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Research Article

An Effective Segmentation Pattern Using Multi-class Independent Component Analysis on High Quality Color Texture Images

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Abstract: An efficient segmentation pattern proposes to improve the efficiency of segmentation through Multi-Class Independent Component InfoMax Analysis (MICIA) on multi-class high-quality color images. To attain richer segmentation of color, textures with minimal computation time, MICIA combines the watershed cuts principle and Minimal Spanning Forest method. The higher quality texture image is segmented by using the watershed cuts principle. Watershed cuts principle in MICIA is associated with regional minima of the map to handle multi-class poorly defined boundary images. Independent Component Analysis (ICA) is based on InfoMax which achieves richer segmentation of color textures with maximum likelihood function. ICA is based on InfoMax. It handles multi-class texture images. Because of the ICA maximum likelihood ensures higher independence on segmentation cuts.This produces an effective segmentation which can be used to improve the appearance of the high-quality images. To prove the efficiency, the experiment is conducted on factors such as sub-pixel accuracy rate on segmenting, multi-class image segmentation time and true positive rate.

Keywords: Color texture image segmentation, independent component analysis, maximum likelihood, minimal spanning forest method, watershed cut principle

INTRODUCTION

The effective segmentation pattern is still a challenging task, though many segmentation methods and approaches have been presented in the recent years. With the increasingly high-quality texture images, application of image segmentation has received greater attention ever before.

Realizing its need, HAIRIS (Gonçalves *et al*., 2011) has presented a method to perform segmentation on a pair of images on the basis of relaxation parameter. HAIRIS has also applied histogram modes via the area among the objects. It is an efficient method for image registration and is proven as a robust statistical-based method for effective object matching. HAIRIS with different spectral content is applied only to single-band images. But it is not implemented towards multi-band image segmentation and it also consumes more computational time during single-band segmentation stage.

A novel mathematical and algorithmic model is called as UIS (McCann *et al*., 2014) which has designed to perform unsupervised image segmentation. Flexible segmentation framework with the unsupervised method is, even though well suited for the segmenting wide range of multi-class poorly defined boundary images, it consumes more time on simply segmenting the colors from multi-class images. Model-based adaptation framework (Ecabert *et al*., 2011) includes multi-class feature and left atrium. The proximal part of the pulmonary veins, including coronary sinus evaluate various sizes of heart chambers in a significant and consistent manner. Generalized Hough Transformation is applied to multi-class images to minimize the computation time. Even though the efficiency is improved, it is not efficient in addressing other modalities.

For effective recognition of objects, image segmentation plays the significant task of detailed understanding and analysis of images. Two novel methods (Ghamisi *et al*., 2012), namely Fractional-Order Darwinian Particle Swarm Optimization (FODPSO) and Darwinian Particle Swarm Optimization (DPSO) have been developed for measuring the optimal threshold level for a specific image given as input. Even though more stable with less CPU time is ensured, the computational complexity of the algorithm remains low. To improve the complexity related to computation, a method is called as Minimum Spanning Tree (MST-based graph) (Zhong *et al*., 2011) has been presented using K-means. With minimal parameters, the effect is achieved. It does not suit for high dimensional datasets.

One of the critical tasks related to medical image processing is automatic image segmentation. It might be applied for effective diagnosis of disease and

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provisioning of treatments accordingly. Image Segmentation Automated Oracle (ISAO) (Frounchi *et al*., 2011) is presented to build an oracle which forms the basis for automatic verification and validation for image segmentations. The method not only reduces the use of resources, but also, efficient classification is made between consistent and inconsistent segmentation pairs with respect to each segmentation pair. Even though the method seems to be promising, the number of iterations required to perform the entire process remains unaddressed.

A maximum likelihood approach (Chen *et al*., 2011) has efficiently performed an automatically tuned process by using the Cramer-Rao Bound method. With this, the registration accuracy is improved in addition to optimally fused performance.

One of the most popular methods for sensing remote objects over the past few years is geographic object-based image analysis, which is used for evaluating and measuring high spatial resolution images. A new automated model for parameterizing multi-scale image segmentation is presented in Drăguţ *et al*. (2014). Automation and objectivity are increased and the scale to which it can be applied is relatively less addressed. In order to improve the level of scalability (Chen *et al*., 2010), a joint segmentation and registration technique is designed by using data fusion hierarchical structures.

For effective interpretation of dynamic scene representation, segmentation of structure-and-motion is of high significance for performing effective segmentation. A combinatorial framework (Thakoor *et al*., 2010) has been designed to keep in mind the optimization of the cost function. It combines three factors, namely, maximum likelihood of hypotheses, cost involved in clustering and distribution of an outlier in a uniform manner to minimize computational complexity. The drawback of the framework highly relied on the initial value of hypothesis. An improved threshold-based segmentation (Abdullaha *et al*., 2012) has been presented to the partition of the natural images in a clear manner and reduces the complexity involvement during computation applying an inverse technique.

