Texture Segmentation from Non-Textural Background Using Enhanced MTC

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Abstract: *In image processing, segmentation of textural regions from non-textural background has not been given a significant attention, however, considered to be an important problem in texture analysis and segmentation task. In this paper, we have proposed a new method, which fits under the framework of mathematical morphology. The entire procedure is based on recently developed textural descriptor termed as Morphological Texture Contrast (MTC). In this work authors have employed the bright and dark top-hat transformations to handle the bright and dark features separately. Both bright and dark features so extracted are subjected to MTC operator for identification of the texture components which in turn are used to enhance the textured parts of the original input image. Subsequently, our method is employed to segment the bright and dark textured regions separately from the two enhanced versions of the input image. Finally, the partial segmentation results so obtained are combined to constitute the final segmentation result. The method has been formulated, implemented and tested on benchmark textured images. The experimental results along with the performance measures have established the efficacy of the proposed method.*

Keywords: *Texture segmentation, top-hat transformation, bottom-hat transformation, MTC.*

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1. Introduction

Over a half century, image, texture has been viewed as an interesting entity in many areas, especially psychology, computer vision, computer- graphics and image processing. With the passage of time, it has evolved as a fertile field of research, drawing numerous algorithms and various mathematical techniques, but still in its true sense, is a mystery for computer vision scientists. The main challenge in texture study and analysis is lack of universally acceptable definition and a mathematical model that can be applied to all known textures. However, for human beings, it is always proved to be an important cue that leads to the identification and discrimination of many real world objects and animals. The human visual system can easily differentiate different textures even present in the same image, although such discrimination is not so easy for computers despite of much progress in mathematical modelling and analysis. Researchers are trying for designing the ways so that texture processing would become as near to computer, as it is to the human visual system. Texture is, basically, a collective effect produced in human eye due to different groups of pixel present in the image, in the form of definitive patterns in terms of shape, scale, orientation, color and spatial frequency. Texture Analysis techniques have been classified broadly into three main categories: pixel based, local feature based and region based [8]. Different methods are used for texture analysis, including Gray Level Co-occurrence Matrix (GLCM) [4, 5], filtering in the spatial and frequency domain [6, 7, 8], histogram processing, gabor filter [17] energy measures and Local Binary Pattern (LBP) [2] operator. Some of these methods are based on pixel based techniques, whereas others belong to a family of local features [1] and region based techniques. Also, there are some model based techniques like Markov Random Field (MRF) [9, 10] and fractal based techniques [15]. Of late morphology [3, 11, 12, 16], based methods have been employed for texture analysis and segmentation. A number of methods have been employed for texture classification and segmentation task. In this regard a powerful approach established by Ojala *et al*. [13] proposes a pair of independent texture descriptors. The descriptor includes two things, first one is the application of original LBP operator associated with intrinsic textural properties and the second and final one is linked to textural contrast based upon variations of gray levels defined within the strictly defined neighborhood. Variance based descriptors have a problem that they may produce high responses even for individual features which are not a part of the texture. On the other hand, these descriptors were also strictly dependent on the mask size. In view of these disadvantages Zingman *et al*. [17, 18] have proposed Morphological Texture Contrast (MTC) descriptor invariant to illumination, that does not blur the border of the textural region.

In this paper, we have proposed a novel method of segmentation of textural regions in gray level images by employing morphological operations using MTC for finding the intermediate enhanced feature images.

Section 2 presents a brief description of the tools used in the proposed algorithm. In section 3 proposed method has been presented, this section also throws some light on the necessity and significance of the proposed method. Section 4 starts with experimental results and describes the shortcomings of MTC, later on in the same section, we have drawn a comparison of the proposed algorithm with the results of ground truth and original MTC and at last we added a quantitative performance analysis. Finally concluding remarks are presented in section 5.

2. A Brief Description of Tools used in the Proposed Algorithm

2.1. Mathematical Morphology

The basic assumption in mathematical morphology [3] is that an image is composed of a set of points and morphological transformation ψ gives the relation of this image with another small point set called Structuring Element (S.E.). In morphology dilation $f \oplus r$ and erosion $f \otimes r$ are the fundamental operations and all others are a combinational variation of them.

2.1.1. Dilation and Erosion (Gray Scale)

The dilation of $f(x, y)$ by a structuring element r at any location (x, y) is defined as the maximum value of the image in the window outlined by $\hat{r}$, when the origin of $\hat{r}$ is at (x, y), here $\hat{r} = r(-x, -y)$ i.e., reflection of structuring element about its origin.

$$[f \oplus r](x, y) = \max_{(s,t)\in r}\{f(x-s, y-t)\} \quad (1)$$

Similarly, the erosion of an image $f(x, y)$ by an structuring element r at any location (x, y) is defined as the minimum value of $f(x, y)$ in the region coincident with r when the origin of r is at (x, y)

$$[f \otimes r](x, y) = \min_{(s,t)\in r}\{f(x+s, y+t)\} \quad (2)$$

2.1.2. Opening and Closing

Morphological opening $(\gamma_r(f(x,y)))$ is defined as an erosion followed by a dilation and in like manner morphological closing $(\phi_r(f(x, y)))$ is described as a dilation followed by an erosion, where r is an S.E. for both the cases.

