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Top-Down Method Used for Pancreas Segmentation

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Abstract:** Image segmentation is actively an imperative title role in image analysis. Image segmentation is advantageous in many applications like traffic detection, surface crack identification, medical image analysis, face recognition, crop disease detection. Two Approaches are used for automatic pancreas segmentation. Top-Down and Bottom-Up approach used for CT image segmentation. In Top Down approach, Grey Level Co-occurrence Matrix, Simple Linear Iterative Clustering, Scale-Invariant Feature transform, Novel Modified Kernel fuzzy c-means clustering (NMKFCM) and Kernel Density Estimator methods used and automatic bottomup technique is used for pancreas subgrouping in C.T. scans. Top-Dow approach accuracy rate is less than bottom-up approach. Top-down approach required less time period as compare to bottom-up approach. In top-down approach, input image manually selected and processed it. KDE, NMKFCM and SIFT are used to detect feature of image. NMKFCM works on neighborhood point value. In KDE, Edge detection based on the kernel estimation of the probability density function .In SIFT, comprehensive information of local feature of image is focused.

***Keywords**: Abdominal computed tomography (CT),Clustering, GLCM, Kernel Density Estimator, Scale Invariant Transform(SIFT),NMKFCM.*

I. INTRODUCTION

Subgrouping is a captain theme to many image-processing investigations. Image subgrouping of intestinal body part likewise pancreas, liver and spleen in abdominal computed tomography (C.T.) image is a vital job in computer aided diagnosis (CAD), for measureable, qualitative scrutiny and clinical support [1].Automated abdominal subgrouping is grounded on statistical form models or probabilistic atlases [2]. It is acute and vibrant cog of image analysis system [1]. Image segmentation is process of partitioning image into different segment or part (set of pixel)[1][2]. Segment or Part embroils collection of related point value with dissimilar properties of point value like intensity, shade, tone, texture.

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It is fundamental process for medicinal image-processing likewise pancreatic cancer recognition,3-dimensional imagining and injury detection from CT.

Processing on CT image series is problematic job since magnitude and contour of pancreas constantly varying non-linearly with increase in slice number [3]. Image segmentation is implemented by four methodologies like Clustering, Edge Detection, Region Extraction and Thresholding.

II. TOP-DOWN APPROACH

A. Grey Scale Co-occurrence Matrix(GSCM)

Gray Scale Co-occurrence Matrix (GSCM) is mostly compacts with texture descriptor and outcomes achieved after co-occurrence matrix which is superior to another texture discriminations technique. Image of GSCM *(i,j)* abstracts the attribute on pixel and aforesaid succeeding neighbor point of image[4]. It determines the statistical attribute on gray level intensity values of original picture [5]. GSCM of an image is calculated using displacement vector *d* well-defined by its radius,(succeeding adjacent neighbor distance=1) and rotating angles (0^0, 45^0, 90^0, 135^0)[6].

- **Attribute Abstraction from GSCM:**

Image of GSCM (*i* ,*j*) abstracts the attribute based on pixel and aforesaid following neighbor point value in image [5]. GSCM (i,j) is 2-dimension utility function which is collection of *m* point value in the upright way and n point value in horizontal way, *i*, *j* are horizontal and perpendicular co-ordinates of image. The complete number of point value in image *is* $m*n = N$, $0 \leq i \leq m$, $0 \leq j \leq n$. mainly, intensity difference between point value and aforesaid neighbor is evaluate with an intact image. It has acknowledged that related values of point value in scrutiny outcomes in low contrast which causing a poor broadcasting of limits between attributes [6]. This difference intensity is intended through the equation

Contrast:

$$\sum_{i=1}^{m}\sum_{j=1}^{n}((i-j)^2 GLCM(i,j) \quad (1)$$

Energy:

$$\sum_{i=1}^{m}\sum_{j=1}^{n}((GLCM(i,j))^2 \quad (2)$$

Homogeneity:

$$\sum_{i=1}^{m}\sum_{j=1}^{n}\frac{GLCM(i,j)}{1+|i-j|} \quad (3)$$

Correlation that transports in what way correlated a reference point value to aforesaid neighbor by an image, which is uncorrelated to energy, contrast and homogeneity.
The mean and standard deviation for column and row in the GSCM matrix is used for correlation measurement equation as presented in equation 4.

