CHAPTER 4
AN EFFICIENT HIGH QUALITY COLOR IMAGE SEGMENTATION BASED ON MULTI-CLASS INDEPENDENT COMPONENT INFOMAX ANALYSIS

4.1 INTRODUCTION

Image segmentation is a responsibility of measurement and also significant task for detailed understanding and analysis of images. The Multi-Class Independent Component InfoMax Analysis (MICIA) on multi-class high quality color images segmentation pattern are intended to improve the efficiency of segmentation. The MICIA method is the combination of the watershed cuts principle and Minimal Spanning Forest method to attain the richer segmentation of color textures with minimal computational time and to evaluate the image at minimum timing interval respectively. Initially, watershed cuts principle is used for segmenting the higher quality texture image. Watershed cuts principle in MICIA is associated with the regional minima of the map to handle multi-class poorly defined boundary images. Secondly, Independent Component Analysis based on InfoMax achieves the richer segmentation of color textures with maximum likelihood function. ICA based on InfoMax handles multiclass texture images and as a result, the Maximum likelihood ensures higher independency on segmentation cuts.

Although different existing methods for automatic image registration and flexible segmentation framework using unsupervised method have been designed, it has been applied only on single-band images with less functionality included for multi-class defined boundary images. However, the Effective segmentation Multi-Class Independent Component method is used for
segmenting high quality color images. Experiments on a variety of challenging sequences using Corel Image Features Data Set with comparisons to different state-of-the-art methods demonstrate that more robust segmentation efficiency can be achieved using Multi-Class Independent Component InfoMax Analysis. The result analysis prove the efficiency, experiment is conducted on factors such as sub pixel accuracy rate on segmenting, color texture segmentation efficiency, multi-class image segmentation time and true positive rate.

4.2 DIFFERENT METHODS INVOLVED FOR SEGMENTATION OF IMAGES

Effective segmentation pattern is still a challenging task, though many segmentation methods and approaches have been presented in the recent years. With the increasing high quality texture images, the application of image segmentation has received greater attention never ever before.

4.2.1 Automatic Image Registration through Histogram-Based Image Segmentation method

Hernani Gonçalves et al. (2011) presented a method HAIRIS to perform segmentation on pair of images on the basis of relaxation parameter. HAIRIS also applied histogram modes by the area between the objects, between the axis of the images that also formed an efficient method for image registration and was proved as a robust statistical based method for effective object matching. HAIRIS permits for verify the pairs of images with differences in rotation and translation, with small differences in the spectral content, leading to sub pixel accuracy.

The several steps involved in the process of HAIRIS method were explained in Figure 4.1. The processing steps are preprocessing, and Histogram based segmentation, object characterization, Matching, Rotation Estimation and Translation Estimation. The initial step of preprocessing was obtained by image
This enhancement was proposed to obtain an image with fewer aspects than the original version, adjacent to the object recognition which was performed by the human eye. The enhanced images were obtained in segmentation which is valuated to extract the objects in particular boundaries; one may view the image objects which have some texture as a kind of degradation. Therefore, it was intended to eliminate that degradation, which was assumed to be additive random noise. The Wiener Filter was mostly used filters under the level of image restoration methods. Even though the main purpose of image restoration methods was to model and remove the degradation.

Figure 4.1 Flow processing steps of HAIRIS
After the preprocessing, second step Histogram-Based Segmentation method is involved for mode delineation and is supported the analysis of the straight slopes of the histogram. During the characterization process, the extracted objects by the segmentation stage were characterized with four attributes which allow for their adequate morphological description such as area, perimeter, axis ratio and fractal dimension.

The attribute area was simply attained by the number of pixels which form an object, while the perimeter was achieved by manipulative the distance between each adjacent pair of pixels over the border of the region. The axis ratio was defined as the ratio between the major and the minor axis length lead to the attribute. Fractal dimension is one between a numbers of concepts of dimension proposed by mathematicians. In HAIRIS, the special forms of Mandelbrot’s fractal dimension were measured fractal dimension typically consists on the slope of a straight line, fixed to a scatter plot with and on the vertical and horizontal axis, respectively.

