Unsupervised segmentation of OSF by fusion of RGA and DCT with contextual information

Tathagata Ray and Anirban Mukherjee
Department of Electrical Engineering,
Indian Institute of Technology Kharagpur,
Dist-West Midnapore, West Bengal 721302, India
E-mail: tathagata@ee.iitkgp.ernet.in
E-mail: anirban@ee.iitkgp.ernet.in

J. Chatterjee
School of Medical Science and Technology,
Indian Institute of Technology Kharagpur,
Dist-West Midnapore, West Bengal 721302, India
E-mail: jchatterjee@smst.iitkgp.ernet.in

R.R. Paul
Department of Oral and Maxillofacial Pathology,
Gurunank Institute of Dental Science and Research,
Panihati, Kolkata, 700114 West Bengal, India
E-mail: dr_rsspaul@yahoo.com

Pranab K. Dutta*
Department of Electrical Engineering,
Indian Institute of Technology Kharagpur,
Dist-West Midnapore, West Bengal 721302, India
Fax: +91-3222-282262
Fax: +91-3222-255303
Fax: +91-3222-277190
E-mail: pkd@ee.iitkgp.ernet.in
E-mail: pkd14000@yahoo.co.in
*Corresponding author

Abstract: The aim of this paper is to segment Light Microscopic (LM) images of Oral Sub-mucous Fibrosis (OSF) into its constituent layers. In this regard, fusion of features based on Region Growing Algorithm (RGA) and context-enhanced rotational invariant Discrete Cosine Transform (DCT) has been studied. The overall segmentation accuracy of this fused method is higher than that of context-enhanced DCT-based method. Fusion of features based on different methods often eliminates the disadvantages and utilises the advantages of individual method. Fuzzy $c$-means clustering has been found to be little ahead of $k$-means clustering in terms of segmentation accuracy.
Keywords: OSF; oral submucous fibrosis; DCT; discrete cosine transform; region growing algorithm; RGA; fusion; fuzzy c-means clustering.


Biographical notes:

Tathagata Ray received his BE in Electrical Engineering in 1998 from North Bengal University, West Bengal. He did his ME in 2001 from Jadavpur University. He is currently engaged in a PhD programme in Electrical Engineering of Indian Institute of Technology Kharagpur. His current areas of interests are signal processing and image processing.

Anirban Mukherjee received his BE in Electrical Engineering in 1998 from Jadavpur University, Kolkata. He received his MTech and PhD from Electrical Engineering of Indian Institute of Technology Kharagpur. He was with the Centre of Excellence for Embedded Systems, Tata Consultancy Services, in 2004–2005. He is currently serving as Faculty Member in the Department of Electrical Engineering at Indian Institute of Technology Kharagpur. His current areas of interests are signal processing and image processing.

Jyotirmoy Chatterjee obtained his PhD in the field of radiation toxicology and is an ICMR research fellow. Presently, he is a faculty of School of Medical Science and Technology, IIT Kharagpur. During the last 20 years, he is involved in interdisciplinary research in the field of chronic low-dose radiation biology, oral cancer research, wound healing and macro-micro-molecular imaging and analysis. He has more than 30 publications in national and international journals of repute.

R.R. Paul has obtained his PhD in the field of oral pathology. He is presently Professor and Head of the Department of Oral and Maxillofacial Pathology of GNID Science and Research, Kolkata. He is a well-known researcher in the field of oral cancer and pre-cancer. During the last two decades, he has published many important research papers in national and international journals.

Pranab K. Dutta has obtained BE, ME and PhD, all in Electrical Engineering, in 1984, 1986 and 1992, respectively. Since 1993, he is serving as faculty member in the Department of Electrical Engineering at Indian Institute of Technology Kharagpur. He has active interest in technology development and participated in a number of industry-sponsored projects. His current areas of interest are signal processing, image processing and biomedical, multimedia and optoelectronic devices. He has published more than 45 research papers. His work in these areas resulted in more than eight patents and patent applications.

