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A New Texture Based Segmentation Method to Extract Object from Background

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Abstract - Extraction of object regions from complex background is a hard task and it is an essential part of image segmentation and recognition. Image segmentation denotes a process of dividing an image into different regions. Several segmentation approaches for images have been developed. Image segmentation plays a vital role in image analysis. According to several authors, segmentation terminates when the observer's goal is satisfied. The very first problem of segmentation is that a unique general method still does not exist: depending on the application, algorithm performances vary. This paper studies the insect segmentation in complex background. The segmentation methodology on insect images consists of five steps. Firstly, the original image of RGB space is converted into Lab color space. In the second step 'a' component of Lab color space is extracted. Then segmentation by two-dimension OTSU of automatic threshold in 'a-channel' is performed. Based on the color segmentation result, and the texture differences between the background image and the required object, the object is extracted by the gray level co-occurrence matrix for texture segmentation. The algorithm was tested on dreamstime image database and the results prove to be satisfactory.

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A NEW TEXTURE BASED SEGMENTATION METHOD TO EXTRACT OBJECT FROM BACKGROUND

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A New Texture Based Segmentation Method to Extract Object from Background

M.Joseph Prakash [α] & Dr.V.Vijayakumar [σ]

Abstract - Extraction of object regions from complex background is a hard task and it is an essential part of image segmentation and recognition. Image segmentation denotes a process of dividing an image into different regions. Several segmentation approaches for images have been developed. Image segmentation plays a vital role in image analysis. According to several authors, segmentation terminates when the observer's goal is satisfied. The very first problem of segmentation is that a unique general method still does not exist: depending on the application, algorithm performances vary. This paper studies the insect segmentation in complex background. The segmentation methodology on insect images consists of five steps. Firstly, the original image of RGB space is converted into Lab color space. In the second step 'a' component of Lab color space is extracted. Then segmentation by two-dimension OTSU of automatic threshold in 'a-channel' is performed. Based on the color segmentation result, and the texture differences between the background image and the required object, the object is extracted by the gray level co-occurrence matrix for texture segmentation. The algorithm was tested on dreamstime image database and the results prove to be satisfactory.

Keywords : texture, color, image segmentation, GLCM.

I. Introduction

Color segmentation is an essential, critical, and preliminary process in a lot of vision-based tasks such as object recognition, visual tracking, human– computer interaction (HCI), human–robot interaction (HRI), vision-based robotics, visual surveillance, and so forth, because color is an effective and robust visual cue for characterizing an object from the others. Recently, there has been growing interest in the insect segmentation, which aims at detecting insects in an image.

However, color segmentation is not robust enough to deal with complex environments. Especially, changing illumination condition and complex background containing surfaces or objects with similar colors to a target are the major problems that limit its applications in practical real world. The former changes the characteristics of a color and the latter results in increasing false positive pixels. Generally, it is known that robustness in color segmentation is achieved if a color space efficiently separates chrominance and luminance in a color image and a plausible model of chrominance distribution is used [1]. Such chrominance information may be utilized to locate possible regions of a color in a color space and additional features may be adopted in order to validate the hypothesis. Ruizdel-Solar and Verschae [2] have compensated for their color segmentation methods with additional features to obtain more valuable results robust to brightness variations. However, this approach is not included in a pure research area of color segmentation. Dai and Nakano [3] have enhanced skin regions by converting red–green–blue (RGB) color signals to YIQ representation and using the I component, which includes color components from orange to cyan. Fieguth and Terzopoulos [4] have developed a tracking algorithm by heavily relying on a color cue composed of red (R), green (G), and blue (B) color components. Evaluating each component of several color spaces, Gomez [5] has listed top components and made a hybrid color space from those. In above researches, a color is dependent on the intensity of a pixel [6]. In real world cases, however, it is not always possible to control illumination condition. Therefore, many researches have been carried out for invariant detection of a color under illumination variations. Yang and Waibel [7] proposed color histograms in normalized red–green (RG) chromatic color space [6]. McKenna et al. [8] have proposed, however, Gaussian mixture models for the task, which outperform single Gaussian model. Also, color segmentation algorithms have been proposed in order to obtain the robustness toward changes in illumination and shadows by dropping the intensity. Sobottka and Pitas [10] have used chromatic information in hue–saturation–intensity (HSI) color space together with a best-fit ellipse technique to improve robustness of color segmentation. Tomaz et al. [11] have proposed an algorithm for color segmentation in TSL color space. Moreover, various color models have been proposed by using several color spaces such as YCbCr [12], YUV [13], and CIE Lab [14]. Actually, Phung et al. [15] have ascertained that most color space transformations do not bring the assumed benefits. Especially, Jayaram et al. [28] have verified that the best performance of skin color segmentation was obtained in HSI color space, keeping an intensity component. That is, color segmentation is largely unaffected by the choice of a color space. However, segmentation

