Thermal image segmentation based on density slicing of color histogram of images

Dr. Ghada S. Karam [a], **Dr. Ziad M. Abood**[b], **Muntaha Abood Jassim**[c]

[a] Al Mustansereyah University/ Baghdad- Iraq
dr.ziadmabood@yahoo.com
[a] Al Mustansereyah University/ Baghdad- Iraq
ghadasks@yahoo.com
[a] Al Mustansereyah University/ Baghdad- Iraq
muntaha.abood@yahoo.com

Abstract. Thermal imaging has been recently used as a new approach for human biometrics. The formation of thermal image is purely based on the heat distribution of an object. It brings some difficulties to image segmentation due to its over centralized intensity distribution and low intensity contrast. Our approach uses color slicing segmentation method to characterize the texture information using various color models.

The experimental results of present study shows the color slicing technique can make good effect on the segmentation of tumor structure. We have found that segmenting these images can be made easier by using RGB, HSV, YCbCr color models by Color slicing method. We have used many Statistical operations (such as contrast, variation …) to evaluate our segmentation results.

Keywords: Color Image Segmentation, Thermal Image, Segmentation evaluation, color model, image analysis.

1. INTRODUCTION

In general IR radiation covers wavelengths that range from 0.75μm to 100μm, among which the human body emissions that are traditionally measured for diagnostic purposes only occupy a narrow band at wavelengths of 8μm to 12μm [Hairong]. This region is also referred to as the long-wave length IR "thermal imaging" region or body infrared rays in which sensors can obtain a completely passive picture of the outside world based on thermal emissions only require no external light or thermal source, such as sun, moon, or infrared illumination [Taib]. An terminology that is widely used in medical IR imaging is thermal infrared (TIR), which, covers wavelengths beyond about 1.4μm. Within this region, the infrared emission is primarily heat or thermal radiation.

Thermal images are normally gray scale in nature: black objects are cold, white objects are hot and the depth of gray indicates variations between the two. Some thermal cameras, however, add color to images to help users identify objects at different temperatures [Negied]. the color are simply a visual aid to show the temperature differences in each image, the thermal image camera records the differences in the radiation intensity of objects and maps them in the form of a particular color map. a thermal image is basically an index image with a special map [Li, Aggarwal].

2. RELATED RESEARCH WORK

Nermine K. Negied reviews methods for detection, segmentation, and unique feature extraction for human physiological biometrics. he investigates specialized algorithms that would extract vasculature information. Create a thermal signature that identifies the individual.

Takanashi et al introduced a semi-automatic technique for segmentation a large cryo-sliced human brain data set. Jehad Odeh, et al presented an approach based on slicing the images to equally sub-area, then applying the density slicing to the color histogram of these areas combined with the color pair technique. Recently Kai and Arens proposed a local feature based pedestrian detector on thermal data. They used a combination of multiple cues to find interest points in the images.

3. THERMAL IMAGE SEGMENTATION

Segmenting thermal medical images is a mean of identifying diseased tissues [Li, Aggarwal]. Once diseased tissue has been segmented, it is useful to compare it with the normal tissue (region) to see how it changes with pathology. Thermal imaging provides clues to the potential of developing vascular disease that may lead to stroker or cancer.

Each pixel of a thermal image represent a temperature at the acquired scene. The simplest way to represent thermal imaging is through of shades of gray. So, a change in temperature is related to the variation in gray tone of the image .the purpose of segmentation is to sub-divide an image into its constituent regions or object.

Color slicing technique has been used in this paper as a segmentation method, this technique is very useful method for sperating the warm region from its background [Taib]. Color slicing and color coding is one of the simplest kind of pseudo color image processing. Which is highlight a specific range of colors to separate objects from surroundings by displaying the color of interest or use the region defined by colors as a mask.