1 Introduction

Nowadays, cases of oral cancer are increasing at a very alarming rate, mostly in developing countries like India, Bangladesh and Sri Lanka, mainly due to late diagnosis of the pre-cancerous condition (Parkin et al., 1999; http://www.oralcancerfoundation.org/facts/index.htm; http://www.cancerresearchuk.org/cancerstats/type/oral) owing to
chewing habits of tobacco-based product. Annually, 83,000 new cases and 46,000 deaths occur due to oral cancer in India (http://www.medscape.com/viewarticle/505919). LM images of pre-cancerous OSF consist of different layers or zones. By observing the structure and features of the different layers, the cancerous growth may be predicted. Prior to this, the segmentation of LM image into its constituent layers is a primary task. As different layers of LM image have definite textural pattern, textural methods for segmentation of LM images have been used in general. If a texture undergoes rotation, rotational invariant textural features help identifying the texture. Several studies (Porter and Canagarajah, 1997; Ray and Dutta, 2007; Zhang and Tan, 2002; Zhang et al., 2002; Arivazhagan et al., 2006; Acharyya and Kundu, 2000; Deng and Clausi, 2004; Jafari-Khouzani and Soltanian-Zadeh, 2005; Manthalkar et al., 2003a, 2003b) of different rotational invariant textural feature based methodologies have been reported till date. Among them, DCT has been widely used as textural feature extractor owing to its inherent simplicity and fast implementation. Contextual features of different forms (Jain and Farrokhnia, 1991; Hsiao and Sawchuk, 1989; Haddon and Boyce, 1990; Mirmehdi and Petrou, 2000; Nguyen and Cohen, 1993; Kumar and Hebert, 2003; Hui and Bouman, 2001) have been used for finer segmentation based on textural features.

In this regard, RGA has been proven to be successful to an extent in the extraction of different layers of LM images, but the accuracy of achieved classification is not promising (Jadhav et al., 2006). Recently, Hybrid Segmentation Algorithm (HSA) has been found superior to RGA (Ray et al., 2008). But input images have been pre-processed, which is a difficult task from the point of view of biomedical image segmentation.

The availability of multi-sensor data makes sensor fusion a state-of-the-art technique in the applications like remote sensing, medical imaging, machine vision and military applications. The definition of sensor fusion is very broad and fusion may take place at signal, pixel, feature and symbol level (Luo and Kay, 1992; Kirankumar and Devi, 2007; Aggarwal, 1993). Here, feature-level fusion problem (Clausi and Deng, 2004; Yonghong and Deren, 2004; Qaiser et al., 2008; Clausi, 2001) has been addressed.

In this paper, rotational invariant textural features based on DCT have been enhanced by contextual information. Instead of pixel-based processing, the features are extracted from non-overlapping blocks. Thereafter, statistical measures like mean and ratio of difference between number of black, white pixels and summation of number of black, white pixels have been extracted from the region grown image obtained by the application of RGA on input image. These measures are then fused with features of context-enhanced rotational invariant DCT. Fuzzy c-means and k-means clustering have been invoked for converting feature map into meaningful segmented output class map. Thus, obtained output test map has been compared with ideal segmented class map for obtaining percentage of misclassified pixel. Ideal segmented class map has been prepared by considering common independent maps prescribed by two oral oncologists. A relative improvement in classification accuracy has been observed after the fusion. Input image size has been kept as it is without cropping.

The paper has been organised as follows. The necessary theoretical background has been covered in Section 2. Results and discussion are presented in Section 3. Finally, conclusion comes in Section 4.
2 Materials and methods

2.1 Discrete Cosine Transform (DCT)

2.1.1 Background

Discrete Cosine Transform (DCT) being a local linear transform is a useful tool for extracting textural features (Unser, 1986; Ng et al., 1992) of an image. These 64 two-dimensional DCT masks of dimension $8 \times 8$ have been formed by taking the outer product of eight DCT basis masks of size $1 \times 8$. Figure 1 can be represented as $T = \{t_{00}, t_{01}, \ldots, t_{77}\}$ where $t_{ij}$ \{i = 0, 1, \ldots, 7; j = 0, 1, \ldots, 7\} designates 64 number of two-dimensional DCT basis masks. Here $t_{00}$ and $t_{77}$ are the lowest and highest frequency masks, respectively.

