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Visualization of Hidden Structure and Shape in Ct Image via Non-Linear Perspective Foreground and Back Ground Projection

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Abstract:

The neurologist analyse the brain images to diagnose the disease via structure and shape of the part in the scanned Medical images such as CT, MRI, and PET. The Medical image segmentation perform less in the regions where no or little contrast, artefacts over the different boundary regions. The manual process of segmentation show poor boundary differentiation due to discernibility in shape and location, intra and inter observer reliability. In this paper, we propose a dyadic Cat optimization (DCO) algorithm to segment the regions in the brain from CT and MRI image via Non-linear perspective Foreground and Back Ground projection. The DCO algorithm remove the artefacts in the boundary regions and provide the exact structure and shape of the brain regions. The DCO algorithm show the region boundary such as plerygomaxillary fissure, occipital lobe, vaginal process zygomatic arch, maxilla and piriform aperture with high visibility in the regions of inadequately visible boundary and distinguish the deformable shape. The DCO algorithm show the increased SSIM and 90 percent accuracy.

Keywords: Dyadic CAT algorithm, CT, MRI, Boundary differentiation.

1. Introduction

In medical imaging, CT image prone to artifact and low contrast in the boundary region due to reconstruction of image from independent detector located in order for measurement. The artifact classify into four types such as physics based artifacts, patient-based artifacts, scanner-based artifacts and helical and multisection artifacts. The physics based artifacts arise during the acquisition of data from CT. The patient based artifacts arise due to movement of the patient during scanning. The scanner based artifacts cause due to improper function of scanner in CT machine. In addition, streaks appear in CT image because of dense object. The dense objects in the image lack in contrast and clear boundary, when X-ray beam pass through the object the photon with lower energy absorb more quickly than Photon with higher energy.
The brain structure change along with the person age. The changes in structure various with individuals and the person with same age. Furthermore, for detection of neurodegenerative disease, such as Alzheimer’s disease (AD), Parkinson’s disease (PD), Prion disease, Motor neurone diseases (MND), Huntington’s disease (HD), Spino cerebellar ataxia (SCA) and Spinal muscular atrophy (SMA) need the clear boundary edge and shape of the brain organs to identify the deformation. The neurodegenerative disease easily identify with the brain structure variability from CT atlas via nonparametric and parametric approach.

The structure in brain measure through the CT or MRI imaging with some correction or adjustment in size variation. Such variation obtain through ventricle-brain ratio, in which the size of the brain structure is proportion to the head size estimation. Furthermore, regression analysis and volumetric measure technique apply for structure measures, which come under the parametric measurement. However, the non-parametric measure execute through the ROI, segmentation algorithms which perform both manually and automatically.

The brain structure measurement through parametric and non-parametric algorithm in MRI and CT image has certain disadvantages such as resolution, beam hardening artifacts, view limit in posterior fossa and low visualization in white matter disease for CT image and the disadvantages of MRI for structure of brain such as Claustrophobia, long exam and scanning is ineligible for the patients with pacemakers. Both CT and MRI provides the physical structure of the brain in the static image. However, CT image provide the detail information about spinal cord or brain in which x-rays passing through the organs in different angles. The x-rays are attenuated in the regions of high density materials such as bone and calcium, where the structure of these regions appear white and the structure which permit the x-rays looks in the dark appearance in the image. The attenuation, beam Harding, artifacts, steaks lead to inaccurate measurement of structure in the brain, due to unclear boundary region, shape and edges in the CT image.

In this paper, the proposed DCO method contribute for the superior neurodegenerative diagnosis via brain structure analysis and measurement from CT image.

(i) Improve the manual and automatic segmentation in the regions with little or no contrast in the boundary region due to artifacts and steaks
(ii) The hidden such sub structures such as thalamus and white matter are fully discernible through the Non-Linear Perspective Foreground and Background Projection.
(iii) Provides the spatial relationship between the structures in the brain and identifies the deformation of the structure via specific boundary condition such as length and shape.