The density slicing technique [6] can be summarized as follows:

Let [0, L-1] represent the gray scale. Suppose that M planes are defined at levels l1, l2, l3, l4, … LM and let l_o represent black [f(x ,y)=0] and l_{L-1} represent white [f(x, y)=L-1]. Then, assuming that 0<M<L-1, the M planes partition the gray level scale to M+1 intervals (regions) [R1, R2, …, RM+1] gray levels to color assignments are made according to the relation:

$$f(x, y)= c_k \text{ if } f(x, y) \in R_k \tag{1}$$

Where c_k is the color associated with the k th intensity interval R_k defined by the partitioning planes at l= k-1 and l= k.

Color offers a number of visual cues that can be used to distinguish features in the data set. The tumor can be distinguished from the background relatively easily by using color information. A number of different color space model including RGB, YCbCr, gray scale, and HSV, was used in this paper in attempt to find one that give best result for detecting a tumor material from its surrounding.

The formula was applied to convert from RGB to HSV color space is [8, 9]:

$$H = \begin{cases} \frac{G-B}{V-\min\{R,G,B\}} \cdot 60^\circ, & \text{if } V = R \text{ and } G \geq B; \\ \left(\frac{B-R}{V-\min\{R,G,B\}} + 2\right) \cdot 60^\circ, & \text{if } G = V; \\ \left(\frac{R-G}{V-\min\{R,G,B\}} + 4\right) \cdot 60^\circ, & \text{if } B = V; \\ \left(\frac{R-B}{V-\min\{R,G,B\}} + 5\right) \cdot 60^\circ, & \text{if } V = R \text{ and } G < B \end{cases} \qquad H \in [0^\circ, 360^\circ] \tag{2}$$

$$S = \frac{V - \min\{R, G, B\}}{V} \qquad S \in [0, 1]$$
$$V = \max\{R, G, B\} \qquad V \in [0, 255] \tag{3}$$

The transformation from RGB color model to YCbCr model given by [Lin Zhang]:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.000 \\ 112.000 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

4. STATISTICAL OPERATIONS

- Mean $\overline{X}$: The average, and calculated from: [Gonzalez, Woods] [Breckon, Bisch]

$$\overline{X} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} I(i,j)}{n*m} \tag{5}$$

Where I (i, j) is the pixel value at point (i, j) of an image of size m*n.

- Standard deviation σ: is a statistical measure of the precision for a series of repetitive measurements. The advantage of using σ to quote uncertainty in a result is that it has the same units as the mean value. It is calculated from:

$$\sigma = \sqrt{\frac{1}{n*m}\sum_{i}^{n}\sum_{j}^{m}\left(I(i,j)-\overline{X}\right)^2} \tag{6}$$

- Variance : Average total square deviations of the values from the middle of the arithmetic:

$$\sigma^2 = \frac{1}{n*m}\sum_{i}^{n}\sum_{j}^{m}\left(I(i,j)-\overline{X}\right)^2 \tag{7}$$

- Energy : Energy is used to describe a measure of "information" when formulating an operation under a probability framework; the equation was formulated as follows:

$$\text{Energy} = \sum_{i}\sum_{j} P_{i,j} \tag{8}$$

where $P_{i,j}$ refers to the probability distribution functions, which contains the histogram counts. The energy reaches its maximum value of 1 when an image has a constant gray level. The larger energy value corresponds to the lower number of gray levels, which means simple. The smaller energy corresponds to the higher number of gray levels, which means complex.