**Figure 1** Sixty-four numbers of 2D DCT masks each of dimension $8 \times 8$

2.1.2 Proposed rotational invariant features

The highest DCT filter coefficient mask of size $8 \times 8$ ($t_{77}$) i.e., the mask at the bottom right corner of Figure 1 is given in Table 1. The mask $t_{ij}$, $i,j = 0, 1, \ldots, 7$ may be represented as

$$t_{ij} = \begin{bmatrix} A_{36} & V_{36} \\ H_{36} & D_{36} \end{bmatrix}.$$  

It has been assumed that the $4 \times 4$ sub mask $A_{ij}$ serves as approximation filter mask. Consequently, $V_{ij}$ and $H_{ij}$ have been treated as vertical and horizontal filter mask, respectively. It is to be noted that these sub masks $V_{ij}$ and $H_{ij}$ are the vertical and horizontal flipped version of $A$ with a negative sign where each element of $V$ and $H$ is related to that of $A$ by the following equation

$$V_{ij}(k,l) = -A_{ij}(k,3-l)$$

$$H_{ij}(k,l) = -A_{ij}(3-k,l) \quad i,j = 0,1,\ldots,7 \quad k,l = 0,\ldots,3.$$
Table 1  Approximation of horizontal and vertical parts of the highest DCT filter coefficient mask $r_{ij}$

<table>
<thead>
<tr>
<th>$A_{ij}$</th>
<th>$V_{ij}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0396</td>
<td>-0.1127</td>
</tr>
<tr>
<td>-0.1127</td>
<td>0.3209</td>
</tr>
<tr>
<td>0.1686</td>
<td>-0.4802</td>
</tr>
<tr>
<td>-0.1989</td>
<td>0.5665</td>
</tr>
<tr>
<td>0.1989</td>
<td>-0.5665</td>
</tr>
<tr>
<td>-0.1686</td>
<td>0.4802</td>
</tr>
<tr>
<td>0.1127</td>
<td>-0.3209</td>
</tr>
<tr>
<td>-0.0396</td>
<td>0.1127</td>
</tr>
</tbody>
</table>

The energy measure of zero frequency component of the convoluted image with the $A_{ij}$ part of lowest DCT mask and energy measure of a particular combination of convoluted image with $V_{ij}$ and $H_{ij}$ part of 64 DCT masks have been taken as rotational invariant DCT features. So the feature vector $F$ has been expressed as

$$ F = \left( dc_1^d \ \ ec_1^d \ \ ec_2^d \ \ ... \ \ ec_64^d \right)^T $$

where $dc_1^d$ represents energy of the lowest DCT mask and $ec_1^d \ ... \ ec_64^d$ represent energy of a summation of images convolved with $V$ and $H$ part of 64 DCT basis functions. The dimension of the feature vector $F$ is 65 \times 1.

An experiment has been performed to study that these DCT features are invariant to rotation. The inter-block dependency has also been studied. The DCT feature vector, $F$ has been extracted for 13 numbers of monochrome textures (size = 512 \times 512) (http://sipi.usc.edu/database). The images have been rotated by 0°, 30°, 60°, 90°, 120°, and 150°. Feature extraction has been carried out in non-overlapping contiguous blocks of dimension 64 \times 64. As a result ((512/64) \times (512/64)) = 64 number of non-overlapping and contiguous blocks (dimension 64 \times 64) have been created from a monochrome textural image of wood having different orientations as shown in Figure 2. A feature matrix $F^d$ has been formed from the feature vector $F$. The dimension of $F^d$ is now 65 \times 384 as total number of block in six orientations are 64 \times 6 = 384. Variance has been found out for each of the 65 features after normalising each row of $F^d$ ranging from 0 to 1.

$$ \sigma_i^2 = \frac{1}{384} \sum_{j=1}^{384} \left[ F(i,j) - \bar{F}(i,j) \right]^2 \quad \forall i = 1, 2, \ldots, 65 $$

and

$$ \sigma_{\text{max}} = \max_{i=1,2,\ldots,65} (\sigma_i). $$

Maximum ($\sigma_{\text{max}}$) of thus calculated 65 variances ($\sigma$) of rotational invariant DCT features has been shown in Table 2 for 13 numbers of monochrome textures (http://sipi.usc.edu/database). The maximum among these 13 variances ($\sigma_{\text{max}}$) is found to be 0.062204 for
wood as observed from Table 2. So, it can be concluded that proposed features are almost rotational invariant indeed.