2. RELATED WORK

The segmentation is especially well suited for structures with weakly visible boundaries as it simultaneously estimates the image inhomogeneities, explicitly models the boundaries through a deformable shape model, and segments the MR images into anatomical structure [1]. Furthermore, software platform integrates algorithms for image analysis and processing. The image-processing block includes segmentation, visualization, reconstruction and registration for image analysis. However, Conventional Quality assessment of 3D image segmentation algorithm done by comparing segmentation quality with datasets. The comparison determines systematic segmentation problem. The authors propose a clustering algorithm to compare quality of
segmentation with different 3D images [2]. Furthermore, connectivity criterion applies with clustering algorithm for better segmentation quality assessment [3]. Furthermore, Organ medical image segmentation requires prior knowledge of location and appearance of organs. The detailed prior knowledge of organ shape is challenging. The solution space of organ in 2-D image determine with MAP-MRF contour segmentation method. The contour has prior knowledge of boundary – edges, shape and appearance [4]. Furthermore, a master slave decomposition help in labelling each iteration. However, conformal geometric algebra (CGA) provide optimal solution for complex geometric problems. The conformal geometric algebra, highly inconvenient due to computational complexity and high dimensionality [5]. The complexities of conformal geometric algebra reduce by ConformalALU and CGA operators. The ConformalALU apply for 3D modelling and image segmentation of medical images. Furthermore, multiple channel local binary fitting model (M-L) applies for medical image segmentation [6]. Conventional image segmentation improves with region limit function in M-L model for multilayer image segmentation. The robustness and accuracy of image segmentation results improve by Gaussian kernel function. Image Segmentation via Level set method apply to improve boundary accuracy. The accuracy of segmentation results hinder by inhomogeneities and weak edges [7]. Segmentation with an active contour along with level set method apply for medical image. The level set reduce objective energy function depending on boundary importance. The importance compute depending on edge features of adjacent region both inside and outside of contour [8]. Furthermore, combined interpolation 3D LSM (Level set method) apply on highly anisotropic throat MRI. The interpolation help reconstruct MRI volumes, increasing segmentation accuracy. The accuracy of tumour boundary in image improve with Edge stop functions (ESF) along with edge based active contour segments. The image segmentation achieves by probability score and gradient information of standard classifiers. The ESF build from classifier and with level set method apply to any edge-based model for image segmentation [9]. Automated method of image segmentation impossible for Anatomic structures in medical imagery. For easy use, an open loop system without human intervention acquires better image segmentation. The segmentation results conflict with human expert’s decision on image data. The segmentation results acquire better by closed loop system comprising of automated boundary detection with human interface for better judgement [10]. Furthermore, Bias field apply to correct intensity in MRI images. A modified version of Mumford-shah performs segmentation and bias correction simultaneously. Initially the L0 gradient regularizes to model bias field. The segmentation step comprises of two steps. The first step recovers intensity of bias field. The second step applies thresholding for image segmentation [11]. Medical image comprises of complex foreground and background density distributions. Noise and low contrast further make it hard for boundary identification in foreground and background images. A SVLS (Supervised variation level set) apply to differentiate intensity differences in foreground and background images [12]. Segmentation of 3D High-frequency Ultrasound Images of Human Lymph Nodes Using Graph Cut with Energy Functional Adapted to Local Intensity Distribution. A 3D quantitative ultrasound imaging differentiates cancer free lymph nodes from metastatic lymph nodes. The method perform by automatic segmentation method to differentiate fat from ultrasound processing for attenuation. The lymph nodes and the fat have varying intensity [13]. A heteroscedastic model (2D-GARCH) captures marginal distributions and dependencies of wavelet coefficient. The model improves image restoration from noisy image and characterization of subband ultrasound image [14]. Multi Atlas patch based label fusion (MAS-PBM) apply for image segmentation in MRI images. The MAS-PBM analyze patch similarity between atlas images and target image. The atlas images comprises of labelled image (or) map and MRI image. The map use to measure similarity between images [15]. Furthermore,
the sparse patch-based label fusion method apply for image segmentation on labels of patch. Gliomas tumour shortens the life expectancy faster than other tumours. The tumours assess by MRI imaging technique. Manual segmentation on MRI imaging make impossible due to limited time. Hence, convolutional neural network (CNN), automated segmentation method apply for MRI image segmentation. The CNN comprises of 3x3 kernels, providing deeper architecture and lesser weights in network.