The main focus is made on improving the efficiency of segmentation using the watershed cuts principle and independent component analysis based on informatics method. With the application of the Watershed cuts principle, richer segmentation of color textures with minimal computation time has been attained. The Watershed cut principle in MICIA is associated with regional minima of map effectively and handles multi-class poorly defined boundary images by using dilation and erosion of points on two-dimensional multi-class images.

Independent Component Analysis is based on InfoMax which achieves richer segmentation of color, textures with maximum likelihood function. As a result of ICA based on InfoMax handling multi-class texture images, the Maximum likelihood ensures higher independence on segmentation cuts. Finally, the Minimal Spanning Forest method evaluates the image at minimum timing intervals. High-quality texture image reduces the computation time on multi-class images and improves the sub-pixel accuracy rate on segmenting.

LITERATURE REVIEW

Different clustering methods have been designed for performing image segmentation. The artificial bee colony algorithm (Ouadfel and Meshoul, 2012) has been applied to improve the performance of the image being segmented. In addition to that, a new mutation strategy is also introduced to improve the process involvement during exploitation. Effectiveness and efficiency of segmentation (Mignotte, 2012) are achieved at the cost of time. An image segmentation framework using nonlinear dimensionality reduction is introduced. To minimize the complexity with respect to time, a contour is integrated with texture cues and performed subsequent segmentation.

Retrieval and segmentation of images using a range of colors, modularity of texture and shape are significant research areas of study with widened scope. A new framework (Jain *et al*., 2012) is designed to integrate all the three metrics namely color, texture and information regarding shape in order to perform effective segmentation and to enhance the retrieval rate at a lesser amount of time using the dominant color feature. Even though the precision is improved, the complexity increases with the increasing number of features applied.

To reduce the complexity involved during segmentation (Salah *et al*., 2011), multi-region graph cut image partitioning is applied to evaluate the deviation from the original images by improving the flexibility of the model involved. However, dimensionality remains unaddressed by minimizing the retrieval rate. A hierarchical approach (Jayaraman *et al*., 2011) is designed and combines both iris color and texture to improve the retrieval rate of the iris images. An algorithm called Speeded-up Robust Features algorithm is used to improve the performance of iris recognition with respect to the hit rate and high penetration rate.

The discussed techniques presents the design of multi-class independent component Informax analysis for improving the efficiency of segmentation on high-quality color texture images.

METHODS AND MATERIALS

This section provides a brief overview of design considerations involved in multi-class independent