2.1.3. Top-Hat Transformation

Moreover Combining image subtraction with *opening* and *closing* results in top-hat and bottom-hat transformations. The top-hat transformation of a grayscale image $f(x, y)$ is defined as $f(x, y)$ minus its opening:

$$f_{top} = (f(x, y - \gamma_r f(x, y)) \quad (3)$$

Similarly, the *bottom-hat transformation* of $f(x, y)$ is defined as the closing of $f(x, y)$ minus original image $f(x, y)$):

$$f_{bot} = \phi_r(f(x, y)) - f(x, y) \quad (4)$$

Top-hat and bottom-hat transformations are also known as bright top-hat and dark top-hat respectively. In this paper, we have used the term bright and dark top-hat for referring top-hat and bottom-hat transformations respectively.

In fact the simplest tool used for studying texture in a binary image is erosion by a structuring element consisting of two pixels at a specified distance apart, followed by counting of remaining pixels. This may be repeated for a number of different distances and orientations. The remaining number of pixels after erosion, as a function of distance, summarizes the texture of the binary image.

2.2. Morphological Texture Contrast (MTC)

MTC is a texture descriptor that gives a high response in textured areas while a low or zero response in the areas of no texture or in the areas of constant intensity. Let us consider a non-negative and a bounded function $f(x, y)$ defined over a domain S and having maximum value of the used data type as M. This function $f(x)$ will represent a non-negative 1D signal if $S \subset R$ and if $S \subset R^2$ then it will represent a 2D signal or an image. MTC is defined in terms of morphological transformation $\psi(x)$ based on the difference between texture envelopes obtained by means of morphological compositions given by

$$\begin{aligned}[\bar{\psi}(f)](x) &= [\gamma_r\phi_r(f)](x) - [\phi_r\gamma_r(f)](x) \\ [\psi(f)] &= \max([\bar{\psi}(f)](x), 0)\end{aligned} \quad (5)$$

Where, $\gamma_r\phi_r(f)$ denotes morphological closing followed by opening. Accordingly, $\phi_r\gamma_r(f)$ denotes morphological opening followed by closing. Individually, these are known as alternating morphological filters and used for image denoising.

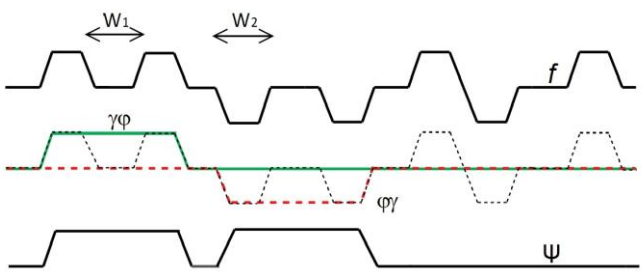


Figure 1. MTC on a one dimensional signal.

In Figure 1 the behavior of MTC has been illustrated by applying on an artificial 1D signal. The signal is composed of two textured regions and two individual features. The texture details are separated by a distance W_1 however W_2 is the detail size. Green color in the figure showing closing followed by an opening, whereas red dashed line is representing an opening followed by closing. At the bottom, ψ is representing final MTC transformation which clearly signifies a zero or diminished response for individual features, however responding proportional to the texture contrast in textural areas. The benefit of using MTC over other operators is the localization of textural border, ensuring the proportionate preservation of texture boundary.

Table 1. Summary of symbols used in this paper.

Symbol	Description
$f(x,y)$	Original Input Image
r	Structuring Element
ϕ_r	Morphological Closing
γ_r	Morphological Opening
$\gamma_r\phi_r$	Morphological closing followed by opening
f_{top}	Bright Top-hat
f_{bot}	Dark Top-hat
f_{mtc}^{bright}	Bright feature Image
f_{mtc}^{dark}	Dark Feature Image
f_{enh}^{bright}	Bright Enhanced Feature Image
f_{enh}^{dark}	Dark Enhanced Feature Image
$f_{contour}^{bright}$	Bright Segmented Image
$f_{contour}^{dark}$	Dark Segmented Image
$f_{contour}^{final}$	Final Segmented Image
$f_{contourthin}^{bright}$	Final Contour after Thinning
$otsu\lvert\square\rvert$	Otsu's Thresholding
ψ	Morphological Transformation

However, other operators like variance based, DMP etc., blurs the border of textured region. MTC satisfies the three well known properties (a) Invariance to a constant gray level bias, Where $a \in R$ is a constant, (b) Self complementary $\psi(f) = \psi(f^c) = \psi(M - f)$, and (c) Linearly, proportional to the texture contrast, $\psi(af)=a\psi(f)$ which are foremost necessary for any operator to be a texture contrast descriptor. A bias invariant and self-complementary transformation also satisfies the equality $\psi(f)=\psi(a-f)$, where $a \in R$ is any constant. MTC transformation applied to $log(f)$ become logarithmically proportional to the ratio contrast i.e.,

$$\psi(log(f)) = \frac{\gamma_r\phi_r(f)}{\phi_r\gamma_r(f)} \tag{6}$$

As MTC operator works only for high contrast textured regions. This limitation has been overcome in the proposed method.