Correlation:

$$\sum_{i=1}^{m}\sum_{j=1}^{n}\frac{\{i\times j\}\times GLCM(i,j)-\{\mu_x\times\mu_y\}}{\sigma_x\times\sigma_y} \quad (4)$$

GSCM is ignoring spatial relationship sandwiched between sensitive and texture outline towards image noise. In GSCM approach, more number of grey level introduced into computation calculation so classification accuracy varies.

B. Novel Modified Kernel Fuzzy C-Means Clustering (NMKFCM)

It is adapting neighbor point value cost in objective function. This system is revised form of K-FCM and which is integrate neighbor point value cost by 3×3 or 5×5 window and incorporate into objective function [7]. 'α' parameter is educated for governor load of neighbor's point value which is succeeded greater cost through penetrating of noise. Series of α cost lies inside 0 to 1, if ratio of noise is low at that point, elect cost of α ranges 0 and 0.5 and ratio of noise is higher at that point elect cost of α ranges 0.5 and 1.0. After, every iteration, cost of objective function is reduced with neighbor point value [8]. In equation 5, announce mask around point value and α parameter.

$$J_{NMKFCM_{obj}}(\mathrm{U},\mathrm{W})=\sum_{y=1}^{Q}\sum_{x=1}^{P}\mathrm{U}_{xy}^{m}(1-\mathrm{K}_T(\mathrm{Z}_x,\mathrm{W}_y))(\frac{N_R-\alpha\sum_{k\in N_i}U_{yk}}{N_R}) \quad (5)$$

Where: Ni: Collecting Zi point values of neighbors, NR: The cardinality, K_T: Gaussian kernel. Objective function Jnmkmobj defines a constrained optimization problem. It will convert constrained optimization problem to decision-boundary optimize problematic by relating Lagrange multiplier method [8].

Evaluate membership function U_{ij} :

$$U_{xy}=\left(\frac{((1-\mathrm{K}_T(\mathrm{Z}_x,\mathrm{W}_y))(\frac{N_R-\alpha\sum_{l\varepsilon N_i}U_{yl}}{N_R}))^{-\frac{1}{m-1}}}{\sum((1-\mathrm{K}_T(\mathrm{Z}_x,\mathrm{W}_y))(\frac{N_R-\alpha\sum_{l\varepsilon N_i}U_{kl}}{N_R}))^{-\frac{1}{m-1}}}\right) \quad (6)$$

Update Cluster center W_j:

$$W_y=\frac{\sum_{y=1}^{Q}U_{xy}^{m}K_T(\mathrm{Z}_x,\mathrm{W}_y)\,\mathrm{Z}_x}{\sum_{x=1}^{P}U_{xy}^{m}(\mathrm{Z}_x,\mathrm{W}_y)} \quad (7)$$

NMKFCM work very fit in neighborhood pixel material.

C. Kernel Density Estimator (KDE)

Kernel density estimation method is worked on the basis of non-parametric density estimation. Edge detection based on the kernel estimation of the probability density function [9]. Minimum pixel values of density function are labeled as edges. For image segmentation, feature space is collected of two domains like spatial and color. The overall kernel density estimate at the point x, is mathematically defied below:

$$\hat{f}(x)=\frac{1}{nh^d}\sum_{i=1}^{n}K(\frac{x-x_i}{h}) \quad (8)$$

Where points $x_i, i=1,2.....n$. Due to different nature of area, the kernel is using product of two different profiles. Mathematically feature space explain in below equation.

$$\hat{f}(x)=\frac{m}{n(h_s)p(h_r)q}\sum_{i=1}^{n}k_s\left(\left\|\frac{x-x_i}{h_s}\right\|^2\right)k_r\left(\left\|\frac{x-x_i}{h_r}\right\|^2\right) \quad (9)$$

Where x is pixel, k_s and k_r kernel profile used as per respective domain. h_s and h_r are bandwidth in spatial domain and m is constant. The response of mask at any feature space of image is given by:

$$S=\sum_{i=1}^{t}z_i.f_i \quad (10)$$

Where, f_i is the gray level of pixel in the image below coefficient z_i used in mask. The value of S is marked to central pixel of mask in output image. Edge point satisfies $|S|>u$, where u is a non-negative threshold value.