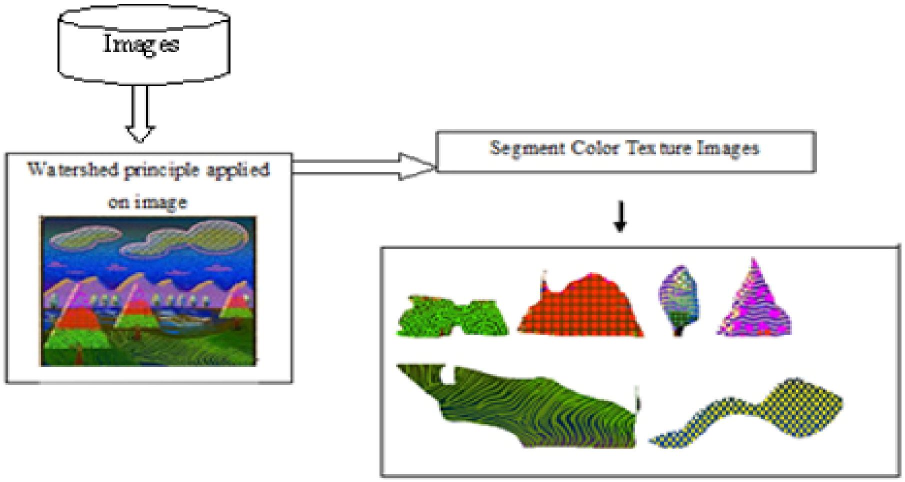


Fig. 1: Watershed-based image segmentation

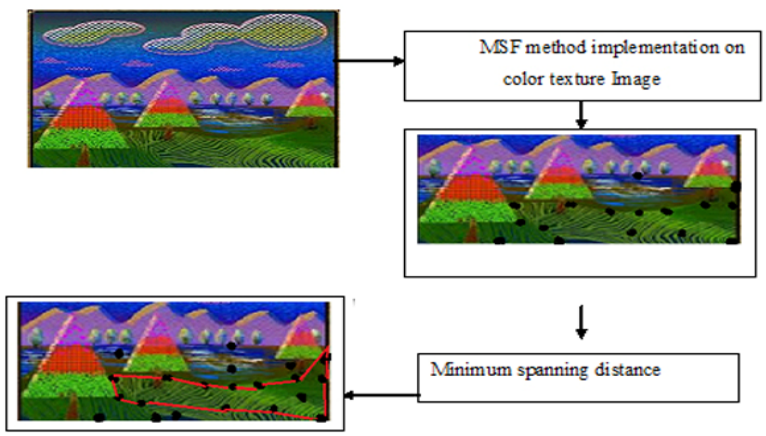


Fig. 2: Minimum spanning forest processing procedure

component infomax analysis for efficient segmentation process. High-quality texture image segmentation (Gonçalves *et al*., 2011) with mathematical morphology helps to reduce the computational time on multi-class images and improves the sub-pixel accuracy rate on segmenting. The watershed cut principle is used in MICIA based segmentation for segmenting region-based texture similarity. The process of segmentation also uses the independent component analysis to improve the region based texture segmentation without dependency. To establish the consistency level on multi-class texture images, the watershed cut principle uses the minimum spanning forest method. The minimum spanning forest method in MICIA based on segmentation processes the multi-class images with minimal computation time.

The watershed principle in MICIA based on segmentation uses dividing lines to separate different color textures. The color texture of the regions is efficiently segmented in MICIA even though the boundary images are poorly defined. The steps involved in the design of the watershed principle are clearly depicted in Fig. 1. The three steps involved in watershed principle are (a) fetch the image from the database (b) application of the watershed principle on the selected image and (c) perform segmentation on color texture images.

The watershed principle is efficiently constructed to provide the symbolic representation of the segmentation process by using MICIA based segmentation. With the application of mathematical minimum spanning forest method, the operations involved during the image segmentation reduce the computational time with effective segmentation results. With this, the minimum spanning forest method eventually segments the images with minimal computation time by traveling through the shortest distance to segment the multi-class images. In addition, the watershed cut principle satisfies optimality property in MICIA based segmentation using the MSF method. The minimum spanning forest represented on the color texture image is depicted in Fig. 2.

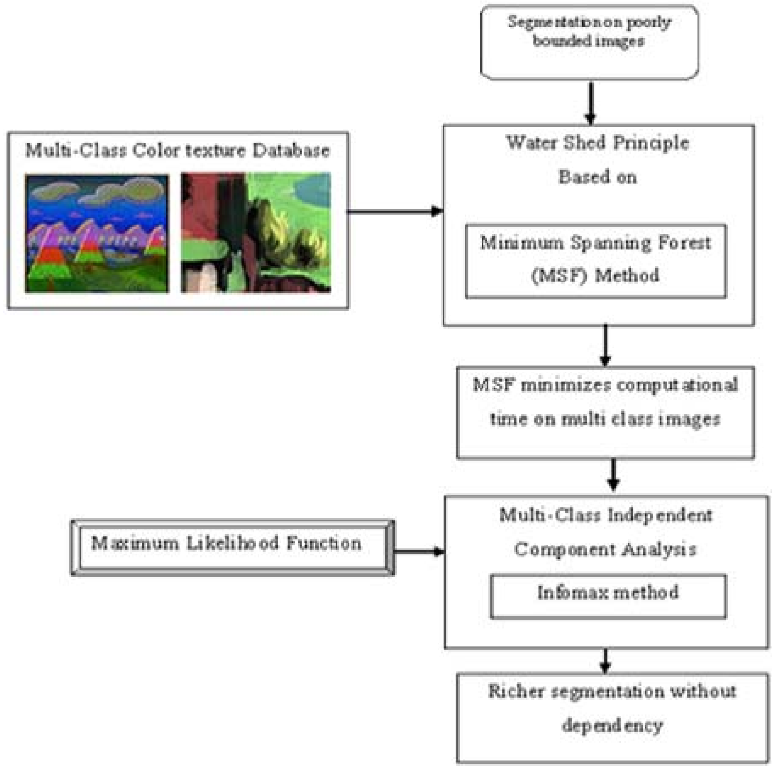


Fig. 3: Architecture diagram of MICIA method

Figure 2 depicts the procedure involved in the design of a Minimum Spanning Forest (MSF) method on multi-class high-quality color texture images. The spanning tree is constructed with minimal computation time on high quality images. The Watershed principle with pixel cuts using the MSF method rapidly performs the segmentation process.

The overall process of MICIA method is depicted in Fig. 3 using the architecture diagram.