2.3. Otsu's Method

The method was proposed by Otsu [14] used to perform clustering based image thresholding. The Otsu's method tries to make the segmented clusters, as tight as possible by minimizing their overlap. Suppose $f(x,y)$ be a grayscale image having gray scale values ranging from 0to L-1 and the components of an image thresholding be denoted by,

$$P_q = \frac{n_q}{n} \quad q = 0,1,2,...L-1 \tag{7}$$

Where $n$is the total number of pixels in the image, n_q is the number of pixels having intensity level q and L is the total number of possible intensity levels.

Suppose threshold k is chosen such that C_1 is the set of pixels with levels {0,1,2,….,k} and C_2 is the set of pixels with levels {k+1,k+2,...L-1}.Otsu's method is optimum as it chooses the threshold value k that maximizes the between class variance $\sigma_B^2(k)$, defined as

$$\sigma_B^2(k) = P_1(K)[m_1(k) - m_G]^2 + P_2(K)[m_2(k) - m_G]^2 \tag{8}$$

Where $m_1(k)$, $m_2(k)$ are mean intensities of the pixels in sets C_1 and C_2 respectively, m_G is the mean intensity of global mean. All the mean intensities are defined mathematically as

$$m_G = \sum_{i=0}^{L-1} iP_i \tag{9}$$

$$m_k = \sum_{i=0}^{k} iP_i \tag{10}$$

The probabilities involved are also defined mathematically as:

$$P_1(k) = \sum_{i=0}^{k} P_i \tag{11}$$

$$P_2(k) = \sum_{i=k+1}^{L-1} P_i = 1 - P_1(k) \tag{12}$$

$$\sigma_B^2 = \frac{[m_G P_1(k) - m(k)]^2}{P_1(k)[1 - P_1(k)]} \tag{13}$$

The idea of maximizing the between class-variance is that the larger this variance is, the more likely it is that the threshold will segment the image properly. This optimality measure is based primarily on parameters that can be obtained directly from the image histogram. We simply step through all possible gray level values of k and compute the variance at each step and select that value of k which gives the largest value of $\sigma_B^2(k)$. This value of k is the optimum threshold. If the maximum is not unique the threshold used is the average of all optimum k's found.

3. Proposed Method

A gray level image characteristically consists of both bright and dark textural features. The main aspect of a segmentation algorithm is to segregate the utmost optimum contours of these bright and dark features. The proposed method is region based as texture is a regional descriptor and in due course of segmentation it generates curves that encloses pixels having properties distinguishable from their direct neighbors. Moreover MTC operator is employed as a texture descriptor mainly because it does not disturb the textural features near the textural boundaries within the image.

In comparison to other descriptors like Differential Morphological Profiles (DMP) and variance based descriptors, the texture discrimination is relatively stronger in case of MTC operator. The MTC was originally developed to segment the high contrast textured regions from the areas of constant intensity present in remotely sensed imageries. Enhanced MTC is proposed as a new method based on MTC but more influential in comparison to MTC, as it uses the advantages of MTC and overcome its limitations in order to make it a general tool for segmenting the textured regions from the un-textured one's. The method has been divided into three compulsory and one optional subsection as described below:

3.1. Feature Extraction

The proposed method consists of two parallel passes Pass 1 and Pass 2. All the operations performed in Pass 2 are morphologically inverse of Pass 1. In pass 1 first of all, morphological opening is performed on the original input image which is subtracted further from the input image in order to compute bright top-hat as depicted in Equation (3). In the similar fashion, in Pass 2 also, morphological closing is determined from the input image from which the input image is subtracted in order to find out dark top-hat. The bright and dark feature as given below depicts the bright and dark features detected by the structuring element. These features include both textured and non-textured features. The textured bright and dark features are identified with the help of MTC operator in the subsequent and parallel steps of the two passes as given below:

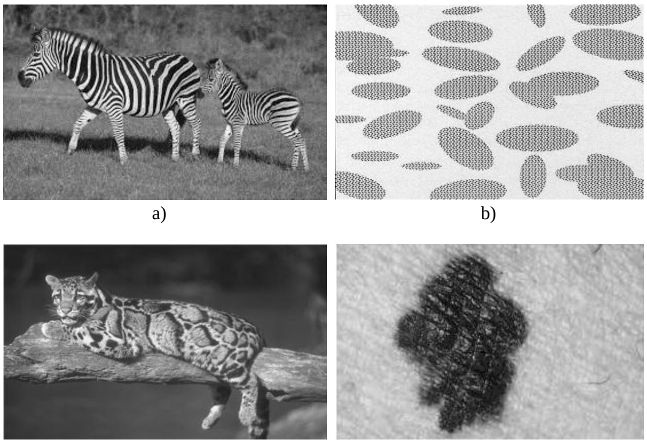
$$f_{mtc}^{bright} = \max([\gamma_r \phi_r (f_{top})](x,y) - [\phi_r \gamma_r (f_{top})](x,y), 0) \quad (14)$$

$$f_{mtc}^{dark} = \max([\gamma_r \phi_r (f_{bot})](x,y) - [\phi_r \gamma_r (f_{bot})](x,y), 0) \quad (15)$$

where f_{mtc}^{bright}, f_{mtc}^{dark} are bright and dark texture feature images respectively, r represents a structuring element, $\gamma_r \phi_r$ denotes morphological closing followed by opening and $\phi_r \gamma_r$ denotes morphological opening followed by closing as already mentioned in the previous section.

3.2. Feature Enhancement

The feature images find out in the previous sub-section are of poor quality. Thus, for a better enhancement of both bright and dark texture features the above two images constituted in Equations (14) and (15) are recombined separately with the input image to constitute the following two images.



a) b) c) d)

Figure 2. Original input images.

$$f_{enh}^{bright}(x,y) = f(x,y) + f_{mtc}^{bright}(x,y) \quad (16)$$

$$f_{enh}^{dark}(x,y) = f(x,y) + f_{mtc}^{dark}(x,y) \quad (17)$$

Where $f_{enh}^{bright}(x,y)$ and $f_{enh}^{dark}(x,y)$ are bright and dark enhanced texture feature images respectively.

3.3. Contour Segmentation

The Otsu's method is applied separately on the two images obtained in Equations (16) and (17) of the two parallel passes, in order to produce two more images which contains the segmenting contours highlighting the bright and dark texture regions.

$$f_{contour}^{bright}(x,y) = otsu(f_{enh}^{bright}(x,y)) \quad (18)$$

$$f_{contour}^{dark}(x,y) = otsu(f_{enh}^{dark}(x,y)) \quad (19)$$

Where $f_{contour}^{bright}(x,y)$ and $f_{contour}^{dark}(x,y)$ represents bright and dark segmented images respectively, $otsu|\cdot|$ represents the application of Otsu's method on $|\cdot|$. The segmenting contours corresponding to both bright and dark texture regions are further combined to constitute a single contour image as mentioned below:

$$f_{contour}^{final}(x,y) = f_{contour}^{dark}(x,y) + f_{contour}^{bright}(x,y) \quad (20)$$

Where $f_{contour}^{final}(x,y)$ represents a final segmented image.

3.4. Thinning

The contours coming from the two constituting images may be spatially adjacent. It may cause a formation of thick contours at some spatial regions to make all the contours single pixel thick, suitable thinning (morphological thinning) algorithm is executed.