**Figure 2** Six rotated versions of wood texture (0°, 30°, 60°, 90°, 120° and 150°) are shown as a, b, c, d, e and f, respectively.

![Wood Texture Rotations]

<table>
<thead>
<tr>
<th>Name of the texture</th>
<th>Maximum value of second order centralised moment of 65 features with respect to 6 orientations over 64 blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wool</td>
<td>0.020213</td>
</tr>
<tr>
<td>Water</td>
<td>0.040365</td>
</tr>
<tr>
<td>Bark</td>
<td>0.012052</td>
</tr>
<tr>
<td>Weave</td>
<td>0.013874</td>
</tr>
<tr>
<td>Bubbles</td>
<td>0.015352</td>
</tr>
<tr>
<td>Brick</td>
<td>0.021452</td>
</tr>
<tr>
<td>Straw</td>
<td>0.053667</td>
</tr>
<tr>
<td>Sand</td>
<td>0.0080058</td>
</tr>
<tr>
<td>Raffia</td>
<td>0.023212</td>
</tr>
<tr>
<td>Pigskin</td>
<td>0.015307</td>
</tr>
<tr>
<td>Leather</td>
<td>0.015734</td>
</tr>
<tr>
<td>Grass</td>
<td>0.018568</td>
</tr>
<tr>
<td>Wood</td>
<td>0.062204</td>
</tr>
</tbody>
</table>

**2.2 Contextual information**

Texture is a neighbourhood property. So context or neighbourhood information has been proved to be an important textural feature. Methods like relaxation labelling (Hsiao and Sawchuk, 1989; Haddon and Boyce, 1990; Mirmehdi and Petrou, 2000),
Maximum A Posteriori (MAP) estimation (Nguyen and Cohen, 1993; Kumar and Hebert, 2003; Hui and Bouman, 2001) have been successful for extracting contextual features. In 1991, Jain and Farrokhnia (1991) proposed coordinate location of each pixel as contextual information of a pixel. In this paper, feature extraction has been carried out in non-overlapping blocks. The contextual information of non-overlapping blocks has been proposed as coordinate location of the centre of the block.

2.3 Region Growing Algorithm (RGA)

Region Growth Algorithm (RGA) (Gonzalez and Woods, 2007) consists of region growing and splitting based on suitable criteria, and it is computationally efficient. RGA having over-segmentation problem gives a continuous region. Moreover, it also gives the boundary of grown region. Here, the adaptive region growing technique has been adopted. It uses both grey-level threshold and gradient threshold. In each iteration, new pixels are aggregated. The average grey level and average gradient of current grown region are calculated and updated.

Algorithm

The algorithm is as follows:

1. Start with the given seed pixels
2. Aggregate the neighbouring pixels of given seed pixel (neighbours are decided depending on 4/8 connectivity) if they satisfy homogeneity criteria (described later), otherwise ignore it
3. Define new seed pixels as borders of the current grown region
4. Aggregate the neighbouring pixels of new seed pixels if they satisfy homogeneity criteria, otherwise ignore it
5. If there is no pixel that satisfies homogeneity criteria, then stop; otherwise go to Step 3.

The above homogeneity criterion is as follows: if the absolute difference of grey value of candidate pixel and average grey level of current grown region is less than the grey-level threshold, and if absolute difference of gradient value of candidate pixel and average gradient of current grown region is less than gradient threshold, then homogeneity criteria is satisfied. The block diagram representation of RGA is given in Figure 3.

The output of RGA scheme is binary image. Statistical features (Gonzalez and Woods, 2007) have been extracted from the region grown image. These measures are mean and ratio of difference in the number of black and white pixels and summation of number of black and white pixels of region-grown image.

\[
m = E(Z = z_i) = \sum_{i=0}^{g-1} z_i p(Z = z_i)
\]

\[
n = \frac{(\text{no. of black pixels} \ - \ \text{no. of white pixels})}{(\text{no. of black pixels} \ + \ \text{no. of white pixels})}
\]
where \( Z \in \{0, 1\} \) is a binary valued random variable representing intensity, \( p(Z) \) is probability distribution of \( Z \), \( G \) is the total number of possible intensity levels, i.e., 2 (black and white).