- Homogeneity: It can be calculated homogeneity from the following equation:

$$\text{Homogeneity} = \sum_{i}\sum_{j}\frac{P_{i,j}}{1+(i-j)^2} \tag{9}$$

- Entropy: The entropy of a system as defined by Shannon [l1], gives a measure of uncertainty about its actual structure. Shannon's function is based on the concept that the information gain from an event is inversely related to its probability of occurrence. Shannon defined the entropy of an n-state system as:

$$H = -\sum_{i=1}^{n} p_i \log(p_i) \tag{10}$$

where p, is the probability of occurrence of the event i and

$$\sum_{i=1}^{n} p_i = 1 \; 0 \le p_i \le 1 \tag{11}$$

- Contrast: Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image, Contrast is 0 for a constant image.

$$\sum_{i,j} |i-j|^2 p(i,j) \tag{12}$$

- Correlation: Returns a measure of how correlated a pixel is to its neighbor over the whole image, Range = [-1 1]. Correlation is 1 or -1 for a perfectly positively or negatively correlated image.

$$\sum_{i,j}\frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j} \tag{13}$$

6. EXPERIMENTAL RESULTS

Figure (1) shows the diagram in figure 1 summarizes the step of proposed method.

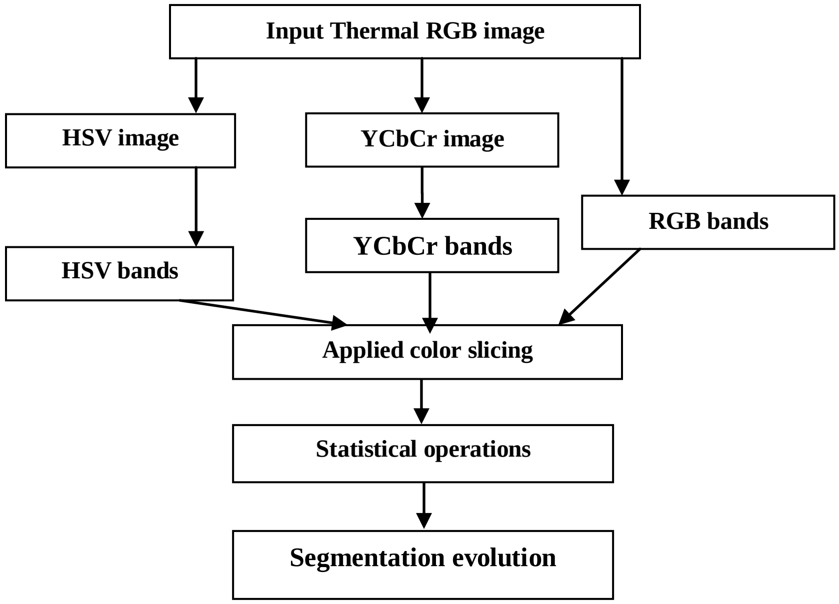


Fig. (1) Block diagram of proposed system for applied color slicing on thermal image

To show the applicability of our approach, we applied it on a set of thermal images collected from the internet, to be able to compare it to existing segmentation algorithms was best. We now present the segmentation results obtained for real image sequences.

Figure (2) shows the convert images from RGB space to Hsv and Ycbcr and others bands.

Fig. (2) convert RGB space to HSV and Ycbcr and others bands	
Original image RGB	**Image bands**

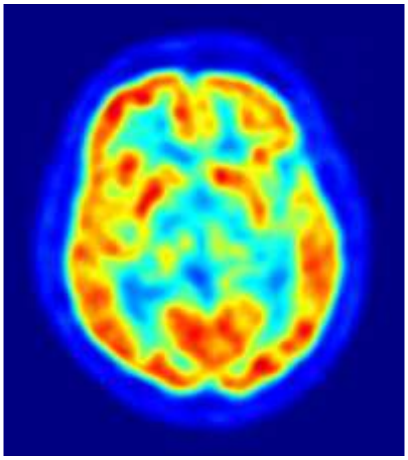
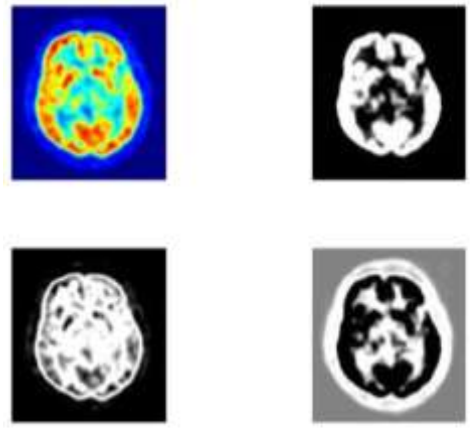
	