As illustrated in Fig. 3, MICIA method initially extracts the multi-class color images from Corel Image Feature database. In order to perform efficient segmentation on multi-class color images, the watershed principle is used to segment different color textures for easy classification process during the upcoming work. The process of segmentation is carried out in MICIA method using the minimum spanning forest method in order to reduce the computational time. Followed by this, the segmentation process uses the multi-class independent component analysis using the Infomax method. The application of multi-class independent component analysis minimizes the class dependencies between two components. Here dependency refers to the regions of the observed vector that has dependent mixture color textures. The independent component used in MICIA method effectually reduces the dependency level (i.e., the rate of dependency of color textures in a given color texture database) and, in turn, improves the likelihood function. A Maximum likelihood function is used in a MICIA method for richer segmentation attainment. The brief note on watershed principle using minimum spanning forest method and multi-class independent component analysis using Infomax is explained in the forthcoming sections.

Water shed principle using MSF method: The watershed principle is applied on two-dimensional images I (x, y) with the region 'R' segmentation, then the watershed gradient on Image 'I' is expressed as:

$$WatershedGradientI \\ (x, y) = (u + D) - (u - E) \quad (1)$$

In (1), 'D' denotes the color dilation of points on two-dimensional, multi-class images whereas, 'E' denotes the erosion of color points (i.e.,) that is highly unrelated to the defined segmented structure and is therefore removed using the dividing units where 'u' represents the gray value of image 'I'. Further, consider that if $I(x, y)$<0 is considered as minimal zones of color while regions with $I(x, y)$>0 is considered as the maximal zone of color texture on two dimensional multi-class images. Then, the watershed principle is applied to a MICIA method in order to successfully identify, dilation or an erosion of color occurs on two-dimensional multi-class images 'I'.

In an MICIA method based on the minimum spanning forest (Zhong *et al*., 2011) creates an optimality of watersheds. Minimum spanning forests relative to sub-pixels of 'P' induce a unique pixel cut by using the watershed principle. The main result of segmentation by using the MICIA method with minimum spanning forest is to identify the relative minimum distance for mapping the pixel points. In fact, MICIA method derives the minimum spanning tree computations using distinct weights. As a result, the weight (where weight represents the sum of vertices and edges) on each pixel point is likely used on the watershed cut property:

$$Weight\ of\ \ 'a'pixelpoint > Weight\ of b' pixelpoin \quad (2)$$

Let 'a' and 'b' denote the two-pixel points on the image 'I' and identify whether the pixel point 'a' is a minimum spanning forest pixel to perform the segmentation process or not. If the condition does not get satisfied, then the 'b' pixel point is checked through its corresponding weight points. Each pixel on watershed principle with MSF is explained through the algorithmic procedure.

//Minimum Spanning Forest procedure:
Begin
Step 1: Let us assume that 'a' and 'b' be the pixel point on image 'I' to perform segmentation
Step 2: Initially, Watershed Principle is applied to compute the dilation and erosion of color, texture image
Step 3: Repeat
Step 4: Compute edge of the region to easily plot color, texture space on two-dimensional images 'I'
Step 5: Check to see that if two pixel points, 'a' and 'b' is within the cycle of the plotted points
Step 6: If pixel points weight (a>b) then
Step 6.1: Pixel point 'a' is chosen for segmentation process
Step 7: Else
Step 7.1: Pixel point 'b' is chosen for segmentation process
Step 8: Until all pixel points in the cycle of 'I' use MSF procedure

Output: MSF reduces the computational time of segmenting multi-class 'I'
End

The above algorithmic step describes the minimum spanning forest procedure for segmenting the regions by traveling through shortest distance. The edges of the poorly bounded images are also segmented effectively in MICIA method. Regional minimal result with minimal computation time is produced by MICIA method. The weight of each pixel point helps to plot effective segmentation regions.

Multi-class independent component analysis: Once, the richer segmentation of color, texture is obtained using watersheds cut principle, the goal of the multi-class independent component analysis is to widely separate the mixed color textures. Assuming a two-dimensional vector image c (t) = [$c_1(t)$, $c_2(t)$, …$c_n(t)$], such that the components (i.e.,) regions$c_i(t)$are mutually independent on time 't'. The vector c (t) corresponds to 'M' independent scalar valued points. The multi-class probability distribution function of the vector is measured as the product of marginal independent distributions:

$$P(c) = \prod_{i=1}^{M} p_i\,(c_i) \quad (3)$$

In (3), 'P' denotes the probability distribution function using MICIA method and the product operations is effectually carried out at all independently scaled value points 'M'. With this, different regions (i.e.,) color textures are segmented effectively.