**Figure 3** Flowchart of the Region Growing Algorithm (RGA)

2.4 Fusion of features

Any block-based feature extraction technique like rotational invariant DCT yields a class map, which suffers from blocky artefacts. So, the continuity and smoothness of the boundary of the different layers are in question. RGA, on the other hand, produces a smooth and continuous binary map. But, it is highly dependent on input parameters owing to its pixel-based nature. Moreover, RGA always produces binary class map independent of number of classes or textural regions present in the input image. Here, the idea is to fuse the features of rotational invariant DCT, context and statistical features derived from binary class map obtained from RGA.

In this paper, fusion of features based on RGA, rotational invariant DCT and contextual information has been done with equal weight as shown in Figure 4. So, the feature vector after fusion is concatenation of all the individual features as shown here \( F = (F^d, i, j, m, n) \), where \( (i, j) \) is coordinate location of centre of non-overlapping blocks. The pairs namely \( (i, j) \) and \( (m, n) \) carry contextual and statistical information, respectively. The fused method is found suitable compared with contextual enhanced rotational invariant DCT, RGA.

**Figure 4** Block diagram of fusion of rotational invariant DCT features, contextual features and statistical features extracted from region grown image
2.5 Fuzzy c-means clustering

Fuzzy c-means is a well-known clustering technique used in case of overlapping or touching regions. It requires the determination of ‘fuzzy boundary’ between the clusters. Each object belongs to a particular cluster with a degree of membership \(0 \leq M_q(.) \leq 1\) (Jain and Dubes, 1988; Hanmandlu et al., 2004). The membership function is ‘crisp’, i.e., it has a value of either 0 or 1 for ordinary clusters like in \(k\)-means clustering. \(K\)-means clustering assigns data to different clusters depending upon some distance criteria from different cluster centres. Normally for fuzzy clusters, a data, \(x\), is assigned a membership value of \(M_q(x) \geq 0\) for belonging to cluster \(q\), where \(\sum_q M_q(x) = 1\). Confidence of a data, \(x\) belonging to a cluster, \(q\) increases with the rise of \(M_q(x)\). Absolute certainty of this belongingness demands for membership value to be 1.

The steps of fuzzy c-means algorithm are as follows:

1. Initialisation of the cluster centres, membership function and the exponent.
2. Minimisation of objective function, which is the product of membership value of a data and distance between the data point and cluster centres.
3. Update the membership value of each data point and cluster centres.
4. Go to Step 2–4 until and unless objective function is less than certain threshold.

In this paper, fuzzy c-means is used for clustering the features assuming that the number of clusters is known. Membership function has been assumed here to be random. Feature vector is normalised before applying fuzzy c-means clustering (features having variance less than 0.0001 are neglected) such that each feature has zero mean and unity variance.