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performance degrades when only chrominance channels are used in classification. [28] Cho et al. [29] have proposed a method called an adaptive skin color filter that detects skin color regions in a color image by adaptively adjusting its threshold values. Soriano et al. [30] have demonstrated a chromaticity-based constraint to select training pixels in a scene. In [31], histograms have been dynamically updated, based on feedback from the current color segmentation and prediction of a Markov model to get changing geometric parameters of color distribution and to track those. Adaptive or learning methods for color segmentation dynamically allocated a color through various illumination conditions while those models were adjusted for every image sequences and the adjustment needs heavier computational load to track targets than a static color model. Since there are a number of models for color segmentation as above, Martinkauppi et al. [32] have selected four types of color segmentation and compared their performance each other under significantly changing illumination conditions. Phung et al. [15] have investigated nine different color pixel classification algorithms. It was found for the Bayesian classifier to have higher classification rates than the other tested classifiers.

Generally, color image segmentation approaches can be divided into the following categories: statistical approaches, edge detection approaches, region splitting and merging approaches, methods based on physical reflectance models, methods based on human color perception, and the approaches using fuzzy set theory [33], [34].Histogram thresholding is one of the widely used techniques for monochrome image segmentation [35]. As for color images, the situation is different due to the multifeatures [36]. Since the color information is represented by tristimulus R, G and B or some linear/nonlinear transformation of RGB, representing the histogram of a color image in a three-dimensional (3-D) array and selecting threshold in the histogram is not a trivial job [37]. One way to solve this problem is to develop efficient methods for storing and processing the information of the image in the 3-D color space. [38] used a binary tree to store the 3-D histogram of a color image, where each node of the tree includes RGB values as the key and the number of points whose RGB values are within a range centered by the key value. [39] also utilized the same data structure and similar method to detect clusters in the 3-D normalized color space (X, Y, I). Another way is to project the 3-D space onto a lower dimensional space, such as two-dimensional (2-D) or even one-dimensional (1-D). [40] used projections of 3-D normalized color space (X, Y, I) space onto the 2-D planes (X-Y, X-I, and Y-I) to interactively detect insect infestations in citrus orchards from aerial color infrared photographs. [41] Provided segmentation approaches using 2-D projection of color space. [42] Suggested a multidimensional histogram thresholding scheme using threshold values obtained from three different color spaces (RGB, YIQ, and HSI). This method used a mask for region splitting and the initial mask included all pixels in the image. For any mask, histograms of the nine redundant features (R, G, B, Y, I, Q,H,S, and I) of the masked image are computed, all peaks in these histograms are located, the histogram with the best peak is selected and a threshold is determined to split the masked image into two sub regions for which two new masks are generated for further splitting. This operation is repeated until no mask left unprocessed, which means none of the nine histograms of existing regions can be further thresholded and each region is homogeneous.

This paper proposed a new color texture based image segmentation approach for insect extraction from complex background. In section II, GLCM was discussed. Automatic OTSU threshold was discussed was given in section III. Methodology of the proposed algorithm was presented in section IV. Results & discussions were given in section V. Finally, conclusions were given in section VI.

II. GLCM

Your Gray level co-occurrence matrix (GLCM) has been proven to be a very powerful tool for texture image segmentation [16,17]. The only shortcoming of the GLCM is its computational cost. Such restriction causes impractical implementation for pixel-by-pixel image processing. In the previous works, GLCM computational burden was reduced by two methods, at the computation architecture level and hardware level. D. A. Clausi et. al. restructures the GLCM by introducing a GLCLL (gray level co-occurrence linked list), which discard the zero value in the GLCM [18].This technique gives a good improvement because mostly GLCM is a sparse matrix where most of its values are equal to zeroes. Thus the size of GLCLL is significantly smaller than GLCM. Then the structure of the GLCLL was improved in [19, 20]. Another work is presented in [21] where fast calculation of GLCM texture features relative to a window spanning an image in a raster manner was introduced. This technique was based on the fact that windows relative to adjacent pixels are mostly overlapping, thus the features related to the pixels inside the overlapping windows can be obtained by updating the early calculated values. In January 2007, S. Kiranyaz and M. Gabbouj proposed a novel indexing technique called Hierarchical Cellular Tree (HCT) to handle large data [22]. In his work, it was proved that the proposed technique is able to reduce the GLCM texture features computation burden.