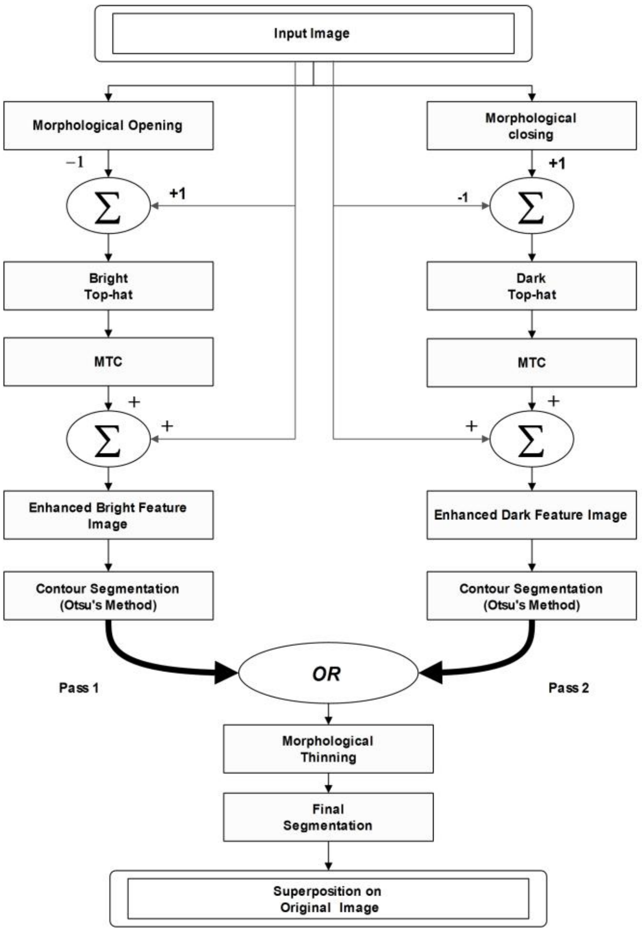


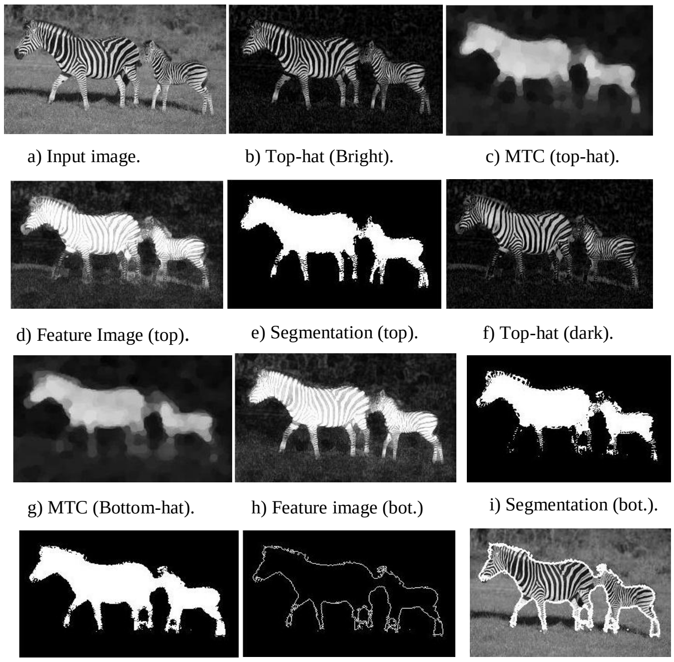
Figure 3. Proposed method.

$$f^{final}_{contourthin}(x,y) = Thin(f^{final}_{contour}(x,y)) \qquad (21)$$

Where, $f^{final}_{contourthin}(x,y)$ represents thinned contour image which is then superimposed on the original input image to visually verify the correctness of our proposed algorithm. The entire scheme is presented in the schematic diagram Figure 3.

4. Experimental Results

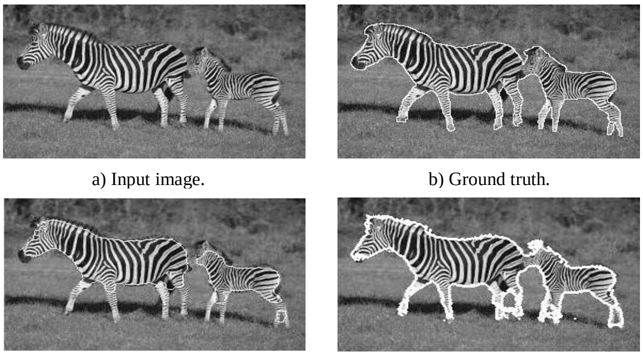
In this section, we have illustrated the application of the proposed method to segment the textural regions in different real and artificial images. In this work, some images used are of those animals which are recognized only on the basis of textural characteristics of their skin, whereas others are artificially generated with significant texture content. We have also included the image of skin melanoma that has to be segmented out from the rest of the skin. All the experimental works have been implemented and executed in MATLAB 2010. For the sake of simplicity, the size of structuring element for each image has been taken as constant in all the phases of the algorithm. Equally important, the size is decided on the basis of inter textural distance i.e., for coarser texture large value of structuring element is chosen whereas for finer texture smaller values are taken. Additionally, the shape of the structuring element is taken as circular and flat in the light of boundary contours present in most of the object shapes. A set of input images is shown in Figure 2 and there is a gradation of coarseness of texture in the input images. Figure 4-a is showing real image of two animals having the characteristic texture of their skin. The background contains very fine texture and can be assumed as a region of constant intensity in comparison to the foreground region. Here, the main objective is to segment the two animals (textured regions) from the background (non-textured region).



a) Input image. b) Top-hat (Bright). c) MTC (top-hat).
d) Feature Image (top). e) Segmentation (top). f) Top-hat (dark).
g) MTC (Bottom-hat). h) Feature image (bot.) i) Segmentation (bot.).
j) Combined image. k) Contour image. l) Final result.

Figure 4. Intermediate images for segmentation of zebra image.

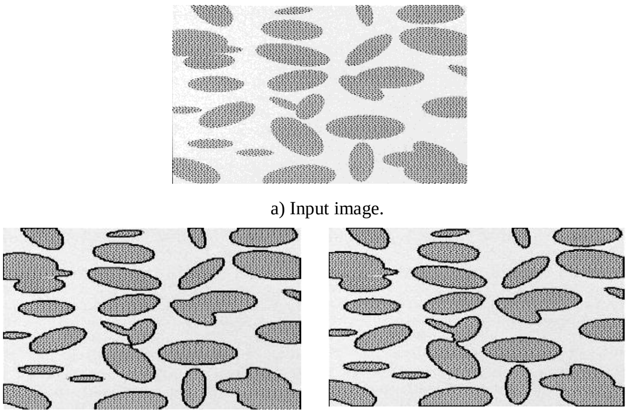
With reference to block diagram given in Figure 3 the original input image Figure 4-a is first of all subjected to morphological opening and top-hat transformation Figure 4-b, subsequently MTC operator is applied on the computed top-hat, Figure 4-c which is further combined with the original image to form the enhanced bright feature image Figure 4-d. We perform contour segmentation on the enhanced feature images obtained in the previous step Figure 4-e which constitute the one half of the partial results for final segmentation. Operations of pass 2 are same as that of pass 1 in the algorithm takes care of the dark features. At last, we get Figure 4-i as other partial results to be combined for final segmentation. Finally, after combining the partial result of the two passes, image Figure 4-j is produced. Morphological thinning is applied to the combined image to get the contour image which is subsequently superimposed to give the final result Figure 4-a. The use of the enhanced feature image is advantageous in emphasizing as well as boosting the textural features and localizing the boundaries of the textural regions. In contrast to the fact that structuring element in image morphology has a tendency to reject the details lesser than its size, that's why we have made a good use of top-hat transformation for getting the details both darker than their surrounding and brighter than their surroundings.