Once the characterization step was accomplished consequently matching process initiates with the assessment of a cost function, among all possible 2x2 combination of objects obtained by the segmentation of the two images. The rotation and translation were established based on a statistical approach. The dataset contains in a photograph and a rotated and shifted edition of the equal photograph, with particular levels of added noise. It was also employed to a satellite images with distinct spectral content and created translation. An accuracy of the certain image reached below 1 degree for rotation and at the sub pixel level intended for translation estimation was obtained, for the most part of the considered situations. HAIRIS allows for the registration of pairs of images with variation in rotation and translation, with small differences in the spectral content, guiding to sub pixel accuracy. During the rotation or translation process, the HAIRIS does not connect any other search period either
since it is a completely automatic procedure. HAIRIS with different spectral content was applied only to single-band images but not implemented towards multi-band image segmentation and it also consumed more computational time during the single-band segmentation stage.

### 4.2.2 Unsupervised segmentation method

Michael T McCann et al. (2014) described novel mathematical and algorithmic model called UIS designed to perform unsupervised image segmentation. Flexible segmentation framework with unsupervised method was though well suited on segmenting wide range of multi-class poorly defined boundary images, but consumed more time on simply segmenting the colours from multi-class images. In UIS segmentation frame work, the images were created from multiple tissues. The segmentation algorithm was processed with local histogram transform, factorization, and de convolution.

![Flow diagram for segmentation algorithm](image)

**Figure 4.2 Flow diagram for segmentation algorithm**

Figure 4.2 illustrates the block diagram of Histogram based segmentation flow diagram defined by Michael T Mc Cann et al. (2014). Implementation of the local histogram transform is a straightforward process based on its definition. The single convolution process used to perform all the
levels of local histogram. The window size and shapes were calculated by the local histogram was a more significant parameter. Generally, the window has limited preserves, the resulting segmentation has the improved localized boundaries, but it may be noisy. In addition, the particular quantization method was used for the segmentation process which was effectively handling the bandwidth value of local histogram transformation. The local histogram transform was a filtering operation and consequently balance well with input image size.

The factorization was computed based on arrangement of matrix form. Which increase the robustness of the algorithm. This process was repeated multiple times with different random initializations as a result with the lowest error. Moreover, factorization step illustrated it involves inserting a matrix that develops in size with the square of the number of pixels in the image, but if the number of textures remains low and no texture region was very small, then in practice a random subset of pixels can be used for factorization, reducing the complexity.

The deconvolution process was obtained for each row of the matrix can be reshaped into an image of weights that characterize a distorted version of one level of the labeling function. The histogram based segmentation performed two different deconvolution methods. The initial method was a basic method which was very useful since it very fast and does not need any specific knowledge about the properties of the labels. The next method was parametric deconvolution which was helpful basically on images so as to suitable for this model.

4.2.3 Different segmentation techniques for analysis of images

Model-based adaptation framework that included multi-class feature, left atrium and the proximal part of the pulmonary veins, including coronary
sinus in order to evaluate various size of heart chambers in a significant and consistent manner. Generalized Hough Transformation was applied to multi-class images to minimize the computation time. Though efficiency was improved, was not efficient in addressing other modalities.

For effective recognition of objects, image segmentation plays a key role and also significant task for understanding and study of images. Two novel methods namely Fractional-Order Darwinian Particle Swarm Optimization (FODPSO) and Darwinian Particle Swarm Optimization (DPSO) were developed for measuring optimal threshold level for a specific image given as input. Though more stability with less CPU time was ensured, the computational complexity of the algorithm remained low. To improve the complexity related to computation, a method called as Minimum Spanning Tree (MST-based graph) was presented using K-means. Though with minimal parameters, the effectiveness was achieved, but not suited for high dimensional datasets.