GLCM is a matrix that describes the frequency of one gray level appearing in a specified spatial linear relationship with another gray level within the area of investigation [23]. Here, the co-occurrence matrix is computed based on two parameters, which are the relative distance between the pixel pair d measured in pixel number and their relative orientation φ. Normally, φ is quantized in four directions (00, 450,900 and 1350) [23]. In practice, for each d, the resulting values for the four directions are averaged out. To show how the computation is done, for image I , let m represent the gray level of pixels (x, y) and n represent the gray level of pixels (x±dɸ0, y±dɸ1) with L level of gray tones where 0 ≤ x ≤ M −1, 0 ≤ y ≤ N −1 and 0 ≤ m, n ≤ L −1. From these representations, the gray level co-occurrence matrix Cm, n for distance d and direction ɸ can be defined as.

$$C_{m,n,\emptyset} = \sum_x \sum_y P\{I(x,y) = m \& I(x \pm d\emptyset_0, y \mp d\emptyset_1) = n\} \quad (1)$$

Where P{.} =1 if the argument is true and otherwise, P {.} =0. For each ɸ value, its ɸ0and ɸ1 values are referred as in the Table 1.

Table 1 : Orientation constant

ϕ	ϕ_0	ϕ_1
0^0	0	1
45^0	-1	-1
90^0	1	0
135^0	1	-1

In the classical paper [24], Haralick et. al introduced fourteen textural features from the GLCM and then in [25] stated that only six of the textural features are considered to be the most relevant. Those textural features are Energy, Entropy, Contrast, Variance, Correlation and Inverse Difference Moment. Energy is also called Angular Second Moment (ASM) where it measures textural uniformity [23]. If an image is completely homogeneous, its energy will be maximum. Entropy is a measure, which is inversely correlated to energy. It measures the disorder or randomness of an image [23]. Next, contrast is a measure of local gray level variation of an image. This parameter takes low value for a smooth image and high value for a coarse image. On the other hand, inverse difference moment is a measure that takes a high value for a low contrast image. Thus, the parameter is more sensitive to the presence of the GLCM elements, which are nearer to the symmetry line C (m, m) [23]. Variance as the fifth parameter is a measure that is similar to the first order statistical variables called standard deviation [26]. The last parameter, correlation, measures the linear dependency among neighboring pixels. It gives a measure of abrupt pixel transitions in the image [27].

III. Otsu Thresholding

This method, as proposed by [25] is based on discriminate analysis. The threshold operation is regarded as the partitioning of the pixels of an image into two classes C0 and C1 (e.g., objects and background) at grey-level t, i.e., C0 = {0, 1, 2, t} and C1 = {t + 1, t +2,….L-1}. Let σ2w, σ2B and σ2T be the within-class variance, between-class variance, and the

$$\lambda = \frac{\sigma_B^2}{\sigma_W^2}, \eta = \frac{\sigma_B^2}{\sigma_T^2}, \kappa = \frac{\sigma_T^2}{\sigma_W^2} \quad (2)$$

The optimal threshold t is defined as

$$t = \text{ArgMin } \eta \quad (3)$$

$$\sigma_T^2 = \sum_{i=0}^{L-1} [1-\mu_T]^2 P_i, \qquad \mu_T = \sum_{i=0}^{L-1} [iP_i] \quad (4)$$

$$\sigma_B^2 = W_0 W_1 (\mu_0 \mu_1)^2 \quad (5)$$

$$W_0 = \sum_{i=0}^{t} P_i, \qquad W_1 = 1 - W_0 \quad (6)$$

$$\mu_1 = \frac{\mu_T - \mu_t}{1-\mu_0}, \mu_1 = \frac{\mu_t}{W_0}, \mu_t = \sum_{i=0}^{t} (iP_i) \quad (7)$$

$$P_i = \frac{n_i}{n} \quad (8)$$

$$n = \sum_{i=0}^{L-1} n_i \quad (9)$$

Where ni is the number of pixels with grey-level and n is the total number of pixels in a given image defined as total variance, respectively. An optimal threshold can be determined by minimizing one of the following (equivalent) criterion functions with respect to:

Moreover, Pi is the probability of occurrence of grey-level i. For a selected threshold ‘t’ of a given image, the class probabilities w0 and w1 indicate the portions of the areas occupied by the classes C0 and C1. The class means $\mu 0$ and $\mu 1$ serve as estimates of the mean levels of the classes in the original grey-level image. Moreover, the maximum value of η , denoted by η*, can be used as a measure to evaluate the separability of classes C0 and C1 in the original image or the bimodality of the histogram. This is a very significant measure because it is invariant under affine transformations of the grey-level scale. It is uniquely determined within the range 0≤ η≤1.The lower bound (zero) is obtained when and only when a given image has a single constant grey level, and the upper bound (unity) is obtained when and only when two-valued images are given.

IV. Methodology

In the first step RGB image is converted to 1976 CIE LUV color space. This color space is approximately perceptually uniform. The perceptual non-uniformity of this color space greatly improves over the CIE XYZ color space. In CIE LUV color space, L^* specifies brightness of colors on a scale from 0 to 100, u^* specifies color location approximately along the red-green axis with grey located at 0 and v^* specifies color location approximately along the yellow-blue axis with grey located at 0.The color corresponding to $u^*=v^*=L^*=0$ is black and $u^*=v^*=0$, $L^*=100$ is white.

Each color space has its own appear background and application region. When segmenting a color image, the selection of color space plays a decisive role on the segmentation results. The common color spaces used in color image processing include RGB color space, HSI color space, CIE color space, and so on. At present, the general color digital images are RGB format. RGB color space is based on the theory of three-basic color to build. RGB format is the most basic color space. Other color space models can be obtained through the RGB format conversion. But the RGB color space is not a homogeneous visual perception space, it is not conducive to image segmentation based on color feature. HSI color space uses color characteristics of a direct sense of the three quantities: the brightness or lightness (I), hue (H), saturation (S) to describe the color. This method is more in line with the human eye habits to the description of the color, but the expressed colors are incomplete visual perceived color.

One problem with the CIEXYZ colour model is its lack of perceptual balance. Colours which are the same distance from one another are not necessarily perceptually equidistant. In 1976, the CIE proposed the CIE LUV colour model to address this problem. CIELUV is a perceptually uniform colour space. This means that distance and difference can be interchanged as required. If colours A and B are twice as far apart as colours C and D, then the perceived difference between A and B is roughly twice the perceived difference between C and D. The equations for computing CIE LUV assume you have (X, Y,Z) of the colour to convert, and (Xw,Yw, Zw) of a standard white. Given these values, the corresponding LUV colour is:

$$L^*=116(Y/Yw)1/3-16,(Y/Yw)>0.01 \quad (10)$$

$$u^*=13L^*(u'-u'w) \quad (11)$$

$$v^*=13L^*(v'-v'w) \quad (12)$$

$$u'=(4X)/(X+15Y+3Z) \quad (13)$$

$$v'=(9Y)/(X+15Y+3Z) \quad (14)$$

$$u'w=0.2009,\ v'w=0.4610 \quad (15)$$

L^* encodes the luminance or intensity of a given colour, while u' and v' control its chromaticity.

The 'v' component is extracted from the transformed LUV color space in the second step. In the third step the extracted v- component is subjected to OTSU thresholding. The two-dimensional OTSU algorithm automatically selects the optimal threshold for segmentation. Because two-dimensional OTSU algorithm not only takes into account the grayscale information of pixels, but also considers the space-related information of pixels and their neighborhoods. GLCM is obtained for the otsu thresholded image. For each image and with distance set to one, four GLCMs having directions 0°, 45°, 90° and 135° are generated. The co-occurrence matrix is often correlated with the directions. It is necessary to select more than one direction of gray level co-occurrence matrix for a comprehensive statistical processing. The synthetic gray level co-occurrence matrix of an image can be got by averaging the values of energy matrices in 0 degree, 45 degree, 90 degree and 135 degree.

In the fifth step, image negative is applied for better enhancement of insect region. In the last step, morphological closing operation is performed in order to fill small holes. A hole is defined as an area of dark pixels surrounded by lighter pixels or may be defined as a background region surrounded by a connected border of foreground pixels. This process can be used to make objects in an image seem disappear as they are replaced with values that blend in with the background area. This function is useful for image editing, including removal of extraneous details or artifacts.

