returned as solution.

IV. Implementation

The motion artifacts are caused due to the motion of the organs. To reduce this motion artifacts CTX algorithms is used. In CTX algorithm the motion artifacts are removed using the back-projection, and the frame of reference of back-projection moves with the moving organ. In this algorithm the origin point $(x0, y0)$ is taken and shift and magnification of the organ is modelled about this point. In short CTX algorithm is performed using the projection data of a point at the time of measurement.

The proposed system uses the PSO for the back projection. In back projection method, the sinogram is determined by the Radon transform. After the transformation, the sinogram will be used for the back projection. During the projection activity, the particles are initialized. The particles are assumed as parallel particles in which the positions are calculated for the particles to project. The particles are made as the parallel particles and they are moved on to the path as initialized. The rotator paths specify the particles movement in different directions with the angle as thetas. The particle movements are then recorded and initialized.
The following image shows the parallel particles at rotation angle θ, and f(x,y) as the cross section of the organ.

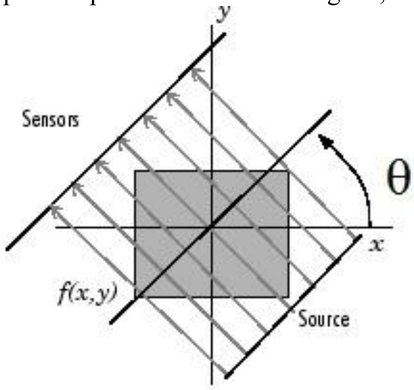


Figure 4. Projection diagram for cross section of an organ.

The multiple projections can be considered into account by performing radon transform on the data, and filtered back projection is used for reconstruction. These can be evaluated using following equations;

$$\big(x(z), y(z)\big) = (zsin\alpha + scos\alpha, -zcos\alpha + ssin\alpha)$$

And

$$R_\mu f(\phi, s) = \int_{x\in\mathbf{L}(\phi,s)}\int f(x)\mu(\phi, x)dx$$

After considering the shift and magnification factors, the algorithm can be explained as follows:
Let's say that f(x,y) is cross section of the organ that is to be reconstructed. After applying shift factors (α_x,α_y) and magnification factors (β_x, β_y) the updated version f'(x,y) of f(x,y) is given by

$$f^{'}(x, y) = f(\alpha_x + \beta_x x, \alpha_y + \beta_y y)$$

Where, the shift and magnification factors are function of the projection angle θ, which means they are function of time. Method of parallel projection is followed. CTX algorithm uses x' and y' are used instead of x and y, due to the involvement of shift and magnification factors. After simplifying the parallel projection equation the limit of the integration changes from 0 to π with respect to θ. After simplification we get

$$f(x, y) = \int_0^\pi q_\theta \left(\left[\frac{x - \alpha_x}{\beta_x}\right] cos\theta + \left[\frac{y - \alpha_y}{\beta_y}\right] sin\theta\right) d\theta$$

Where the filtered projection of $f(x', y')$ is q_θ and defined as:

$$q_\theta = \int_{-\infty}^{\infty} S^{'}(\theta, \omega)|\omega|g(\theta)e^{j2\pi\omega t}\, d\omega$$

Where,

$$g(\theta) = \left|1 + \frac{sin2\theta}{2}\left(\frac{\beta_{x\theta}}{\beta_y} - \frac{\beta_{y\theta}}{\beta_y}\right)\right|$$

This is the CTX algorithm for parallel projection. Here $f(x, y)$ is achieved from the projections obtained from$f'(x, y)$. Same analogy is used for fan beam data.

V. Psbpalgorithm

The CTX algorithm does not describe the motion of the organs in the chest. This model is only valid in the small region around the pixel. The shift and magnification factors may change in different region, to avoid this local corrections can be made in CTX algorithm.
The local corrections are done by describing the motion of by the warping functions G and H. Warping function gives us final warped coordinates x' and y' as a function of space and projection angle.

$$x^{'} = G(x, y, \theta)$$
$$y^{'} = H(x, y, \theta)$$

The shift and magnification model is approximated for each pixel in the image and new values of α and β are extracted from the warping functions G and H as:

$$\alpha_x = G - \frac{\partial G}{\partial x}, \alpha_y = H - \frac{\partial H}{\partial y}$$

And

$$\beta_x = \frac{\partial G}{\partial x}$$

$$\beta_y = \frac{\partial H}{\partial y}$$

Then the equation obtained in CTX algorithm can be modified after considering warping functions as follows:

$$f(x,y) = \int_0^{\pi} q_\theta([G^{-1}(x,y,\theta)]cos\theta + [H^{-1}(x,y,\theta)]sin\theta)d\theta$$

Where q_θ and $g(\theta)$ is already defined above. The function $f(x,y)$ is reconstructed from warped function$f(x',y')$. Same analogy is used for fan beam data.

VI. Results And Discussions

The proposed architecture is programmed in MATLAB. The back projection is carried out using following steps:

Step 1. Particles are initialized.
Step 2. The particle movement path is provided with the sinogram of the images.
Step 3. The particle project themselves to the image, the mid index position is calculated.
Step 4. The particles are projected with the various angles of thetas namely 0 to 179 degree or 0 to 359 degree.
Step 5. The projected particles and the path, which are formed in the projection, are viewed and drawn.
Step 6. The particle based back projection image is viewed and the motion artifacts are removed by these particles after the projection of the particles movement.
Step 7. The particles simulation can be viewed during the execution of the code.

Figure: The input image

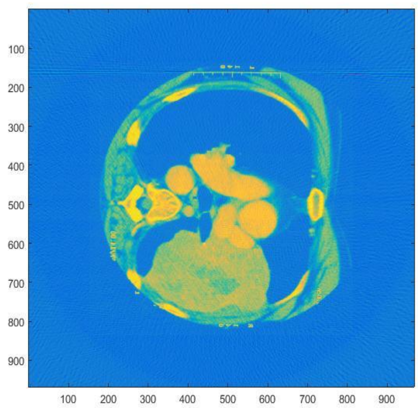


Figure: the reconstructed output image

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