Infomax method: An input pixel vector points in MICIA method is observed at each time point t, such that the regions of the observed vector are no longer dependent. The regions of c (t) are designed in such a way that if one source pixel points are normally distributed, then it is possible to extract the remaining pixel points to be segmented from image 'I'. With this, the multi-class normal distribution point is formalized as:

$$I(c_1, c_2, c_3 \dots c_n) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} p(c_1, c_2, c_3 \dots c_n) \times$$
log*pc1, c2, c3…cni=1Mpi(ci)dimensionn*×*n*
(4)

The component independence is checked through (4) where the regions '$c_1, c_2, c_3 \dots c_n$' on two-dimensional vectors are mutually independent. The above equation in Infomax method for independent component analysis is simplified as:

$$I(c) = \int p(c) log \frac{p(c)}{\prod_{i=1}^{M} p_i(c_i)} dc \quad (5)$$

From above, the mutual information in MICIA method is always positive and also equals to zero only when the components are independent on mapping the segmented regions.

Maximum likelihood function: Maximum likelihood function in MICIA method achieves richer segmentation processing signal with lesser dependency rate. MICIA picks up the higher order values of the normal distribution and performs the redundancy reduction:

$$\{c_n\}\epsilon\{argmaxlikelihood\ (c: c_1, c_2, c_3 \dots c_n 0\} \quad (6)$$

In order to form richer segmentation, with the application of maximum argument likelihood, 'c_n' in (6) is the identified regions. Maximum likelihood based on the journal "IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 20, NO. 5, MAY 2011" with the titled " A Maximum Likelihood Approach to Joint Image Registration and Fusion" by the authors "Chen *et al*. (2011)", enables to separate independent components in MICIA method input data with normally distributed function value. Maximum likelihood provides the unified result in richer segmentation without dependency rate.

RESULTS AND DISCUSSION

Multi-Class Independent Component Info Max Analysis (MICIA) based segmentation method is used to improve the color texture segmentation with higher efficiency rate. High-quality image segmentation using MICIA method is implemented in MATLAB. Segmentation processing uses the Corel Image Features Data Set from UCI repository for experimental work. Corel Image Features Data Set holds 68,040 photo images from a mixture of categories such as high quality and low-quality images.

Each set of features in Corel Image Features Data Set is stored in a separate file and each line corresponds to a single image used for segmenting the color textures. The initial value of the corel image features Data set is the image ID and the succeeding standards are the feature vector (e.g., Color textures) of the image. The similar image has the equivalent ID in all files, but the image ID is not same as the image filename in Corel Image Features Data Set. Co-occurrence Texture contains 16 dimensions (4×4) which are transformed to 16 grayscale images. The co-occurrence in 4 directions is worked out horizontal, vertical and two diagonal directions. The 16 values are Second Angular Moment, Contrast, Inverse Difference Moment and Entropy.

Multi-Class Independent Component InfoMax Analysis (MICIA) based segmentation is compared against the existing Automatic Image Registration through Histogram-based Image Segmentation (HAIRIS) method and Flexible segmentation framework. Experiments evaluation is conducted with the set of images with varying parametric metrics namely, sub-pixel accuracy rate of segmenting, color, texture segmentation efficiency, Multi-class image segmentation time and True positive rate.

The sub pixel accuracy rate (SPA) on segmenting is given as:

$$SPA = \frac{(I_n - I_y)}{(2 * I_n - I_x - I_y)} \quad (7)$$

where, is the maximum allowed value in two-dimensional images with and which are the samples to be considered for left and right of the sub-pixel? The efficiency of color, texture segmentation (CTS) is measured by using (4) and (5) that evaluates the rate of efficiency of the regions, '$c_1, c_2, c_3 \dots c_n$' with that of the multi-class distribution point, p_i:

$$CTS = \frac{p(c)}{p_i(c_i)} \quad (8)$$

The multi-class image segmentation time $MCISeg_{time}$ measures the time was taken to perform multi-class image segmentation using the watershed gradient on two dimensions, $I(x, y)$:

$$MCISeg_{time} = Time\ [WatershedGradientI(x, y) \quad (9)$$

The True Positive Rate (TPR) in MICIA method uses a maximum likelihood function that performs redundancy reduction. There is the total number of true positive pixel points, $Truepositivepixels_n$ is divided by the actual positive pixel points $Actualpositivepixles_n$:

$$TPR = Truepositivepixels_n / Actualpositivepixles_n \quad (10)$$

Multi-Class Independent Component InfoMax Analysis (MICIA) on multi-class high-quality color images are compared against the existing Histogram-based Image Segmentation (HAIRIS) (Gonçalves *et al*., 2011) and Unsupervised Image Segmentation (UIS) (McCann *et al*., 2014). The evaluation value is given below with the help of the table and the graph describes the MICIA on multi-class high quality a color image which improves the sub pixel accuracy rate. Figure 4 evaluates the sub-pixel accuracy rate measured in terms of percentage (%) achieved with different number of sub-pixel ranging from 100 to 700 and a comparison is made with the two existing schemes, namely, Histogram-based Image Segmentation (HAIRIS) (Gonçalves *et al*., 2011) and Unsupervised Image Segmentation (UIS) (McCann *et al*., 2014).