One of the critical tasks related to the area of medical image processing is automatic image segmentation that may be applied for effective diagnosis of disease and provisioning of treatments accordingly. Image Segmentation Automated Oracle (ISAO) was presented that was efficiently used to build an oracle, which formed as the basis for automatic verification and validation for image segmentations. The method not only reduced the use of resources but also efficiently classified between consistent and inconsistent segmentation pairs with respect to each segmentation pair. Though the method seemed to be promising but the number of iterations required to perform the entire process remain unaddressed.

A maximum likelihood approach presented performs efficiently the automatic tuned process using Cramer-Rao Bound method. With this, the registration accuracy was improved in addition to optimal fused performance.
One of the most popular methods for sensing remote objects over the past few years is geographic object-based image analysis for evaluating and measuring the high spatial resolution images. A new automated model for parameterising multi-scale image segmentation was presented. Though automation and objectivity was increased, but the scale to which it can be applied was relatively less addressed. In order to improve the level of scalability, a joint segmentation and registration technique was designed using data fusion hierarchical structures.

For effective interpretation of a dynamic scene representation, the segmentation of structure-and-motion is performed effective segmentation. A combinatorial framework was designed keeping in mind the optimization of cost function that combined three factors namely, maximum likelihood of hypotheses, cost involved in clustering and distribution of outlier in a uniform manner to minimize the computational complexity. But the drawback of the framework was that it highly relied on initial value of hypothesis. An improved thresholding-based segmentation was presented to partition the natural images in a clear manner and reduced the complexity involved during computation by applying an inverse technique.

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

Independent Component Analysis based on InfoMax achieves richer segmentation of color textures with maximum likelihood function. ICA based on InfoMax handles multiclass texture images and as a result, the Maximum likelihood ensures higher independency on segmentation cuts. Finally, the
Minimal Spanning Forest method evaluates the image at minimum timing interval. As a result, high quality texture image reduce the computational time on multi-class images and improves the sub pixel accuracy rate on segmenting. MICIA multiclasses textures are explained in forth coming sections.

4.3 **DESIGN OF MULTI-CLASS INDEPENDENT COMPONENT INFOMAX ANALYSIS**

A brief overview of the design considerations involved in multi-class independent component InfoMax analysis for efficient segmentation process. High quality texture image segmentation with the mathematical morphology helps to reduce the computational time on the 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. Moreover to establish the consistency level on multi-class texture images, the watershed cut principle uses the minimum spanning forest method to establish the consistency level on multi-class texture images. The minimum spanning forest method in MICIA based segmentation processes the multi-class images with minimal computational time.

The Watershed Principle in MICIA based 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 watershed principle are clearly depicted in Figure 4.3.

Figure 4.3 shows the Watershed based Image Segmentation principle is efficiently constructed to provide the symbolic representation of segmentation process using MICIA.
With the application of mathematical minimum spanning forest method, the operations involved during the image segmentation reduces the computational time with effective segmentation result. With this, the minimum spanning forest method eventually segments the images with minimal computation time by travelling through the shortest distance to segment the multi-class images. In addition, the watershed cut principle satisfies an optimality property in MICIA based segmentation using the MSF method. The minimum spanning forest represented on color texture image is depicted in the Figure 4.4 given below.

Figure 4.4 depicts the procedure involved in the design of Minimum Spanning Forest (MSF) method on multi-class high quality color texture images. The spanning tree was constructed with minimal computational time on high quality images. Watershed principle with pixel cuts using the MSF method rapidly performs the segmentation process. The overall process of MICIA method is depicted in Figure 4.5 using the architecture.
As illustrated in Figure 4.5, MICIA method initially extracts the multi-class color images from the Corel Image Feature database. In order to perform efficient segmentation on multi-class color images, watershed principle is used to segment the different color textures for easy classification process during the upcoming work. The process of segmentation was carried out in MICIA method using the minimum spanning forest method in order to reduce the computational time. Followed by this, the segmentation process next uses the multi-class independent component analysis using the InfoMax method. The independent component used in MICIA method effectually reduces the dependency level and in turn improves the likelihood function. Maximum Likelihood Function was used in MICIA method for richer segmentation attainment. The brief note on water shed principle using minimum spanning forest method and multi-class independent component analysis using InfoMax is explained in the forthcoming sections.
4.3.1 Water Shed Principle Using MSF method