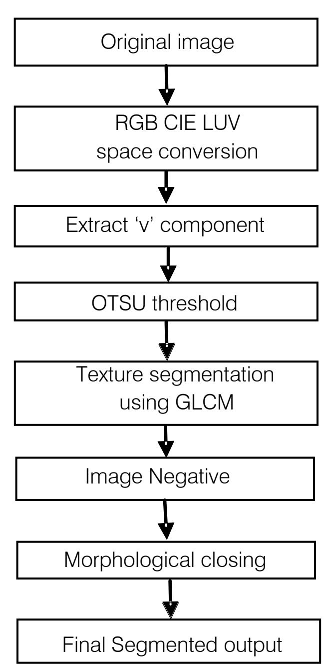


Fig. 1 : Flowchart of proposed algorithm

V. Results

The proposed algorithm is tested on dreamstime image database. In this paper step wise results of insect images are shown in Figs.2-4. The results in Figs.2-4 clearly show the extraction of insect from the background. The results clearly indicate that the green and yellow backgrounds in the images are converted to black Otsu threshold is applied for enhancing the 'v' component output. The Figs.2-4 (d) show that the object is smoothened after texture segmentation. The Figs.2-4 (f) clearly show that morphological closing step is applied to fill small gaps in the object for obtaining the final segmented insect region.

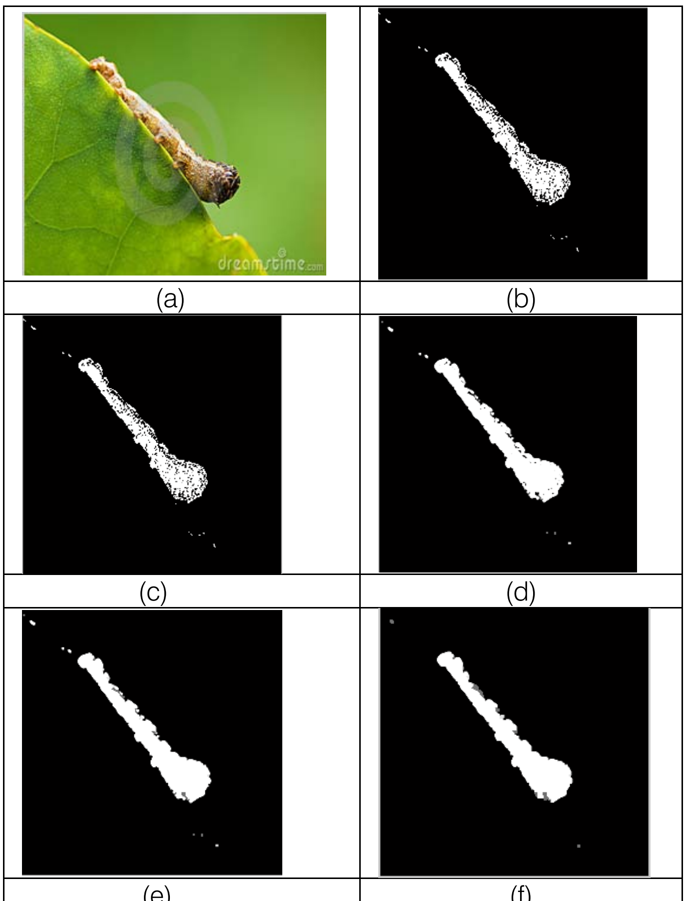


Fig. 2 : Step wise results of the proposed algorithm for insect extraction

(a) Original image (b) 'v' component
(c) OTSU thresholded (d) GLCM output
(e) negative (f) final output

