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Color Image Segmentation

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***Abstract* - Image segmentation is a field Relevant research in image processing. Many advanced algorithms have been developed to separate a region of interest in a color image of its background (snakes, live-wire, among others). However, the results obtained are not satisfactory in many cases. More accurate methods are based on representing the image as a graph and separate it into two sub-graphs that represent the region of interest (foreground) and background. The GrabCut algorithm belongs to this category. In this work we present the functional theoretical data and detailed implementation of the Grabcut algorithm with some improvements not presented in its original version. In particular, the calculations of the N-Link, T Link and minimum cut-off were modified. These changes allow better results in the pixels of the border between the foreground and background as well as speed up the minimum cut algorithm. Our implementation shows good results for test images used.**

***Index Terms* - Image segmentation, Grabcut, Maximum flow, minimum shear, Gaussian mixed models.**

I.INTRODUCTION

Color Image Segmentation is the term that is used in many computer-based applications that is Adobe Photoshop, MATLAB and others. In Photoshop different tools are used for digital image segmentation purpose. It is the simple application in which the images segmented in different parts like Layers and magic wand tool are used in this. The MATLAB is also the computer-based application in which we edit the digital images. But the in this software we do many things by using an algorithm. In which we also used Algorithm for doing segmentation. The many models are also used in MATLAB software like RGB Model, CMYK Model for color segmentation. The many authors are also used these models and also update models in his Research papers.

We also work on Segmentation model for developing another algorithm to do better outputs.

The treatment and use of digital images in the field of photography has evolved so accelerated. The transition from analog cameras to digital cameras has allowed photographs to be represented and treated in a digital format of simple and efficient way. This has allowed digital images are used for a large number of applications, creating an interest in the public in general who want to integrate technologies more into their daily Homeworks.

In recent years, the use of Segmentation has been an area of extensive study by the scientific community. Segmentation consists of identify and extract areas of interest within an image generation. There are various segmentation tools that can be very useful for various applications, example. Vehicle detection in security cameras, extraction of objects in photographs for special effects specials in film and television, etc. However, the segmentation-Image implantation is not a simple problem anymore that techniques can work very well for a specific application and will not give the most suitable results squares for another.

This paper gives the review study of GrabCut algorithm by using color image T-LINK, Gaussian Model, N-LINK.

II. SEGMENTATION WITH GRABCUT

GrabCut is a technique for image segmentation generates where little user intervention is required. Initially the user must select a box around the object of interest and then segmentation is performed automatically. Subsequently, the user can select certain areas of the image manually to improve the result obtained.

The technique consists of creating a network flow graph [11] from the image to be segmented, where for each pixel a node is generated that represents it in the graph. Then, each node connects to its 8 close neighbors through of undirected arcs which are called N-Link.

Additionally, 2 special nodes are required in the flow graph: source and destination. The source node represents the object to segment in the image (foreground), and the distance represents the background of the image (background). Each one of the nodes of the graph is connected through an arc with the source and with the destination, these arches are called T-Link. The weight of the arches is calculated using a potential energy function based on mixed models Gaussians (Gaussian Mixture Models - GMM) [12], one for the foreground and another for the background. Each GMM is formed by 5 Gaussian components.

III. GAUSSIAN MIXED MODEL

In statistics, when a set of values is plotted res is always about comparing the generated graph with some known distribution [15]. However, in certain cases it is not possible to make such a comparison. The same time, it is desirable to calculate the density function of probability generated by said graph. To do this, a mixed model, where the initial graph is divided in two or more components, each one resembling a known probability density function. Then the probability is calculated as the sum of the probabilities of the density functions of each of these components' speakers, called Gaussian components.

In a Gaussian mixed model (Gaussian Mixture Model-GMM), the initial probability function is divided into Gaussian components. In this work 5 components, as proposed by Rother et al. [3]. Dice Since each pixel in color images is RGB, the gauges generated are multivariate [16]. Therefore, calculate various values to obtain the value of the component: the covariance matrix, its inverse and determinant. At the same time, for the calculation and division of the components Gaussian it is necessary to obtain the eigenvalues and eigenvectors of the covariance matrix [17]. Chuang et al. [12] present the mechanism of creation and initialize the GMMs and their components. First i know creates a component to the GMM where all the pixels belonging to it. In our proposal, all pixels with matte foreground value are added to GMM foreground. After the calculation of the mean is performed, the component weight, covariance matrix, inverse.