Figure 4 describes the sub-pixel accuracy rate based on the number of sub pixel being measured using the Table 1 in the range of 100 and 700 taken for experimental purpose using MATLAB. The application of mathematical morphology on High Quality, texture image reduces the computational time on multi-class images and improves the sub pixel accuracy rate on segmenting by 6-11% when compared to HAIRIS

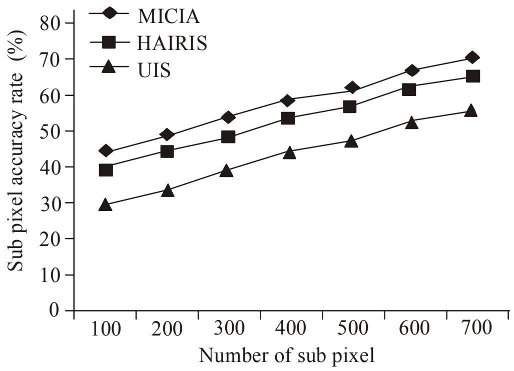


Fig. 4: Measure of sub pixel accuracy rate with respect to number of sub pixel

Table 1: Tabulation for sub-pixel accuracy rate

Number of sub pixel	Sub pixel accuracy rate (%)		
	MICIA	HAIRIS	UIS
100	45.54	40.51	30.47
200	49.85	45.83	34.79
300	54.55	49.53	39.49
400	60.25	55.23	45.19
500	63.45	58.42	48.38
600	68.55	63.51	53.47
700	72.00	67.00	57.00

Table 2: Tabulation for color, texture segmentation efficiency

Number of regions (c_n)	Color, texture segmentation efficiency (%)		
	MICIA	HAIRIS	UIS
c_1	56.75	51.72	43.70
c_2	61.26	56.23	48.22
c_3	66.76	61.73	53.71
c_4	75.25	70.22	62.21
c_5	80.35	75.32	69.31
c_6	82.45	77.42	69.40
c_7	85.00	80.00	72.00

(Gonçalves *et al*., 2011). Furthermore, the application of color dilation and erosion of points on two dimensional, multi-class images separately increases the sub pixel accuracy rate by 20-33% when compared to UIS (McCann *et al*., 2014).

In Table 2, the color, texture segmentation efficiency of MICIA with the existing two schemes, namely Histogram-based Image Segmentation (HAIRIS) (Gonçalves *et al*., 2011) and Unsupervised Image Segmentation (UIS) (McCann *et al*., 2014) is provided.

The color, texture segmentation efficiency of our work MICIA with the existing two schemes, namely Histogram-based Image Segmentation (HAIRIS) (Gonçalves *et al*., 2011) and Unsupervised Image Segmentation (UIS) (McCann *et al*., 2014) is provided in Fig. 5.

Figure 5 depicts the rate of color, texture segmentation efficiency with respect to the number of regions. From the Fig. 5 it is illustrative that with the

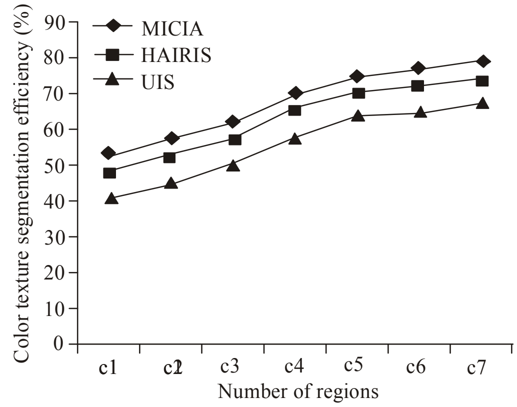


Fig. 5: Measure of color, texture segmentation efficiency

Table 3: Tabulation for multi-class image segmentation time

Number of regions (c_n)	Multi-class image segmentation time (ms)		
	MICIA	HAIRIS	UIS
c_1	0.235	0.322	0.446
c_2	0.245	0.332	0.456
c_3	0.267	0.354	0.478
c_4	0.285	0.372	0.496
c_5	0.315	0.403	0.527
c_6	0.335	0.422	0.548
c_7	0.345	0.432	0.559

increase in the number of regions, the color, texture segmentation efficiency is improved by using the proposed MICIA when compared to the two other existing methods namely, HAIRIS (Zhong *et al*., 2011) and UIS (Drăguţ *et al*., 2014). Independent Component Analysis based on InfoMax achieves the richer segmentation of color, textures with maximum likelihood function which improves the color, texture segmentation efficiency by 5-8% when compared to HAIRIS (Gonçalves *et al*., 2011). As a result of handling the multiclass texture images by ICA based on Infomax, the maximum likelihood ensures higher independence on segmentation cuts improving the color, texture segmentation efficiency by 13 -22% when compared to UIS (McCann *et al*., 2014).