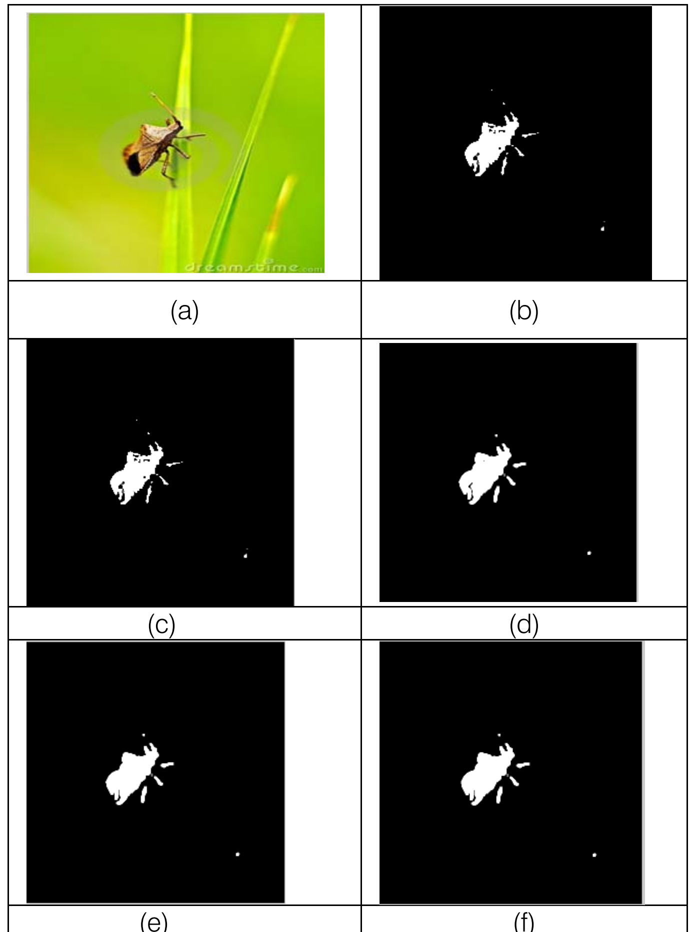
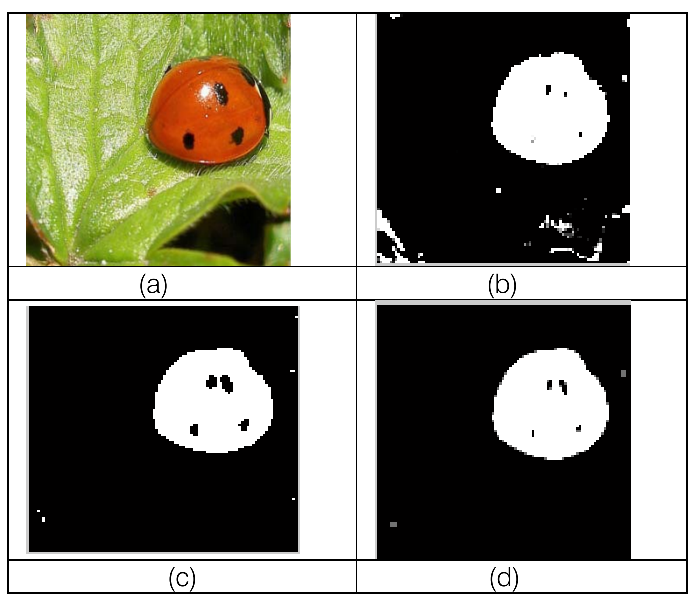
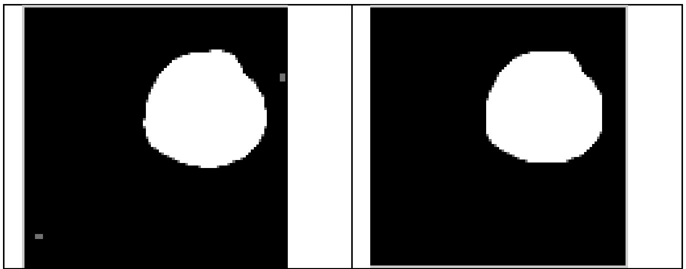


Fig. 3 : Step wise results of the proposed algorithm for insect extraction

(a) Original image (b) 'v' component
(c) OTSU thresholded (d) GLCM output
(e) negative (f) final output





(e) (f)

Fig. 4 : Step wise results of the proposed algorithm for insect extraction

(a) Original image (b) 'v' component
(c) OTSU thresholded (d) GLCM output
(e) negative (f) final output

VI. Conclusion

The information which the commonly used grayscale images contain is not enough for insect segmentation. The images consisting of insects when collected in nature, the background is generally more complex and more close to the target color, so there are some limitations in these conditions if we only use gray level information. However, the color images are able to provide more information. There are colors and color depth information, in addition to its provision of brightness and color images can be expressed by a variety of color space. Therefore, segmentation based on color image can overcome some shortcomings of gray-scale image. In this algorithm both color and texture features are considered. In this method, segmentation speed is faster and without human participation, the segmentation result is also deal. The results show the efficiency of the above algorithm.

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