D. Scale Invariant Feature Transform(SIFT)

SIFT is used for detect feature of image and give comprehensive information of local feature of image [10]. Intensity of the input grey-scale image by $P_0(x,y)$, where x, y are pixel coordinate. Intensity of image lies between 0 to1. For blur images, Gaussian filter used as kernel:

$$B_g(x,y,\sigma)=\frac{1}{2\pi\sigma^2}(-\frac{x^2+y^2}{2\sigma^2}) \quad (11)$$

Where, σ is blue scale.
Blue Image intensity calculated by equation (12)

$$I_B(x,y,\sigma)=B_G(x,y,\sigma)*P_0(x,y) \quad (12)$$

The points of interest are strictly related to the local relation of the Laplacian-of-Gaussian function

$$L(x,y,\sigma)=\sigma^2\Delta I_B(x,y,\sigma) \quad (13)$$

Scale-space pyramid is calculated on the basis of computation of local relation of $D_L(x,y,\sigma)$. $D_L(x,y,\sigma)$ is difference of Gaussian function equation(14) and c is constant:

$$D_L(x,y,\sigma) = I_B(x,y,c\sigma) - I_B(x,y,\sigma) \qquad (14)$$

Find corrected value of the difference-Gaussian function:

$$D_L(\hat{x},\hat{y},\hat{\sigma}) = D_L(x,y,\sigma) + \frac{1}{2}[D_x(x,y,\sigma)dx + D_y(x,y,\sigma)d_y + D_\sigma(x,y,\sigma)d_\sigma] \qquad (15)$$

Output image is having low contrast and poor localized edge. To eliminate low contrast edge used threshold value α and β.

$$\left|D_L(\hat{x},\hat{y},\hat{\sigma})\right| = \alpha \ , \ \frac{D_{xx}D_{yy} - D_{xy}^2}{(D_{xx} + D_{yy})} \rangle \beta \qquad (16)$$

SIFT point of objects are extracted from set of reference and stored in dataset.

III. EXPERIMENTAL RESULTS

- **Medical Image Data**

Top-Down Methods are estimated on a dataset of 80 3D abdominal portal-venous compare enriched CT photographs assimilated from male: 53 and female: 27 patients. The 63 patients are arbitrarily nominated by a radiologist from the Picture Archiving and Communications System (PACS). The CT database is attained from the National Institutes of Health Clinical Center. Patient age series from 18 to 76 years, with a mean of 46.8 ± 16.7. Scan resolution is 512×512 pixels including slice thickness, Slice thickness range is from $1.5 - 2.5$ mm on Philips and Siemens MDCT scanners.

- **Results**

Table- I: Comparison between Top-down Method with time

Method	A0	A1	A 2	A3	A4
NMKFCM	7.3	7.03	9.778	5.83	7.84
KDE	1.77	1.64	1.86	1.31	1.38
GLCM	0.1672	0.2236	0.1809	0.1724	0.1777
SIFT	3.22	3.282	3.74	3.47	3.51

Above all value in seconds.

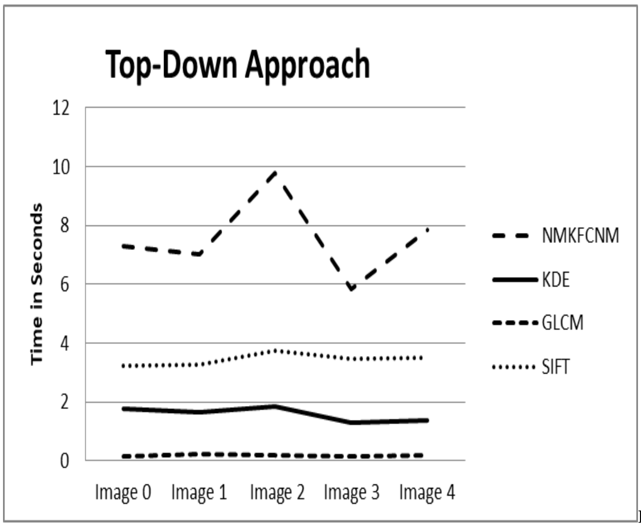

Fig. 1.Comparison between Top-Down Approaches for Medical Image Segmentation

From above graph, NMKFCM method required more time period as compare to other methods. A0, A1,A2,A3,A4, all these images are radomally selected from available medical image dataset.