The multi-class image segmentation time of MICIA method and comparison made with two other existing schemes, namely, Histogram-based Image Segmentation (HAIRIS) (Gonçalves *et al*., 2011) and Unsupervised Image Segmentation (UIS) (McCann *et al*., 2014) is listed in Table 3.

Figure 6 describes the multi-class image segmentation time based on the number of regions taken into consideration for experimental purpose in the range of c_1 to c_7. The number of regions is computed by (4). By using the application of the watershed cuts principle richer segmentation of color, textures are obtained with minimal computation time, which improves the multi-class image segmentation time is achieved by 25-37% when compared to HAIRIS (Gonçalves *et al*., 2011). Watershed cut principle in

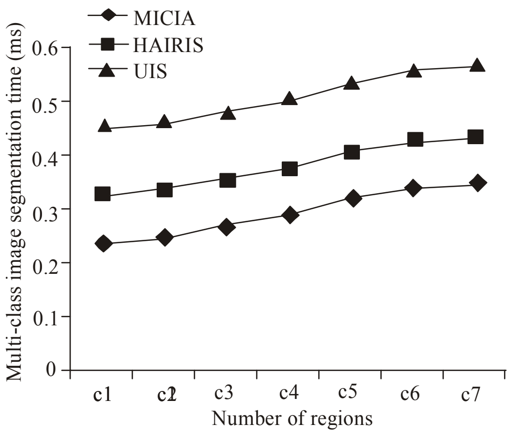


Fig. 6: Measure of multi-class image segmentation time

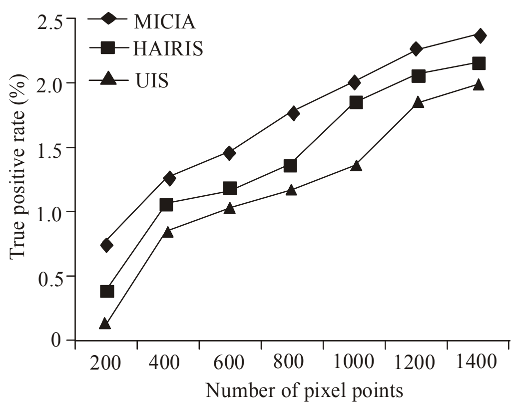


Fig. 7: Measure of true positive rate with respect to number of pixel points

Table 4: Tabulation for true positive rate

Number of pixel points	True Positive Rate (%) MICIA	HAIRIS	UIS
200	0.75	0.35	0.15
400	1.25	1.05	0.85
600	1.45	1.15	1.05
800	1.75	1.35	1.15
1000	2.00	1.85	1.35
1200	2.25	2.05	1.85
1400	2.35	2.15	2.00

MICIA is associated with regional minima of the map to handle multi-class poorly defined boundary images improving the multi-class image segmentation time by 62-89% when compared to UIS (McCann *et al*., 2014).

More accurately the influence of the true positive rate with respect to the number of pixel points is listed in Table 4 and the comparison is made with two other existing schemes. It can also be seen that the true positive rate increases with the increase in the number of pixel points.

More accurately the influence of the true positive rate with respect to the number of pixel points is provided in Fig. 7 and comparison is made with two other existing schemes. It can also be seen that the true positive rate increases with the increase in the number of pixel points.

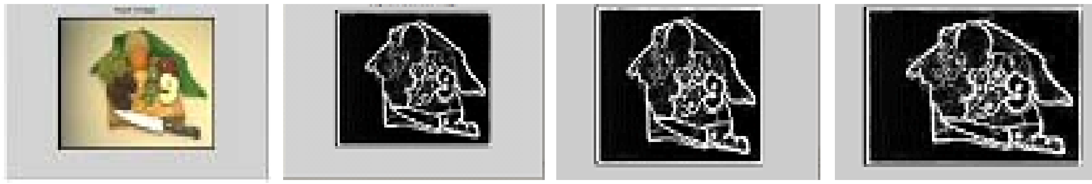
Figure 7 describes the true positive rate based on the number of pixel points in the range of 200 to 1400. From the Fig. 7 it is illustrative that the true positive rate using the proposed MICIA is improved than the two other existing methods, namely, HAIRIS (Gonçalves *et al*., 2011) and UIS (McCann *et al*., 2014) respectively. This is because the independent component used in MICIA method effectually reduces the dependency level and in turn, improves the likelihood function. A Maximum likelihood function is used in the MICIA method for richer segmentation attainment resulting in improved true positive rate by 7-53% and 14-80% when compared to HAIRIS (Gonçalves *et al*., 2011) and UIS (McCann *et al*., 2014) respectively.