3. **DYADIC CAT OPTIMIZATION ALGORITHM**

The medical image on a computer database pave the way for automated image analysis. Medical images process with mathematical modelling for shape and boundary detection in medical images. The output of the mathematical model was different from the view of expert’s in medical images. Novel DCO algorithm consist of dyadic wavelet transform and cat swarm optimization to perform better classification in region of interest, shape and boundary in medical images. Medical images segment with proposed DCO algorithm reduce bandwidth. The figure 1 shows the flow diagram of DCO algorithm.

![DCO algorithm flow diagram](image)

Image pre-processing applies on medical images to suppress distortions. The distortions in region of interest enhance by neighbouring pixel average value. In addition, the region of interest image features enhance for pixel brightness transformation. The pixel brightness varies by brightness correction and grey scale transformations. In brightness correction, the pixel intensity varies depending on pixel brightness in image. In gray scale transformation, the brightness varies without any relation to position in image. The low pass filter smoothen rapid change in pixel intensity by average of pixel values. The smoothened image, background and foreground segment to shape organ boundary. The foreground and background of an image separate with DCO algorithm. The DCO algorithm provide the non-linear perspective foreground and back ground projection. The DCO specify by binary image. The initial contour position defines with boundary region to segment image. The white and black in binary image represent foreground and background respectively. Dyadic transform apply on the region of interest, foreground and background image separation with perspective projection.
3.1 NON-LINEAR PERSPECTIVE FOREGROUND AND BACK GROUND PROJECTION

Dyadic wavelet transform form with low pass, high pass filters and down-sampler. The dyadic wavelet transform obtain by convolution of dyadic dialects with mother wavelet against original image. Due to zero mean and finite support nature of mother wavelet the shape equivalent to an edge.

The dyadic transform dilation represent by

$$\psi_{2^j}(x) = \frac{1}{2^j} \psi\left(\frac{x}{2^j}\right)$$

The wavelet transform at a particular location x define by

$$W_{2^j}f(x) = f * \psi_{2^j}(x) = \int f(t) \cdot \psi_{2^j}(x-t) dt$$

The DWT occur in sequence of functions

$$Wf = (W_{2^j}f(x))_{j \in \mathbb{Z}}$$

W-dyadic wavelet operator

The $$W_{2^j}f(x)$$ fourier transform represent by $$\hat{W}_{2^j}f(x)$$

Which yields

$$\hat{W}_{2^j}f(x) = \hat{f}(\omega) \hat{\psi}(2^j \omega)$$

The positive constants A1 and B1 represent by

$$A_1 \leq \sum_{j=-\infty}^{\infty} \left| \hat{\psi}(2^j \omega) \right|^2 \leq B_1$$

Hence original f(x) recover from DWT. The reconstruction transform should satisfy the property

$$\sum_{j=-\infty}^{\infty} \hat{\psi}(2^j \omega) \hat{\chi}(2^j \omega) = 1$$

Hence the reconstruction formulae represent by

$$W\left(W^{-1}(g_j(x))_{j \in \mathbb{Z}}\right) = (g_j(x))_{j \in \mathbb{Z}}$$

In addition, the filter bank in dyadic wavelet transform produces orthogonal coefficient from even output of high pass filter and coarse coefficient even output of low pass filter. The coarse coefficient expands by dilation to form 2D discrete Dyadic wavelet transform. The different dilation factors perform non-linear perspective foreground and back ground projection. Boundary, edge detection at different levels in the image. The major
edge detection identifies at all dilation levels and remove darkness in the boundary region due to artifacts and
steaks. The minor edge detection identifies only at low dilation levels. For uniform identification of edges at all
levels in M dimensional space CAT optimization apply.

3.2 EDGES AND BOUNDARY OPTIMIZATION:

The CAT optimization algorithm operation is twofold namely seeking mode and tracing mode. In seeing
mode, the CAT rests looking for change in edges. The change in edges represents by change in count of dimension
(CDC), seeking memory pool (SMP), self-position consideration (SPC) and selected dimension (SD). If change
in edges detect the CAT change to tracing mode. In tracing mode, the CAT position change with respect to change
in position, speed and direction of edge.