3 Results and discussions

The histological images of OSF have been optically grabbed with transmitted light microscope from the Haematoxylin and Eosin (H&E) stained sections (Jadhav et al., 2006). The main purpose of this clustering is to segment an image into its constituent zones like background, epithelium and connective tissue. In this regard, 65 rotational invariant DCT features, coordinate of centre of the block and two measures (i.e., \(m\) and \(n\)) derived from region grown image have been extracted for contiguous non-overlapping blocks of varying sizes. Thereafter, fuzzy c-means clustering has been implemented for obtaining segmented class map. Then, the segmented class map has been compared with common class map independently provided by the two oral oncologists for percentage of misclassification error. In the same way, the misclassification error of commonly used segmentation method, i.e., RGA has been obtained. The result of RGA and rotational invariant DCT-based features followed by fuzzy c-means and \(k\)-means clustering has been depicted in Table 3. The result for RGA shows maximum 7.45% and minimum of 1.56% of misclassification for Sample d and Sample k, respectively. The corresponding figures for rotational DCT-based fuzzy c-means clustering are 45.92% and 12.02% for Sample f and Sample a, respectively. But these figures for rotational DCT-based \(k\)-means clustering are 51.56% and 12.57% for Sample l and Sample a, respectively.
It is evident that RGA performs well within the limit for the detection of epithelium layer. Since the segmented class map by RGA is binary, RGA is not able to distinguish between background and connective tissue. Also, for overlapping regions its accuracy is restricted. To study the effect of fusion of features in various ways, three fusion strategies namely Methods A, B and C have been introduced. In Method A, the rotational invariant DCT-based features \((F^d)\) and contextual features \((i, j)\) have been fused with equal weight. The fusion of rotational invariant DCT-based features \((F^d)\), contextual features \((i, j)\) and mean \((m)\) of region grown image is performed with equal weight in Method B. Method C deals with fusion of rotational invariant DCT-based features \((F^d)\), contextual features \((i, j)\) and ratio \((n)\) of difference in the number of black and white pixels and summation of the number of black and white pixels of region grown image with equal weights. The features of the Method A have been successfully adopted to wipe off the mentioned disadvantages of RGA. But it is unable to segment the epithelium layer as accurate as RGA. It has been shown in Table 4 that the maximum 38.15% and minimum 3.40% of misclassification have been found for Sample 1 and Sample a, respectively, in case of Method A followed by fuzzy \(c\)-means clustering. The corresponding figures for k-means clustering of context-enhanced DCT features are 50.22% and 3.22% for Sample 1 and Sample a, respectively. Minimum 3.08% and maximum 31.18% of misclassification error, respectively, for Sample a and Sample d, respectively, have been observed for the features of Methods B and C followed by fuzzy \(c\)-means algorithm. But clustering of the proposed fused features by Methods B and C with \(k\)-means clustering gives maximum and minimum misclassification of 37.49% and 2.98%, respectively, for Sample 1 and Sample a. In Figure 5, the comparison of accuracy of the three methods has been shown for four input image samples. As far as the result is concerned, Methods B and C are superior to Method A.

### Table 3
Performance of Region Growing Algorithm (RGA) and proposed rotational invariant DCT-based method in extracting the mid region, i.e., epithelium layer and three layers

<table>
<thead>
<tr>
<th>Input image</th>
<th>Percentage of misclassification in extracting the three layers for rotational invariant DCT-based features and fuzzy (c)-means clustering</th>
<th>Percentage of misclassification in extracting the three layers for rotational invariant DCT-based features and (k)-means clustering</th>
<th>Percentage of misclassification in extracting the epithelium layer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample a</td>
<td>12.02</td>
<td>12.57</td>
<td>2.71</td>
</tr>
<tr>
<td>Sample b</td>
<td>33.01</td>
<td>32.99</td>
<td>4.05</td>
</tr>
<tr>
<td>Sample c</td>
<td>28.70</td>
<td>30.86</td>
<td>2.46</td>
</tr>
<tr>
<td>Sample d</td>
<td>40.03</td>
<td>39.43</td>
<td>7.45</td>
</tr>
<tr>
<td>Sample e</td>
<td>22.51</td>
<td>23.33</td>
<td>5.29</td>
</tr>
<tr>
<td>Sample f</td>
<td>45.92</td>
<td>46.05</td>
<td>4.17</td>
</tr>
<tr>
<td>Sample g</td>
<td>23.41</td>
<td>23.12</td>
<td>2.81</td>
</tr>
<tr>
<td>Sample h</td>
<td>26.56</td>
<td>26.87</td>
<td>1.60</td>
</tr>
<tr>
<td>Sample i</td>
<td>41.35</td>
<td>39.89</td>
<td>3.13</td>
</tr>
<tr>
<td>Sample j</td>
<td>26.10</td>
<td>26.67</td>
<td>9.37</td>
</tr>
<tr>
<td>Sample k</td>
<td>21.20</td>
<td>20.86</td>
<td>1.56</td>
</tr>
<tr>
<td>Sample l</td>
<td>38.15</td>
<td>51.56</td>
<td>2.95</td>
</tr>
</tbody>
</table>
Table 4  Performance of proposed fusion of features based on rotational invariant DCT, contextual features and statistical features form Region Grown Image (RGA) followed by Fuzzy c-Means (FCM) and k-means clustering in extracting three regions