a) Input image. b) Ground truth.

c) MTC. d) Enhanced MTC.

Figure 5. Comparison of Enhanced MTC on zebra image with ground truth and original MTC.



a) Input image.

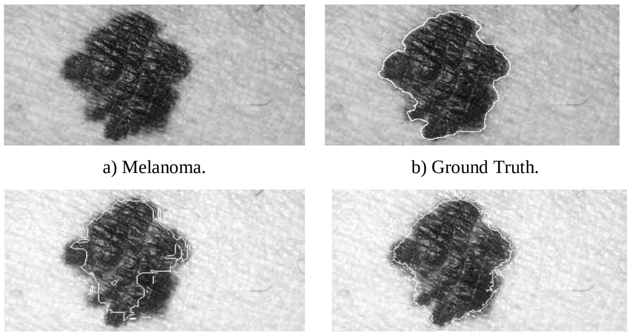
b) MTC. c) Enhanced MTC.

Figure 6. Boundaries are much more localized in enhanced MTC and much nearer to original 5-a.

The results are further improved by dividing the method in two parallel passes each contributing partially, to the final result. In the next Figure 5-8 a comparison of results of the proposed method with the ground truth image and MTC has been drawn. It is worth mentioning that in Figure 6 both MTC and proposed method are segmenting the textural regions in a good manner, but if we keenly observe the boundaries of textural regions Figure 6-c are more localized, preserved and nearer to Figure 6-a. i.e., original input as compare to MTC (Figure 6-b). In Figure 7 proposed method is implemented on skin melanoma image and a comparison with the ground truth and original MTC is drawn further. Figure 7-c is showing an improper segmentation whereas proposed method is showing results that are nearer to ground truth. A thorough experimentation of the proposed method has been made and at last a quantitative analysis based on a synthetic data set has also been performed.

4. Performance Analysis

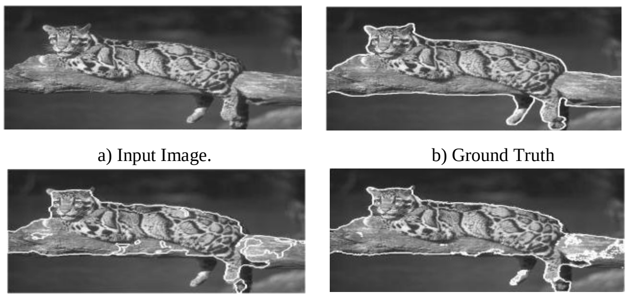
For a better evaluation and comparison with the original MTC we designed a synthetic contour image having contours of different complexities and segmented individually to form a set of ground truth images. In addition to this, these images are treated with different texture images ranging from a fine to a coarser texture to produce a set of synthetic test images. To make the conditions more ideally, in the first place the background is taken as black, alternatively which is changed to some shaded constant region for the last image having in mind to create all the possible test cases.



a) Melanoma. b) Ground Truth.

c) MTC. d) Enhanced MTC.

Figure 7. Segmentation of melanoma image with enhanced MTC.



a) Input Image. b) Ground Truth

c) MTC. d) Enhanced MTC.

Figure 8. Segmentation of panther image with enhanced MTC.

Initially, we have one contour per test image, in the due course which is changes to more than one for the last images. The two quantitative measures Global Consistency Error (GCE) and Variation of Information (VI) with respect to ground truth images are computed for the two algorithms (i.e., MTC and Enhanced MTC). These measures are illustrated below:

GCE is defined in terms of the extent to which one segmentation can be viewed as a refinement of the other. As GCE is defined in terms of Local Refinement Error (LRE) thus it is necessary to describe LRE first. Local refinement error ($E(S_1,S_2,p)$) measures the degree to which two segmentations agree at a single pixel.

Table 2. Comparison of enhanced MTC and MTC.