In seeking mode, the SMP make copies of CAT and if SPC is true the position of CAT is saved.

For every copy of CDC the new position calculate with

\[ X_{cn} = (1 \pm SRD \times R) \times X_c \]

Where, \(X_c\)-Current position, \(X_{cn}\)- new position, \(R\)-Random number

The new position calculate by fitness value for all points. The new CAT position form by random wheel.

In tracing mode,

The CAT velocity \(k\) give by

\[ v_{k,d} = v_{k,d} + r_1 \times c_1 (X_{best,d} - X_{k,d}) \]

The new position of Cat with respect to edge give by

\[ X_{k,d,new} = X_{k,d,old} + v_{k,d} \]

The CAT move to new position according to different edges in region of interest. The work flow of the DCO-
CAT algorithm is shown in figure 2.
Start

Create N cats

Initialize the position, velocities, and the flag of every cat.

Evaluate the cats according to the fitness function and keep the position of the cat, which has the best fitness value.

Yes

Cat \( k \) is in the seeking mode?

No

Moving

Apply cat \( k \) into seeking mode process

Apply cat \( k \) into tracing mode process

Re-pick number of cats and set them into tracing mode according to MR, and set the others into seeking mode.

Terminate?

No

Yes

End

Figure 2 DCO-CAT ALGORITHM FOR CT BRAIN
The dyadic wavelet transform followed by CAT swarm optimization algorithm apply on CT medical image. The Figure 3 shows input CT image. CT image shows bone, muscle and organ masses. The CT image represent in grayscale image.

![Figure 3: CT scan medical image.](image)

The unwanted noise and distortions in the image remove by image preprocessing. The preprocessing also smoothen the medical image uniformly. The foreground and background of processed image segment with dyadic wavelet transform. The segmentation projects the foreground clearly from background as shown in figure 4. The weighted sum of all pixels in gray scale image varies to project bone structure (foreground).

![Figure 4: Foreground segmentation.](image)

Figure 5 shows histogram of projected pixel values histogram. The number of pixel values projected are above 1500. This is due to the foreground image pixel weight is more.
Figure 5: Histogram

Figure 6 shows edge detection in medical image without segmentation. The foreground edge intensity and the background edge intensity consider to preserve weak edges in the region. The pixel intensity value of normal edge computes to single value. The single value applies to control pixel weight of all other pixels in the edges.

![No contrast boundary region intensity between 0 to 500](image)

Figure 6: Edge detection without segmentation

The CAT optimization algorithm projects the edges of bones in foreground image. During projection, discontinuities occur in foreground image. The discontinuities of edges preserve by seeking cat. The Foreground edge projection and segmentation of figure 6 is shown in figure 7. The edge projection is clearly visible in outer region with minimal discontinuities. The minimal discontinuities eliminate by region growing.
Figure 7: Foreground projection.

Figure 8 shows histogram of foreground image in figure 4. The histogram considerably reduces to 700 compared to histogram of figure 2. The histogram validated foreground pixel projection. The foreground projected image show more hidden structure and shape in CT image via non-linear perspective foreground and back ground projection, edges in figure 9 compared to image acquired from different angle. The figure 10 shows foreground projection in MRI images. The figure 11 shows Comparison of the DCO algorithm with fuzzy and PSO for MRI and CT image. Furthermore, the pso and fuzzy algorithm shows the weak boundary region, when compared to the DCO algorithm.