Image # 1	**RGB bands**

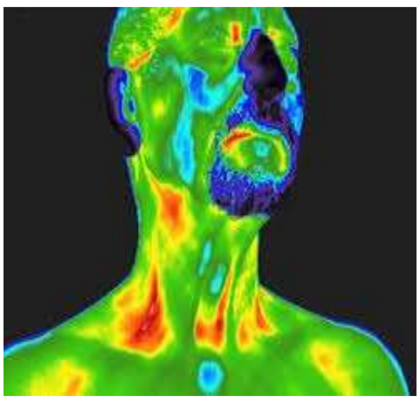



Image # 2	**RGB to ycbcr bands**

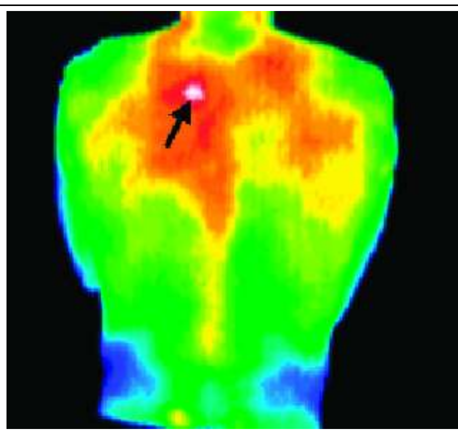
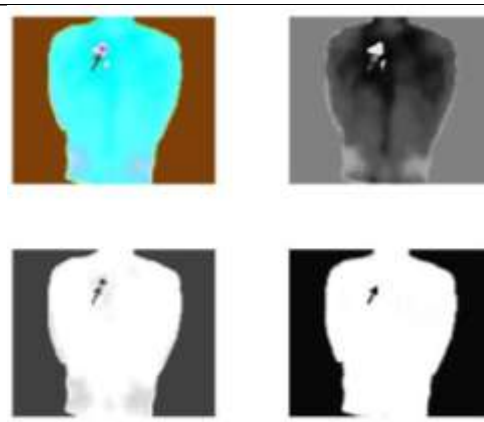
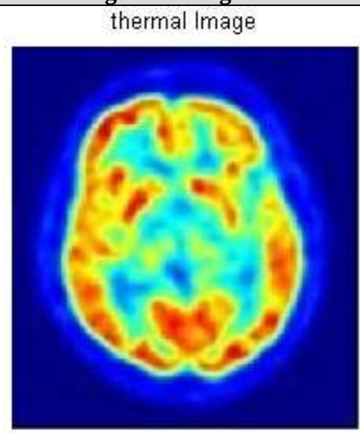
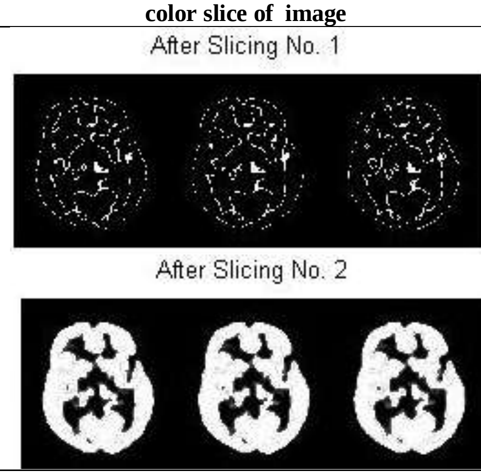
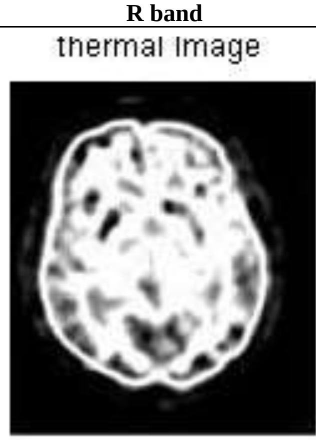
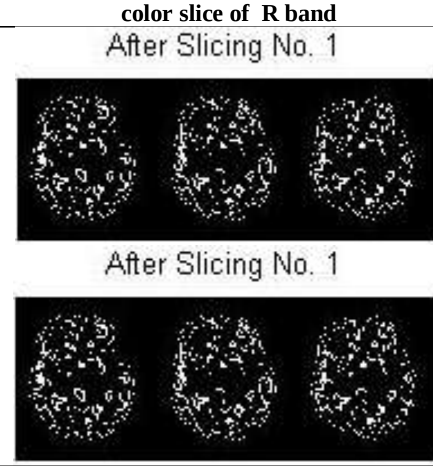