Contour No.	Enhanced MTC		MTC	
	GCE	**VI**	**GCE**	**VI**
1	0.0004	0.0076	0.0018	0.0185
2	0.0112	0.0945	0.0130	0.1065
3	0.0032	0.0310	0.0040	0.0369
4	0.0115	0.0918	0.0115	0.1551
5	0.0080	0.0649	0.0083	0.0666
6	0.0045	0.0423	0.0093	0.0793
7	0.0015	0.0147	0.0029	0.0266
8	0.0031	0.0281	0.0040	0.0377
9	0.0006	0.0069	0.0009	0.0097
10	0.0056	0.0532	0.0062	0.0577
11	0.0003	0.0040	0.0014	0.0142
12	0.0355	0.3028	0.0401	0.5324
13	0.0302	0.2614	0.0359	0.7544
14	0.0920	0.5050	0.0974	0.6590

$$E(S_1, S_2, p) = \frac{|R(S_1, P_i) \setminus R(S_2, P_i)|}{|R(S_1, P_i)|} \qquad (22)$$

Here, $R(S, p)$be the set of pixel in segmentation S which are in the same segment as pixel p and $|\cdot|$ denotes cardinality and $\cdot\setminus\cdot$ the set difference.

$$GCE(S_1, S_2) = \frac{1}{n}\min\{\sum_i E(S_1, S_2, p_i), \sum_i E(S_2, S_1, p_i)\} \qquad (23)$$

Variation of Information defined as the distance between two segmentations, and taken as average conditional entropy of one segmentation over the other, and thus measures the amount of randomness in one segmentation which cannot be explained by the other.

$$VI(X, Y) = H(X) + H(Y) - 2I(X, Y) \qquad (24)$$

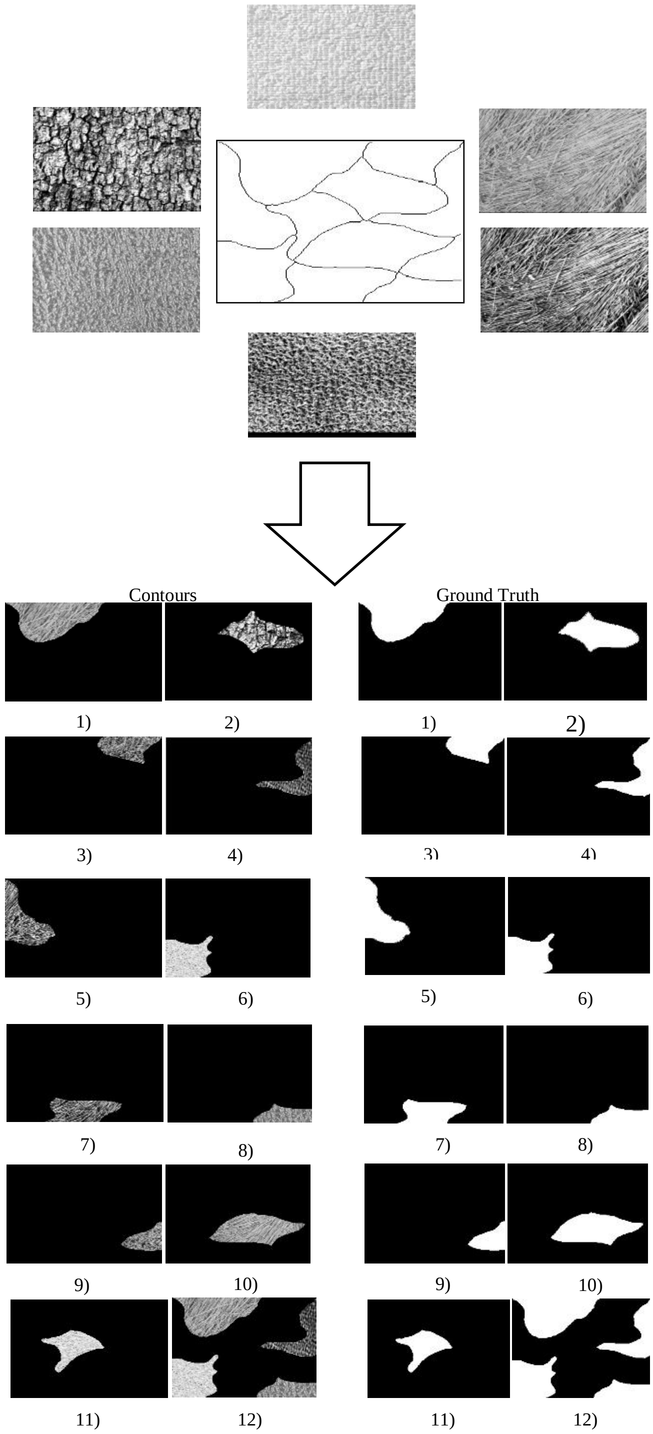
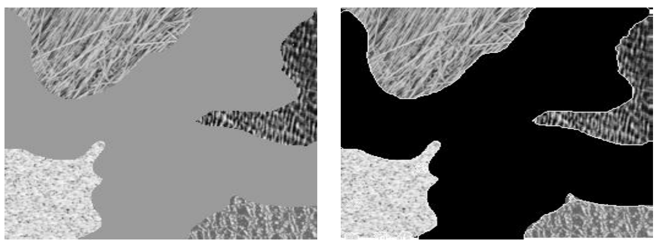


Figure 9. Synthetic data set created after treating contour image with different textures (Brodatz) and corresponding ground truth images for quantitative analysis.



a) contour with gray background. b) corresponding segmentation using Enhanced MTc.