Figure 8: Histogram of foreground projected image.
Figure 9: Non-linear perspective foreground and background projection with improved boundary and edge in CT image.
Figure 10: Non-linear perspective foreground and back ground projection with improved boundary and edge in MRI image
| **DCO** | **FUZZY** | **PSO** |
|-------------------------------|-------------------------------|-------------------------------|
| ![DCO Image](image1.png) | ![FUZZY Image](image2.png) | ![PSO Image](image3.png) |
| ![Input Image](image4.png) | ![Input Image](image5.png) | ![Input Image](image6.png) |

Figure 11: Comparison of the DCO algorithm with fuzzy and PSO for MRI and CT image
The CT, MRI medical images are structured with pixels which exhibit strong dependencies. The pixel dependencies produce intricate details of objects in medical image. Structural similarity index (SSIM) helps analyse similarity between structural dependencies between two images. In medical image processing, the processed image compare with reference image of perfect quality to evaluate similarity index. The SSIM index construct on structural information. Furthermore, latent semantic similarity analysis (LSA), the medical image factorizes and semantic features in image are analysed. The semantic features include structures of bone and organ masses. The semantic features compare between images to determine image feature accuracy. Edge strength similarity measures the fidelity between input medical image and processed medical image. In CT and MRI images, the edge strength of bone and muscular organs assess for regularity and irregularity of anisotropic edges. The table 1 shows the structural similarity index for the MRI and CT images with various algorithms such as PSO algorithm, Fuzzy algorithms.

Table 1 similarity index of MRI and CT images for various algorithms

|       | DCO algorithm |       | Fuzzy Algorithm |       | PSO Algorithm |       |
|-------|---------------|-------|----------------|-------|---------------|-------|
| Images | SSIM LSS ESS  | SSIM LSS ESS | SSIM LSS ESS | SSIM LSS ESS |
| CT 1   | 0.7609 0.26 -0.749 | 0.9458 0.27 0.9 | 0.854 0.28 0.1010 |
| CT 2   | 0.7460 0.26 -0.749 | 0.9652 0.25 0.9 | 0.832 0.25 0.1023 |
| CT 3   | 0.7461 0.25 -0.749 | 0.9221 0.23 0.9 | 0.874 0.23 0.1125 |
| CT 4   | 0.7370 0.23 -0.749 | 0.9870 0.21 0.9 | 0.895 0.24 0.1085 |
| CT 5   | 0.6909 0.25 -0.749 | 0.9632 0.28 0.9 | 0.856 0.28 0.1065 |
| CT 6   | 0.6987 0.25 -0.749 | 0.9514 0.24 0.9 | 0.852 0.22 0.1087 |
| CT 7   | 0.6992 0.26 -0.749 | 0.9862 0.26 0.9 | 0.871 0.21 0.1154 |
| CT 8   | 0.6993 0.25 -0.749 | 0.9741 0.27 0.9 | 0.856 0.20 0.1546 |
| MRI 1  | 0.7609 0.26 -0.749 | 0.9123 0.29 0.9 | 0.832 0.27 0.1002 |
| MRI 2  | 0.7460 0.26 -0.749 | 0.9254 0.20 0.9 | 0.812 0.26 0.1523 |
| MRI 3  | 0.7461 0.25 -0.749 | 0.9487 0.25 0.9 | 0.847 0.27 0.1185 |
| MRI 4  | 0.7370 0.23 -0.749 | 0.9456 0.23 0.9 | 0.888 0.29 0.1199 |
| MRI 5  | 0.6909 0.25 -0.749 | 0.9745 0.22 0.9 | 0.890 0.23 0.1235 |
| MRI 6  | 0.6987 0.25 -0.749 | 0.9532 0.26 0.9 | 0.859 0.24 0.1013 |
| MRI 7  | 0.6992 0.26 -0.749 | 0.9258 0.25 0.9 | 0.865 0.28 0.1041 |
| MRI 8  | 0.6933 0.25 -0.749 | 0.9145 0.28 0.9 | 0.875 0.23 0.1020 |

4. Conclusion

Neurologist asses the brain images to diagnose the disease via structure and shape of the part in the scanned Medical images such as CT, and MRI. The MRI and CT image apply with novel DCO algorithm for the anatomical structure and shape in perspective projection in non-linear approach to show the foreground and Background of the regions. The algorithm suit for both MRI and CT image for the region where the boundaries are less visible and to interprets the deformation shape of the anatomical structures in the brain. The anatomical structure of the brain image show the improvement in the shape and boundaries due to the dilation property of the DCO algorithm and exact edge due to the count of dimensions. Furthermore, the algorithms can be applied in the PET and ultrasound image for the week boundary regions for precise shape and deformation detection.

Declarations

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