	

Image # 3	**RGB to hsv bands**

6.1 Results for brain Thermal Image

Figure (3) shows the results of segmentation by color slice of RGB bands of human brain Thermal images.

Fig. (3) Segmentation by color slice of RGB bands

Image and Image bands	**Image bands**
	
Original RGB image	**color slice of image**
	
R band	**color slice of R band**
	
G band	**color slice of G band**

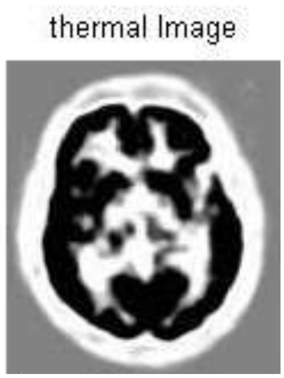
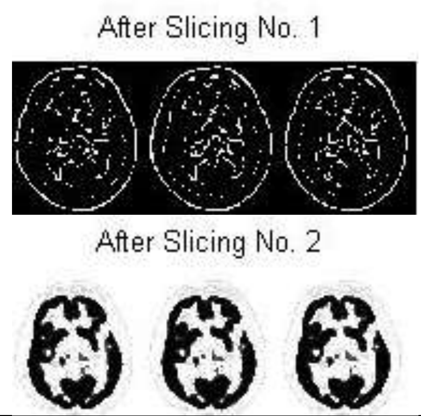
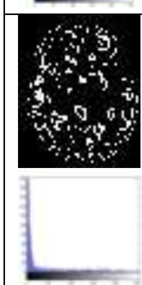
	
B band	**color slice of B band**

Table (1) shows the results of Statistical operations of images in fig. (3), for RGB bands (human brain Thermal images).

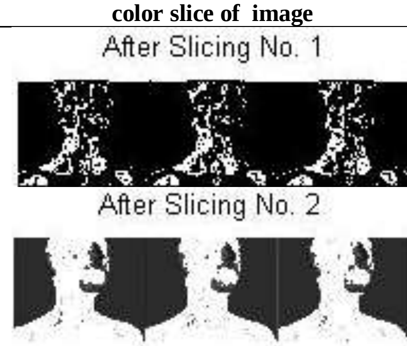
Table (1) Statistical operations of RGB bands

RGB image								
Fig .(3)	**Mean**	**Std.**	**Var. $*10^3$**	**entropy**	**Contrast $*10^7$**	**Correl. $*10^{-15}$**	**Energy $*10^4$**	**Homog. $*10^4$**
	187.54	95.13	9.05	5.82	11.62	5.30	65.6	6.65
	127.54	113.98	12.9	6.05	6.50	1.04	1.44	3.72
	27.99	56.29	3.16	4.85	8.13	6.17	3.19	2.69

	127.78	10.12	12.12	6.51	6.18	-3.78	1.28	0.0010

6.2 Results for face Thermal Image

Figure (4) shows the results of segmentation by color slice of Ycbcr bands of human face Thermal images.