Figure 8 given shows the qualitative analysis of sub pixel accuracy and color text segmentation efficiency using the proposed MICIA method and comparison made with existing HAIRIS and UIS respectively.

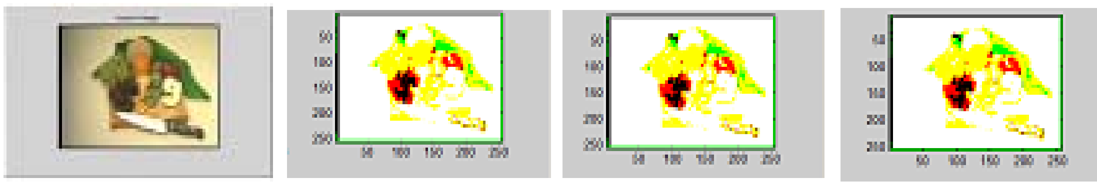
From the Fig. 8, the image provided as input is in Fig. 8a. Sub Pixel accuracy obtained using Multi-Class Independent Component InfoMax Analysis (MICIA) on multi-class high quality color images are given in Fig. 8b and the comparison is made with two other methods Histogram-based Image Segmentation (HAIRIS). Unsupervised Image Segmentation (UIS) is provided in Fig. 8c and d. Color Text Segmentation efficiency measured using the proposed MICIA is provided in Fig. 8f and comparison made with HAIRIS and UIS is provided in Fig. 8g and h respectively.

CONCLUSION

Effective segmentation of multi-class high quality color images has become the key for image processing. To achieve richer segmentation of color, texture with minimal computation time and improve the level of color, texture segmentation efficiency with the relatively lesser amount of multi-class segmentation time remains the objective of this study. In this study, the performance effects of high quality color, texture images and handle multi-class poorly defined boundary images had been investigated by proposing a method, Multi-Class Independent Component InfoMax Analysis (MICIA). The MICIA method based on Watershed cuts principle and Independent Component Analysis based on InfoMax provides an efficient means of richer segmentation of color textures with maximum likelihood function. At first, the use of watershed cut principle minimum spanning forest method that measures the computation time on multi-class images are studied and proposed to use color dilation and



(a) (b) (c) (d)



(e) (f) (g) (h)

Fig. 8: (a): Input image; (b): Sub pixel accuracy, using MICIA; (c): Sub pixel accuracy, using HAIRIS; (d): Sub pixel accuracy, using UIS; (e): Input image; (f): Color text segmentation efficiency using MICIA; (g): Color text segmentation efficiency using HAIRIS; (h): Color text segmentation efficiency using UIS

erosion points on two dimensional, multi-class images for measuring relative minimum distance for mapping the pixel points in MICIA method. Secondly, the multi-class independent component analysis is performed using Infomax method to assess multi-class normal distribution point with varying regions to maximize the true positive rate using Corel Image Features Data Set extracted from the UCI repository. The experiment conducted using Corel Image Features Data Set shows that the MICIA method achieves up to 17.25% improvement in color texture segmentation efficiency compared to the existing methods.

NOMENCLATURE SECTION

MICIA	:	Multi-Class Independent Component InfoMax Analysis
ICA	:	Independent Component Analysis
FODPSO	:	Fractional-Order Darwinian Particle Swarm Optimization
DPSO	:	Darwinian Particle Swarm Optimization
ISAO	:	Image Segmentation Automated Oracle
MSF	:	Minimum Spanning Forest
HAIRIS	:	Histogram-based Image Segmentation
$P(c) = \prod_{i=1}^{M} p_i\,(c_i)$	:	Multi-class probability distribution function of vector where 'P' denotes the probability distribution function using MICIA method, two-dimensional vector imagec (t)
CTS	:	Color Texture Segmentation
$SPA = \frac{(I_n - I_y)}{(2*I_n - I_x - I_y)}$	:	Sub Pixel Accuracy rate where I_n is the maximum allowed value in two dimensional images with I_x and I_y are the samples to be considered left and right of the sub pixel
$MCISeg_{time}$	:	Multi-Class Image Segmentation Time

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