Color image segmentation based on the GRABCUT algorithm of the matrix, the determinant, the eigenvalues, and eigenvectors component. In the calculation of the variables of each component of a pixel m, a three-component vector is stored as follows: (4) Where R, G and B represent the intensities of red, green, and blue respectively of pixel m. For example, a pixel m with maximum intensity of red color, with 1 byte per channel, it is represented as (5) The mean v of a component of the GMM is calculated adding the pixels added to it (sum of vectors) and then dividing the result by the number of Added pixels (scalar multiplication x vector). By For example, given 3 pixels m, n and o to a component with the following values (6) The value of the mean v is calculated as: (7) On the other hand, the covariance (X, Y) between two variables X, Y is a measure that allows studying their relationship quantitative. The covariance matrix allows to store the covariance of all possible combinations of a set of random variables. In our proposal, create 3 random variables, representing the channels RGB of the pixels. The covariance matrix is defined as: (8) Since (X, Y) = (Y, X) the covariance matrix is defined as a symmetric matrix. The covariance of two random variables (X, Y) is defined as: (9) Where E (X) represents the value of the expectation of X, expressed as: (10) where N represents the number of samples and X I the value of the sample i. In the case of a Gaussian component in the second with GrabCut, N indicates the number of pixels added to the component. In the same way, the E (X, Y) is defined as: (eleven) Replacing Equation 10 and 11 in Equation 9, the value of (X, Y) is obtained as: (12) After constructing the matrix exposed in Equation 8, the inverse, the determinant, the eigenvalues, and eigenvectors. Due to the complexity of the calculation and of eigenvalues and eigenvectors, the functions offered by the Open CV library [18].

The next step of the algorithm is to divide this first component in two, using the eigenvectors, selecting a dividing point P. Then, the pixels that will be added to the new component, and those that will remain in the original component. Point P is calculated as: (13) where v (i) represents the mean of component i, symbolizes the first eigenvector of component i. The operation represents the dot product or dot product between two vectors. Then, for each pixel m, being a vector of 3 com- RGB speakers, their weight is calculated m p: (14) If m p > P then the pixel m is added to the new component, if not added to the component being is dividing. After that, the mean is calculated again, the weight and the covariance matrix for the components. I know selects the largest of the eigenvalues of the co- variance of each component and the component with higher eigenvalue. This component is divided and is used your eigenvector to apply Equation 14 again. East process is repeated until the number of components is reached desired, ie 5 components. According to the diagram shown in Fig. 4 once calculated Once the value of the GMMs, step 4 must be applied. To do this, for each pixel in the image, it is calculated which is the component of the GMM it belongs to, to which it is more likely to belong. For example, for a pixel m with matte foreground value the probability P (m, i) is calculated that it belongs to the i-th components of the GMM fore- ground. Then the number of the component that corresponds to the highest probability obtained. Talbot and [14] propose an implementation of the algorithm GrabCut rhythm introducing an improvement in the calculation of the probability P (m, i) that a pixel m belongs to the component i. In this work, this calculation is rewritten as: (fifteen) In Equation 16, the value of α m represents the GMM current, that is, to obtain P (m, i) of a pixel m with matte foreground the value of α m refers to the GMM foreground. Likewise, for a pixel m with matte background, the variable α m represents the GMM background. The value of π (α m, i) equals the weight of component i in the GMM α m. This value is obtained by dividing the number of pixels eles added to component i between the number of pixels aggregated to GMM α m. The value of symbolizes the covariance matrix (see Equation 8) of component i in the GMM α m. Finally, v (α m, i) is a vector with the mean of the component i of GMM α m and you get as shown in Equation 7. After having calculated the most probable component to which a pixel m belongs, the components are re-initialized of both GMMs (covariance matrix, mean, etc.) and each pixel is assigned to the component of its GMM that it obtained the highest probability of belonging to it. Once the way to calculate the value is known of a GMM, it is possible to assign the values of the T-Links.

IV. CALCULATION OF THE N-LINKS

The calculation of the N-Link value for a pixel m and a pixel n (nodes of the graph) is performed using Equation 1 proposed by Mortensen and Barrett [7]: (one) where (m, n) represents the distance between two points and is used so that the diagonal pixels have the same importance than adjacent pixels. On the other hand, || mn || is the Euclidean distance in color space calculated as: (two) Where R m, G m, B m represent the values in the channels red, green, and blue respectively for pixel m. the same reasoning is used for the values of R n, G n, B n. The value of β represents a constant that ensures the ex-presence of different contrast values. Boykov and Jolly [2] suggest using. In this work presents a variation of the calculation of β expressed as: (3) The value of P represents the number of pixels in the image and V the number of neighbors of a pixel (V = 8 , exception- when the edges). Note that for contiguous pixels with similar colors large values will be obtained, and for very different colors small values will be obtained. This factor directly influences specifically in executing the minimum cutoff algorithm in a flow graph. The cut will be made by the N-Links that connect pixels with different colors that represent possible edges.

