Hierarchical Image Segmentation Algorithm in Depth Image Processing

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***Abstract*—Because the traditional iterative graph cut algorithm is time consuming and low in segmentation accuracy, I proposes the method of iterative graph cut to segment images, by analyzing the basic theory of image segmentation, I introduces the balance factor to balance the degree of importance between color texture and depth. Finally it passes detailed experimental simulation, the experiment shows that the result of hierarchical iterative graph cut based on depth image is better than iterative graph cut, while time it takes is much shorter, thus it can segment depth images more effectively.**

***Index Terms*—Image Segmentation, Histogram, Hierarchical Algorithm, Energy Function**

I. INTRODUCTION

As the basis of image understanding and recognition, the image segmentation is very important in computer vision, but because of the complexity of the image, there is no a universal segmentation algorithm which can solve all the problems, even so there are limitless scholars devoting themselves to the research of image segmentation. The researches of the past several decades have made great progress in the image segmentation [1].

Among the past image segmentation algorithms, there are segmentation based on the regional color information and segmentation based on the edge information, but there is limited information, all can not reach ideal segmentation result.

The algorithm based on image segmentation becomes a hot point in research recently as it combines regional color and edge information skillfully, the application of graph cut algorithm in image was finished by Greig and others in 1989, the subsequent research was applied to the binary image, but it did not get much attention until Boykov and others made the definition of the application of graph cut in image and determined the weight, and they proposed a more effective algorithm to solve the maximum flow on the basis of the maximum flow algorithm based on the augmenting path algorithm, their innovative work triggered another graph cut hot, the algorithms based on the graph cut emerged in endlessly [2-6].

Rother and other scholars used iterative graph cut algorithm to reduce the user interaction, an accurate segmentation result can be gotten by three or four times iterations. Because it is time consuming, the subsequent studies based on iterative graph cut usually improves its segmentation speed on the premise of no reduction in the segmentation accuracy, which has achieved a better result, combining the shortcomings of over-segmentation of watershed algorithm with the time consuming of graph cut, the result of the watershed algorithm is taken as the super-pixel of the graph cut, which makes up the disadvantages of two algorithms well [7]. Combining the multi-scale pyramid structure to reduce the data size of Gaussian mixture EM algorithm of graph cut algorithm, adopting the structure of three to four layers, which is close the step number of iterative algorithm by Rother and others, on the condition of reducing the initialization time, it does not reduce the final segmentation accuracy [8-12]. But it uses the highest pixel value to extract the pixel in the upper layer of the pyramid, which is bad for removing the noise. The other branch of the application of graph cut algorithm in image is to add to the shape prior, the segmentation boundary is not only the maximum gradient but also suitable for the restraint of the shape prior, like Kolmogorov and others did, but because its energy function can not meet the requirements of solving the global optimal solution, so it needs other similar method to solve the boundary of segmentation image, but it is always time consuming [12-15]. This paper adopts layered pyramid model on the basis of the predecessors, the corresponding under layer pixel mid-value is used to extract the upper layer pixel, which can solve the noise effectively. The utilization of depth information introduces the balance factor to determine the the degree of importance of the wanted depth information relative to the color information rather than combine directly like Boykov and others, the depth information modeling adopts histogram modeling, the introduction of histogram is to calculate the balance factor easily, and the depth information is one-dimensional information, histogram modeling is very fast [16, 17]. The result of hierarchical iterative graph cut method based on depth image of this paper is superior to the iterative graph cut, while the time it takes is shorter.

This paper mainly does developing and innovative work in the following aspects:

Because the traditional iterative graph cut algorithm is time consuming and low in segmentation accuracy, on the basis of analyzing the image segmentation theory fully, this paper uses the balance factor to determine the degree of importance of the wanted depth information relative to the color information, adopts the histogram to calculate

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the balance factor, proposes the hierarchical iterative graph cut method based on depth image creatively, and improves this algorithm.

In order to further test the correctness and validity of hierarchical iterative graph cut method, by detailed experimental simulation, the experiment shows that the result of hierarchical iterative graph cut based on depth image is better than iterative graph cut, while time it takes is much shorter, thus it can segment depth images more effectively.