Let us apply the watershed principle on two dimensional image $I(x, y)$ with the region ‘R’ segmentation, then the watershed gradient on Image ‘I’ is expressed as,

$$WatershedGradientI(x, y) = (u + D) - (u - E)$$  \hspace{1cm} (4.1)
In (4.1), the ‘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. Let us 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 colour texture on two dimensional multi-class images.

![Figure 4.6 Watershed texture segmentation](image)

**Figure 4.6 Watershed texture segmentation**

The watershed principle is applied in MICIA method and it is shown in above figure 4.6. They successfully identify the images, when dilation or an erosion of color occurs on two dimensional multi-class images ‘I

The Minimum Spanning Forest in MICIA method creates an optimality of watersheds. Minimum Spanning Forests relative to sub pixels of ‘P’ induces a unique pixel cut using the watershed principle. The main result of segmentation using MICIA method with minimum spanning forest is to identify the relative minima distance for mapping the pixel points.
Figure 4.7 Minimum Spanning Forest

Figure 4.7 gives texture segmentation with minimum spanning forest. In fact, MICIA method derives the minimum spanning tree computations using distinct weights. As a result, the weight on each pixel point is likely used on the watershed cut property.

\[ \text{Weight of 'a' pixel point} > \text{Weight of 'b' pixel point} \quad (4.2) \]

Let ‘a’ and ‘b’ denotes the two pixel points on the image ‘I’ and identified whether the ‘a’ pixel point 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 watershed principle with MSF is explained through the algorithmic procedure.

The following algorithmic step describes the Minimum Spanning Forest procedure for segmenting the regions by travelling through shortest distance.
//Minimum Spanning Forest procedure

**Begin**

Step 1: Let us assume ‘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 the 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 point weight (a>b)

Step 6.1: then the pixel point ‘a’ is chosen for segmentation process

Step 7: Else

Step 7.1: then the 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 edges of the poorly bounded images are also segmented effectively in MICIA method. Regional minimal result with minimal computation time is produced in MICIA method. The weight of each pixel points helps to plot the effective segmentation regions.

### 4.3.2 Multi-Class Independent Component Analysis

Once, the richer segmentation of color textures is obtained using watersheds cut principle, the goal of multi-class independent component analysis is to widely separate the mixed color textures. Let us assume a two dimensional vector image \( c(t) = [c_1(t), c_2(t), \ldots c_n(t)] \), such that the components (i.e.,) regions \( c_i(t) \) are mutually independent on time ‘t’. The vector \( c(t) \) corresponds to the ‘M’ independent scalar valued points.
Figure 4.8 illustrate the texture segmentation that obtains high quality color images. The multi-class probability distribution function of vector is measured as the product of marginal independent distributions.

\[ P(c) = \prod_{i=1}^{M} p_i(c_i) \]  

(4.3)

In (4.3), ‘P’ denotes the probability distribution function using MICIA method and the product operations are effectually carried out on all the independent scaled value points ‘M’. With this, the different regions (i.e.,) color textures are segmented effectively.

4.3.2.1 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 formularized as,

\[ I(c_1, c_2, c_3 ... c_n) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(c_1, c_2, c_3 ... c_n) \]
\[ \ast \log \frac{p(c_1, c_2, c_3 ... c_n)}{\prod_{i=1}^{M} p_i(c_i)} \text{dimension}_{n+n} \]

(4.4)

The component independency is checked through (4.4) where the
regions ‘c_1, c_2, c_3 ... c_n’ on the two dimensional vector are mutually independent.

The above equation in InfoMax method on Independent Component Analysis is
simplified as,

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

(4.5)

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.