V. CALCULATION OF THE T-LINKS

There are two types of T-Links: T fore, which connects to a pixel with the foreground and T back that connects it to the background. A Once a pixel m is selected as the trimap foreground, it is ensuring that the minimum cut of the graph does not disconnect this foreground node. The value of T fore from said pixel takes a value of K that represents the greatest possible weight that may exist in the graph. Similarly, the value of T back is 0. The same situation occurs (but in reverse) if the pixel is trimap background .A pixel has the value of trimap unknown , when T fore Y T back they are assigned P fore (m) and P back (m) respectively, where P fore (m) is the probability that pixel m belongs to the GMM foreground and P back (m) the probability that it belongs to the GMM background .The probability P (m) of pixel m is given by:(16)Once the graph with the values of N-Links is built and T-Links for each pixel, the minimum cut is applied with the goal of separating the graph into two disjoint regions. This procedure is explained in detail below.

VI. MINIMUM CUT OF GRAPH

Let a graph G defined as G = (V, A) , where V is a set of nodes and A set of arcs that relate these nodes. A weighted graph is that in which each arch is assigned a weight or cost. TO From this point on, it is assumed that all graphs mentioned are weighted. Cutting a graph consists of eliminating arcs up to that there are two disjoint graphs. The cutting weight of a graph consists of the sum of the weights of the arcs removed to get the cut. The minimum cut of a graph (min-cut) is the cut that has the minimum weight, among all those possible in the graph. As described in [11], to obtain the cut minimum of the graph, the flow algorithm must be executed maximum (max-flow), where the arcs that are saturated (arches with weight 0) by max-flow are the arches that are removed to achieve the minimum cut. With the in order to understand the peak flow algorithm, below Below is a description of the concept of flow graphs and then Ford-Fulkerson algorithm employed in this job.

VII. LITERATURE SURVEY

Image segmentation seeks to separate or group an image into different parts or sections. The simplest form of segmentation is the basic technique. Thresholding. A threshold is a value defined where for each pixel of the image, a comparison. If the pixel is below the threshold then the pixel is marked as background otherwise it is marked as foreground. The technique thresholding is very basic and works fine for simple segmentations. Many graphics packages provide mechanisms for segmentation based on a threshold. An example of them is the magic wand tool (magic wand), including in Photoshop [6], which allows you to select one or more seed pixels and assign a tolerance level. Thus, the segmentation is done by comparing all pixels with the tolerance level. Using this tool, it is easy for the user.

However, on some occasions it is required of more advanced techniques that allow a more precise segmentation. Among these techniques, find the so-called Magnetic Loop or Live-Wire, which uses dynamic programming to solve a search problem in a 2D graph to find the edges of a region. In this technique, the pixels of the image are represented as nodes of a graph, and there are weighted arcs that are defined based on to a cost function. The goal is to get the way minimum cost between an initial node and a final node.

Mortensen and Barrett [1] developed a basic approach in Live-Wire creating an interactive tool called Intelligent Scissors. When a user moves the mouse near the edge in an image, the lasso automatically adjusts to it. The algorithm optimally selects the closest edge.

Boykov and Jolly [2] introduce a technique called GraphCut, where the image is represented as a graph and a minimum cut-off / maximum flow algorithm is used to divide the graph. First, the pixels are nodes of the graph and arcs are weighted defining a function of cost which has information of the edges. Then, a minimum cutoff / maximum flow algorithm is used to segment the image by a minimize function. Is technique is well defined and provides optimal solutions.

Based on the work of Boykov and Jolly [2],

Rother et al. [3] present a novel approach to separate the foreground of the background in an image: GrabCut.

In a recent thoroughly research [4], we present a review of the construction-based segmentation algorithms image-based graphs, for more detail. near. Later, Mortensen and Barrett develop an improved version of the Smart Scissors, another advanced technique for segmentation It is based on energy minimization. The most Known of this classification is the snake. A snake is a spline that minimizes energy guided by conditions of internal external forces and influenced by the force of the edges of the image, who moves it to the lines and edges.