Figure 10. Enhanced MTC is preserving boundaries in spite of the concerned texture.

Table 3. Execution time taken by MTC and enhanced MTC.

Image Name	Image Size	SE Size	MTC (sec)	Enhanced MTC (sec)
Figure 2-a	256×256	3	1.49	2.44
Figure 2-b	256×256	5	1.53	3.25
Figure 2-c	256×256	9	1.39	2.84
Figure 2d	256×256	9	2.07	2.53

Where, $H(X)$ is entropy of X and $I(X,Y)$ is mutual information between X and Y. The results of the three quantitative measures are shown in Table 2 and furthermore, summarizes and concluded by plotting three graphs with measures vs contour number.

Table 2 shows the value of GCE and VI for the synthetic data created in Figure 9. As the table clearly shows that smaller for all the data smaller values are shown for Enhanced MTC when compared to the MTC. Thus, enhanced MTC performs better than MTC.

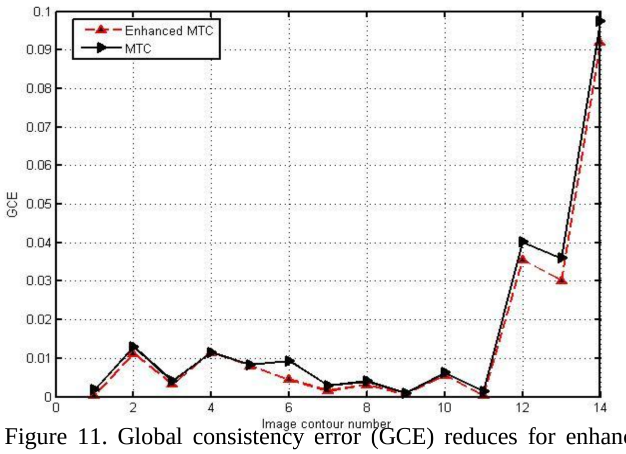


Figure 11. Global consistency error (GCE) reduces for enhanced MTC and decreases more when shape complexity increases.

5. Conclusions

The paper presents a novel algorithm for the segmentation of textural regions from the non-textural ones. A number of real and artificial images with significant textural content are employed for experimentation. The work employs the bright and dark top-hat transformations in order to handle the bright and dark features individually. The extracted bright and dark features are exposed to MTC for the discrimination of textured regions. Consequently, the discriminated texture regions in the two passes are used to enhance the textured parts of the original input image in the corresponding passes to form enhance bright and dark feature images. Subsequently, Otsu's thresholding is performed to segment the bright and dark textured regions separately from the two enhanced versions of the input image. Finally, the partial segmentation results so obtained are combined to constitute the final segmentation result. The main strength of the algorithm is its ability to reliably identify the complex textural areas in a non-textural background and provide segmentation, product that is very close to the perception of human interpreter. The experimental results are encouraging and the subjective performance is confirmed by the objective measures computed with respect to ad-hoc ground truth images.

Of course, there is much space for further improvements and we have already investigated several topics. First of all we have chosen size of the structuring element manually on the basis of textural size; some criteria should be applied to decide the size of the structuring element in order to make it fully automated. Secondly, the method is efficient in discriminating all the texture present, although it is an attainable, but measures should also be taken to identify textural regions from one another. Finally, in this algorithm we have chosen the same size of structuring element in order to retain its simplicity in all the phases of the algorithm. However the introduction of flexibility to the size of structuring element in different phases will definitely increase the accuracy of the algorithm.

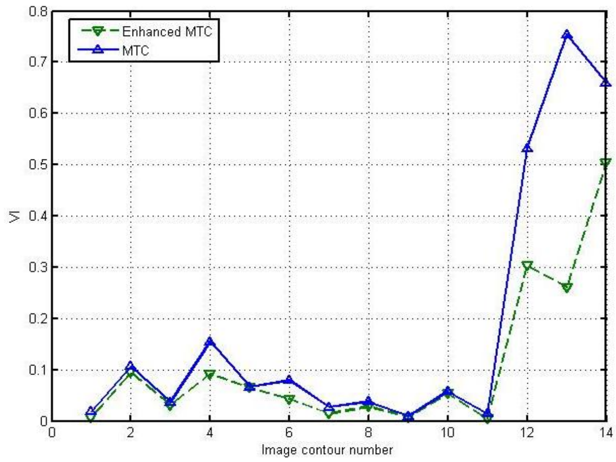


Figure 12. Variation Of Information (VOI) is low for enhanced MTC. When the shape complexity increases it reduces further thus boundary localization improves very much.

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