4.3.2.2 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 perform redundancy
reduction.

\[ \{c_n\} \in \{\text{argmaxlikelihood} \ (c: c_1, c_2, c_3 ... c_n, 0) \} \]

(4.6)

In order to form richer segmentation, with the application of
maximum argument likelihood ‘c_n’ in (4.6) is the identified regions. Maximum
likelihood enables to separate independent components in MICIA method input
data with normally distributed function value. Maximum Likelihood provides
the unified result for richer segmentation without dependency rate.
4.4 EXPERIMENTAL EVALUATION

Multi-Class Independent Component InfoMax Analysis (MICIA) based segmentation method was 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 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 the identical as the image filename in Corel Image Features Data Set. Co-occurrence Texture contains 16 dimensions (4x4) which are transformed to 16 gray-scale 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 was conducted with the set of images with varying parametric metrics namely, Sub pixel accuracy rate on segmenting, Color texture segmentation efficiency, Multi-class image segmentation time and True positive rate.
4.5 RESULT ANALYSIS OF MICIA

Multi-Class Independent Component InfoMax Analysis (MICIA) on multi-class high quality color images is compared against the existing Histogram-Based Image Segmentation (HAIRIS) by Hernani Gonçalves et al. (2011) and Unsupervised Image Segmentation (UIS) by Michael T. McCann et al. (2014). The evaluation value given below with the help of graph describes the MICIA on multi-class high quality color images improve the sub pixel accuracy rate.

4.5.1 Measurement of Sub pixel accuracy rate

The sub pixel accuracy rate $SPA$ on segmenting is given as,

$$SPA = \frac{(I_n-I_y)}{(2*I_n-I_x-I_y)}$$  \hspace{1cm} (4.7)

From above equation, $I_n$ is the maximum allowed value in two dimensional images with $I_x$ and $I_y$ and the samples to be considered left and right of the sub pixel. The proposed MICIA method compared with two existing method namely HAIRIS and UIS.

The evaluation of the sub pixel accuracy rate is calculated in terms of percentage (%) achieved with the different number of sub pixel ranging from 100 to 700 and comparison is made with the two existing schemes namely, Histogram-Based Image Segmentation (HAIRIS) by Hernani Gonçalves et al. (2011) and Unsupervised Image Segmentation (UIS) by Michael T. McCann et al. (2014). As a result, the sub pixel accuracy rate is high in proposed Multi-Class Independent Component Info Max Analysis (MICIA).
Figure 4.9 Measure of sub pixel accuracy rate with respect to number of sub pixel

Figure 4.9 describes the sub pixel accuracy rate based on the number of sub pixel being measured in the range of 100 and 700 taken for experimental purpose using MATLAB. The arithmetical morphology function on High Quality texture image decrease the computational time on multi-class images and improves the sub pixel accuracy rate on segmenting. The application of color dilation and erosion of points on two dimensional multi-class images separately increases the sub pixel accuracy rate. Hence, proposed MICIA method increases accuracy rate by 8.5 % when compared to HAIRIS by Hernani Gonçalves et al. (2011) and by 26.5 % when compared to UIS by Michael T McCann et al. (2014).

4.5.2 Measurement of color texture segmentation efficiency

The efficiency of color texture segmentation $CTS$ is measured using (4.4) and (4.5) that evaluates the rate of efficiency of the regions, $'c_1, c_2, c_3 ... c_n'$ with that of the multi-class distribution point, $p_i$. The color texture segmentation efficiency calculated using following equation (4.8).

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

(4.8)
Multi-Class Independent Component InfoMax Analysis (MICIA) on multi-class high quality color images is compared against the existing Histogram-based Image Segmentation and Unsupervised Image Segmentation. Segmentation efficiency is measured in terms of percentage (%).

The color texture segmentation efficiency of MICIA compared with the existing two schemes namely Histogram-Based Image Segmentation (HAIRIS) by Hernani Gonçalves et al. (2011) and Unsupervised Image Segmentation (UIS) by Michael T McCann et al. (2014).