The classic snake implementation was proposed by Kass et al. [5], which reduce the problem to a matrix form. This work gave rise to the beginning of various algorithms based on energy functions.

Using graphs to solve minimization problems of energy became relevant thanks to Boykov's work and Kolmogorov [6]. Various problems were reformulated to be solved as a minimization problem of energy, instead of the conventional way using dynamic programming.

[7] Recently, it has been used techniques based on cutting the graph for this, and in many of them the graph was built especially for solve the energy minimization problem.

Paper [1] presents classification and detection techniques that can be used for plant leaf disease classification. Here preprocess is done before feature extraction. RGB images are converted into white and then converted into grey level image to extract the image of vein from each leaf. Then basic

Morphological functions are applied on the image. Then the image is converted into binary image. After that if binary pixel value is 0 its converted to corresponding RGB image value. Finally, by using person correlation and Dominating feature set and Naïve Bayesian classifier disease is detected.

In paper [20 there are four steps. Out of them the first one is gathering image from several part of the country for training and testing. Second part is applying Gaussian filter is used to remove all the noise and thresholding is done to get all green color component. K-means clustering is used for segmentation. All RGB images are converted into HSV for extracting feature.

The paper [3] presents the technique of detecting jute plant disease using image processing. Image is captured and then it is realized to match the size of the image to be stored in the database. Then the image is enhanced in quality and noises are removed. Hue based segmentation is applied on the image with customized thresholding formula. Then the image is converted into HSV from RGB as it helps extracting region of interest. This approach proposed can significantly support detecting stem-oriented diseases for jute plant.

According to paper [4] they have proposed for a technique that can be used for detecting paddy plant disease by comparing it with 100 healthy images and 100 sample of disease1 and another 100 sample of disease2. It's not sufficient enough to detect disease or classify it training data is not linearly separable.

In paper [5] detection of unhealthy plant leaves includes some steps are RGB image acquisition. Converting the input image from RGB to HSI format. Masking and removing the green pixels. Segment the components using Ostu's method. Computing the texture features using color-co-occurrence methodology and finally classifying the disease using Genetic Algorithm.

Paper [6] includes tomato disease detection using computer vision. A gray scale image is turned into binary image depending on threshold value. The threshold algorithm is used for image segmentation. The threshold values are given color indices like red, green, blue. But the thresholding is not a reliable method as this technique only distinguishes red tomatoes from other colors. It becomes difficult to distinguish ripe and unripe tomatoes. For this K-means clustering algorithm is used to overcome the drawbacks. K-means create a particular number of non-hierarchical clusters. This method is numerical, unsupervised, non-deterministic and iterative. Then separating the infected parts from the leaf, the RGB image was converted into YcbCr to enhance the feature of the image. The final step is the calculation of the percentage of infection and distinguishing the ripe and unripe tomatoes.

The methodology for cucumber disease detection is presented in paper [7]. The methodology includes image acquisition, image preprocessing, feature extraction with Gray level co-occurrence matrix (GLCM) and finally classified with two types: Unsupervised classification and supervised classification.

Paddy plant is an important plant in continental region. In paper [8] RGB images are converted into gray scale image using color conversion. Various enhancement techniques like histogram equalization and contrast adjustment are used for image quality enhancement. Different types of classification features like SVM, ANN, FUZZY classification is used here. Feature extract6ion uses different types of feature values like texture feature, structure feature and geometric feature. By using ANN and FUZZY classification, it can identify the disease of the paddy plant.

In paper [9] popular methods have been utilizes machine learning, image processing and classification based approaches to identify and detect the disease of agricultural product.

In paper [10] image processing technique are used to detect the citrus leaf disease. This system includes: Image preprocessing, segmentation of the leaf using K-means clustering to determine the diseased areas, feature extraction and classification of disease. Uses Gray-Level Co-Occurrence matrix (GLCM) for feature extraction and classification is done using support vector machine (SVM).

VIII. CONCLUSION

In this work a modification of the GrabCut technique for image segmentation is presented in order to obtain better results. The improvements can be observed in the modification of the calculation of the N-Links and T-Links, which is based on the calculation of the GMMs for the foreground and background, with 5 components each. Our algorithm provides several advantages compared to the original version presented by Rother et al. [3]. First, it allows to obtain a better association of the value of the N-Links in the graph due to the function used. Likewise, the calculation of the T-Links with 5 Gaussian components is considered adequate to obtain a good grouping of the pixels. Finally, the minimum cut algorithm was efficiently implemented in the chosen programming language.

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The above contents and survey we mentioned is true to my knowledge.

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