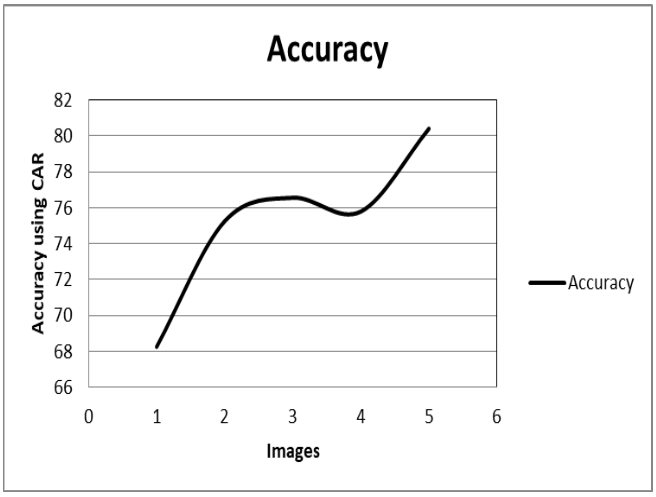

Fig. 2. NMKFCN Accuracy Calculated with Medical Images

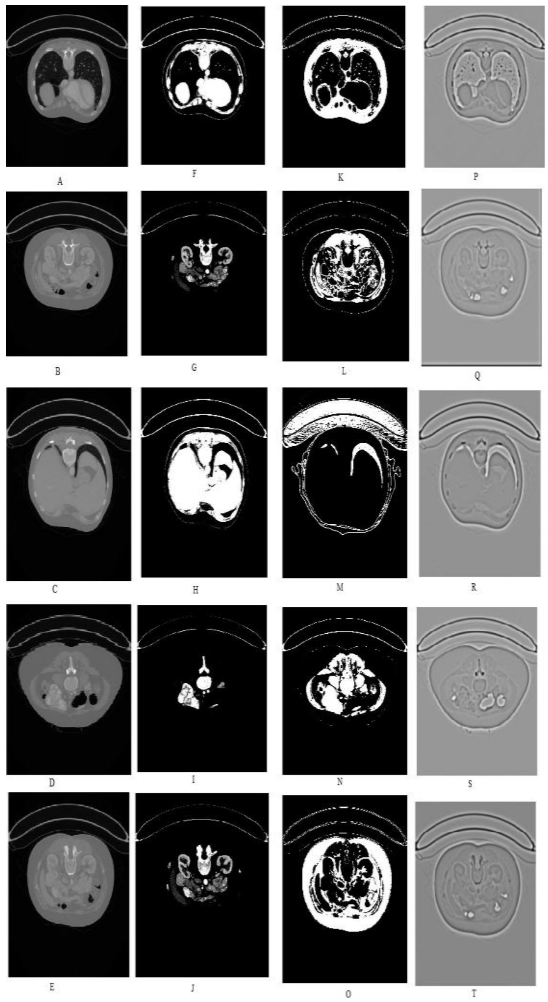

Fig.3 Medical Images with Segmented Image

Original Image: A),B),C),D),E),
Segmented Output Image: 1)Kernel Density Estimator-F),G),H),I),J).
2) NMKFCM-K),L),M),N,O).
3) Scale Invariant Feature Transform-P),Q),R),S),T).

IV. CONCLUSION

Top down approaches are used for pancreas image segmentation but accuracy varies.

NMKFCM method is more efficient as compare to other method but it require more time period for execution. KDE is required less time period as compare to other method but sharp segmentation of pancreas image not to good. In top down approach, accuracy is less and manually selection of image is required from medical image dataset. Overcome this drawback Bottom-Up approach is used with patch labeling deep learning approach. In top-down approach, manually selection of image is major drawback which can be solved by bottom-up approach.

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