![Figure 4.10 Measure of color texture segmentation efficiency](image)

Figure 4.10 depicts the rate of color texture segmentation efficiency with respect to the number of regions. From the Figure 4.10 it is illustrative that with the increase in the number of regions, the color texture segmentation efficiency is also improved. The segmentation for segmenting region based texture similarity is performed by using the watershed cut principle in proposed MICIA method. In addition to the segmentation process, the independent component analysis is used to improve the texture segmentation region. The minimum spanning forest method in MICIA use watershed cut principle for segmentation processes. They process the multi-class images with minimal computational time. Therefore, MICIA method improves the color texture
segmentation efficiency by 6.5 % when compared to HAIRIS by Hernani Gonçalves et al. (2011). Similarly, Maximum likelihood ensures higher independency on segmentation cuts improving the color texture segmentation efficiency by 17.5 % when compared to UIS by Michael T. McCann et al. (2014).

4.5.3 Measurement of multi-class image segmentation time

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

$$MCISeg_{time} = Time [WatershedGradientI(x, y)] \quad (4.9)$$

Equation (4.9) used for performs the multi class segmentation time between proposed MICIA method and Existing HAIRIS, UIS methods. The multi-class image segmentation time is measured in terms of milliseconds (ms).

The multi-class image segmentation time and comparison made with two other existing schemes. The proposed MICIA reduced segmentation time as compared to other existing methods.

![Figure 4.11 Measure of multi-class image segmentation time](image)
Figure 4.11 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 with (4.4). With the application of Watershed Cuts Principle, richer segmentation of colour textures is attained with minimal computational time. Watershed Cuts principle in MICIA is connected with regional minima of the map to handle multi-class images. As a result, improvement over multi-class image segmentation time is achieved by 31% when compared to HAIRIS by Hernani Gonçalves et al. (2011). Multi-class boundary images reducing the multi-class image segmentation time by 75.5% when compared to UIS by Michael T McCann et al. (2014).

4.5.4 Measurement of True positive rate

The true positive rate in MICIA method uses maximum likelihood function that performs redundancy reduction. The true positive rate $TPR$ is the total number of true positive pixels points to the actual positive pixel points $Actualpositivepixles_n$ given as below equation (4.10),

$$TPR = \frac{Truepositivepixels_n}{Actualpositivepixles_n}(4.10)$$

The above equation (4.10) is used for measure the True positive rate of MICIA and comparison made with two existing method. It measured in terms of percentage (%).

More accurately the influences of true positive rate with respect to the number of pixel points are made comparison 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 4.12 Measure of true positive rate with respect to number of pixel points

Figure 4.12 describes the true positive rate based on the number of pixel points in the range of 200 to 1400. From the figure 4.12 it is illustrative that the true positive rate using the proposed MICIA is improved than the two other existing methods namely, HAIRIS and UIS respectively. The independent component used in MICIA method effectively reduces the dependency level and improves the likelihood function. Maximum likelihood function in MICIA method achieves richer segmentation processing signal with lesser dependency rate. Hence, true positive rate is improved by 38.5 % and 24.5 % when compared to HAIRIS by Hernani Gonçalves et al. (2011) and UIS by Michael T McCann et al. (2014) respectively.

4.6 CONCLUSION

An Effective segmentation on 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 relatively lesser amount of multi-class segmentation time. Multi-Class Independent Component InfoMax Analysis (MICIA) method to handle multi-class poorly defined boundary images. 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. Initially, the use of Watershed Cuts Principle with minimum spanning forest method measures the computation time on multi-class images and propose to use color dilation and erosion points on two dimensional multi-class images for measuring relative minima distance for mapping the pixel points in MICIA method. Second, 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 UCI repository. The experiment conducted using Corel Image Features Data Set shows that the MICIA method improves the sub pixel accuracy and also achieves up to 17.5 percent improvement on color texture segmentation efficiency compared to the state-of-art methods.