Fig. (4) seg. by color slice of Ycbcr bands	
Image and Image bands	**Image bands**
	
Original image	**color slice of image**
	
Y Band	**color slice of band**

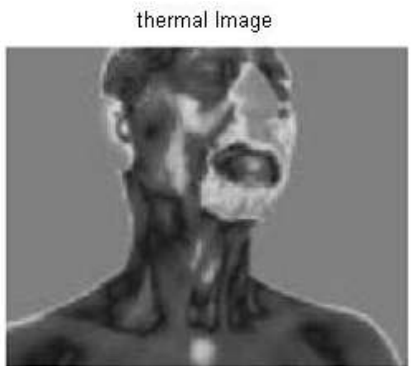
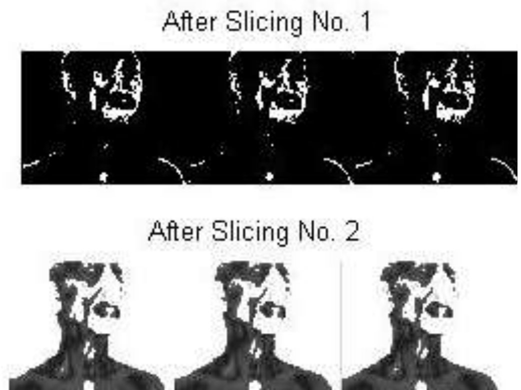
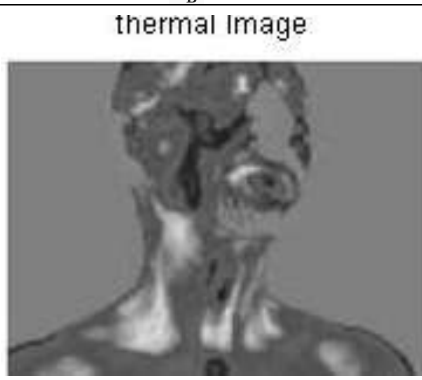
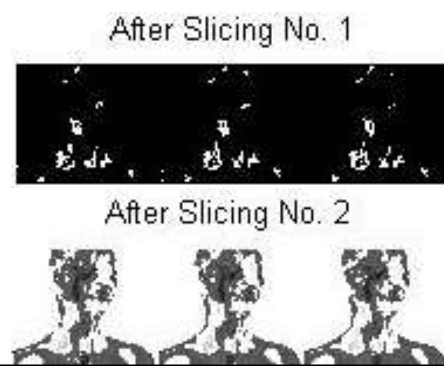
	
C_B **Band**	**color slice of band**
	
C_R **Band**	**color slice of band**

Table (2) Statistical operations of Ycbcr bands

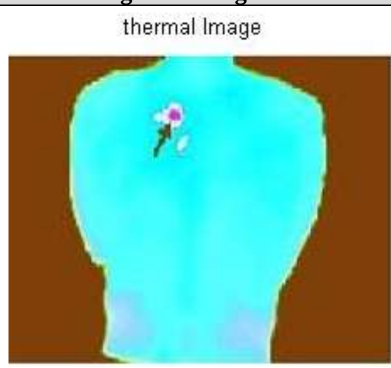
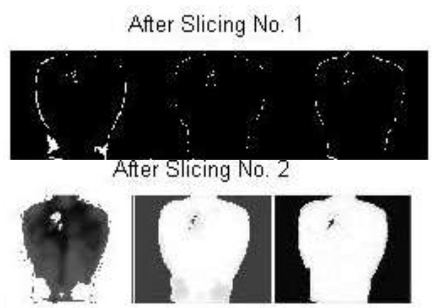
Ycbcr image								
Fig .(4)	**Mean**	**Std.**	**Var. $*10^3$**	**entropy**	**Contrast $*10^7$**	**Correl. $*10^{-15}$**	**Energy $*10^4$**	**Homog. $*10^4$**
	205.51	71.07	5.05	5.43	4.68	NaN	94.1	9.57
	143.55	101.08	1.02	5.27	3.22	3.75	1.49	5.98

	176.21	91.26	8.32	5.29	5.55	-2.98	9.88	9.93
	198.64	74.81	5.59	5.42	5.46	3.90	8.89	9.19

Table (2) shows the results of Statistical operations of images in fig. (4), for Ycbcr bands (human face Thermal images).