<table>
<thead>
<tr>
<th>Input image</th>
<th>Percentage of misclassification for Method A and FCM in extracting three regions</th>
<th>Percentage of misclassification for Method B and FCM in extracting three regions</th>
<th>Percentage of misclassification for Method C and FCM in extracting three regions</th>
<th>Percentage of misclassification for Method A and k-means in extracting three regions</th>
<th>Percentage of misclassification for Method B and k-means in extracting three regions</th>
<th>Percentage of misclassification for Method C and k-means in extracting three regions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample a</td>
<td>03.40</td>
<td>03.08</td>
<td>03.08</td>
<td>03.22</td>
<td>02.98</td>
<td>02.98</td>
</tr>
<tr>
<td>Sample b</td>
<td>32.65</td>
<td>16.90</td>
<td>16.90</td>
<td>22.93</td>
<td>08.93</td>
<td>16.90</td>
</tr>
<tr>
<td>Sample c</td>
<td>13.85</td>
<td>10.97</td>
<td>10.97</td>
<td>13.03</td>
<td>11.76</td>
<td>11.76</td>
</tr>
<tr>
<td>Sample d</td>
<td>34.91</td>
<td>31.14</td>
<td>31.14</td>
<td>11.23</td>
<td>30.97</td>
<td>30.97</td>
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<tr>
<td>Sample e</td>
<td>17.37</td>
<td>15.91</td>
<td>15.91</td>
<td>17.04</td>
<td>16.34</td>
<td>16.34</td>
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<tr>
<td>Sample f</td>
<td>36.23</td>
<td>28.28</td>
<td>28.28</td>
<td>32.95</td>
<td>30.84</td>
<td>30.84</td>
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<tr>
<td>Sample g</td>
<td>15.41</td>
<td>10.68</td>
<td>10.68</td>
<td>15.25</td>
<td>11.99</td>
<td>11.99</td>
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<tr>
<td>Sample h</td>
<td>15.17</td>
<td>08.27</td>
<td>08.27</td>
<td>13.65</td>
<td>08.94</td>
<td>08.94</td>
</tr>
<tr>
<td>Sample i</td>
<td>30.81</td>
<td>30.39</td>
<td>30.39</td>
<td>30.22</td>
<td>29.75</td>
<td>29.75</td>
</tr>
<tr>
<td>Sample j</td>
<td>20.11</td>
<td>12.22</td>
<td>12.85</td>
<td>18.82</td>
<td>12.22</td>
<td>12.22</td>
</tr>
<tr>
<td>Sample k</td>
<td>36.56</td>
<td>08.96</td>
<td>08.96</td>
<td>22.75</td>
<td>09.96</td>
<td>09.96</td>
</tr>
<tr>
<td>Sample l</td>
<td>38.15</td>
<td>26.36</td>
<td>26.36</td>
<td>50.22</td>
<td>37.49</td>
<td>37.49</td>
</tr>
</tbody>
</table>

Figure 5  Segmentation class maps based on RGA (2nd column) and proposed fused technique (3rd column) for input images (1st column). 1st, 2nd, 3rd and 4th rows show results for input Sample k, Sample h, Sample a and Sample b, respectively.
4 Conclusion

The fusion of context-enhanced rotational invariant DCT features with statistical features extracted from output of RGA has been proposed in this paper. RGA has been successful in extracting the epithelium layer but it has not been able to distinguish other two regions, i.e., background and connective tissue, clearly. In that respect, context-enhanced rotational invariant DCT is successful. But the extraction of epithelium layer is critical for context-enhanced DCT. So the fusion of these two techniques is beneficial. Fusion improves the classification accuracy of the context-enhanced rotational invariant DCT by at most around 75%. It has been observed in most of the cases that the performance of fuzzy $c$-means algorithm is better than that of $k$-means-based clustering. As DCT is involved, computational complexity is very small. Once the segmentation task is over, the studies related to further growth of the cancerous tissue can be modelled.

References


Unsupervised segmentation of OSF by fusion of RGA and DCT


Websites

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