6.3 Results for body Thermal Image

Figure (5) shows the results of segmentation by color slice of HSV bands of human body Thermal images.

Fig. (5) segmentation by color slice of HSV bands	
Image and Image bands	**Image bands**
	
Original image	**color slice of image**

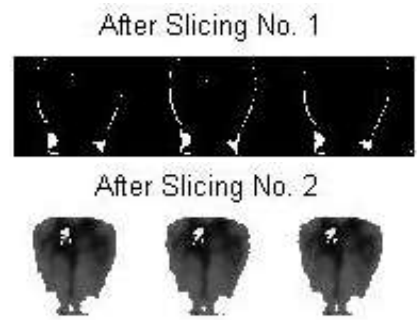
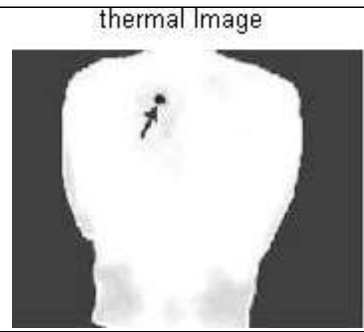
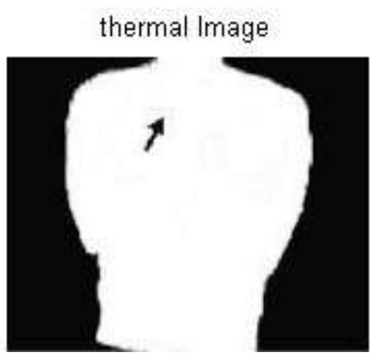
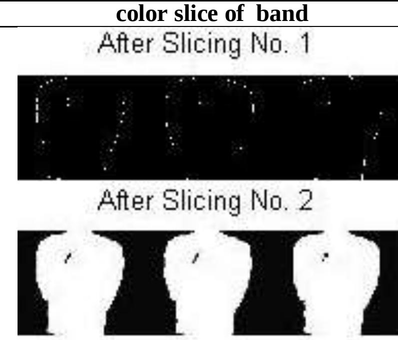
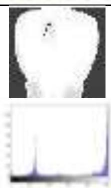
	
H band	**color slice of band**
	
S band	**color slice of band**
	
V band	**color slice of band**

Table (3) shows the results of statistical operations of images in fig. (5), for HSV bands (human body - thermal images).

Table (3) Statistical operations of HSV bands

HSV image								
Fig. (5)	**Mean**	**Std.**	**Var. $*10^3$**	**entropy**	**Contrast $*10^7$**	**Correl. $*10^{-15}$**	**Energy $*10^4$**	**Homog. $*10^4$**
	117.74	87.99	7.74	6.90	1.75	6.83	2.13	0.0022
	108.45	85.70	7.34	6.76	1.22	7.00	2.70	0.0022
	197.64	81.97	6.72	4.93	1.42	7.47	1.76	9.03
	203.01	94.66	8.96	4.11	1.47	1.58	1.80	7.85

5. CONCLUSIONS

We have conducted experiments with a number of different color space including RGB, YCbCr, and HSV in an attempt to find one that would make tumor colored material more visible than its surrounding. HSV works reasonably well, but cannot segment darker regions, and we found that the YCbCr color model works best for selecting the darker part.

The statistical operations show the best results of RGB image and band segmentation of thermal image.

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