II. Improvement of Graph Cut Theory

A. Energy Function

The application of graph cut theory in image processing requires interactive image segmentation, the interactive image segmentation gives the prior information of the object which the user wants to divide, and the prior information can always increase the accuracy and reduce the difficulty of image segmentation. Users give some pixels as the wanted segmentation object, some as the background of the image; all of those are regard as the prior information of the image segmentation, i.e the hard constraint. The other pixels are segmented automatically, and then solve the optimal segmentation which suits for the hard constraint.

First define segmentation as the segmentation boundary of a image, to solve the optimal segmentation, define the penalty function which is also called energy function, the optimal segmentation corresponds to the minimum of the energy function. The energy function can be divided to two parts, one is called boundary term, representing the edge information of the segmentation, the other is called regional term, representing the regional information of the segmentation, these two terms correspond to the soft constraint and the hard constraint of the image at the same time. Hard constraint is the prior information which has been given by the user; soft constraint is introduced to ensure the smoothness of the same background or neighboring pixels of the same background.

Assume that an image is expressed in mathematic as: $O_i = (i = 1...N), O_i$ represents the ith pixel of the image, pixels arrange according to the line of the image, N represents the number of the pixel in the image. Make l_i as the corresponding tag of the i_{th} pixel, the value range of l_i is $l_i \in \{0,1\}$, the expression of the image's energy function gotten by MAP-MRF is shown as follow:

$$E = R(L,O) + \lambda B(L) \tag{1}$$

$$R(L,O) = \sum_i f(o_i \prod i) \tag{2}$$

$$B(L) = \sum_{(i,j)\in N} g(l_i, l_j).\xi(l_i, l_j) \tag{3}$$

And $\xi(l_i, l_j) = \begin{cases} 1 & \text{if } l_i \neq l_j \\ 0 & \text{otherwise} \end{cases}$

R(L,O) in formula (1) corresponds to the regional information of the segmentation, *B(L)*represents the edge information of a segmentation, $\lambda \geq 0$ is the relative importance of regional likelihood term *R(L,O)* to the boundary gradient term *B(L)*. The regional term *R(L,O)* represents the penalty which is given to the foreground or background by a pixel. In actual operation, the hard constraint which the user gives is always firstly used, some pixels belong to the background, some belong to the foreground, according to these pixel, build the probability models of foreground and background respectively, while *R(L,O)* represents the degree of coincidence of the observed pixel value o_i to the foreground or background probability model, if the observed value o_i is similar to the foreground probability model, while it is given the background tag, then the penalty value is very big, otherwise small. The smooth term *B(L)* represents the boundary property of an image segmentation $L.G(l_i, l_j)$ represents the unsmooth penalty between neighboring pixels o_i, o_j, there are many types in penalty term, such as the gradient or the orientation gradient etc.

The regional likelihood term *R(L,O)* represents the level of similarity of the observed pixel value in the image to the foreground and background probability model, according to $f(o_i|l_i)$ in formula (2), we can know if we make the value of tag li as 0, that means the observed value is correspondent to the background probability model, if the value of tag li is 1, that means the observed value is correspondent to the foreground probability model.

The graph cut algorithm of Boykov and others used histogram as the probability model, and they believed that their method can extend to N-dimensional image, but actually it is very different to build models for the data which is higher than 2-dimension using histogram, the Gaussian mixture model is adopted in the color image and the interactions between the users are reduced. This paper introduces the probability model of depth information, which will affect the validity of the segmentation largely, given that the depth information is one-dimension, it can adopt the histogram to modeling fast, the color paperure information still uses the Gaussian mixture model, the trade-off between them is expressed by the balance factor α. It is assumed that *P(Oi|F)* represents the foreground probability model, *P(Oi |B)* represents the background probability model, then we can define the probability model with the depth information according to above descriptions:

$$p(o_i|f) = (1-a)\Pr(c_i|\phi_f) + a\Pr(d_i|\vartheta_f) \tag{4}$$

$$p(o_i|b) = (1-a)\Pr(c_i|\phi_b) + a\Pr(d_i|\vartheta_b) \tag{5}$$

And $\alpha \in [0\text{-}1]$.

In it c_i represents the RGB observed value of the image pixel, d_i is the depth information of the image, θF is the parameter of the foreground Gaussian mixture

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model, θB is the parameter of the background Gaussian mixture model, θ is the parameter of the foreground histogram probability model, ϕ_b is the parameter of the background histogram probability model. The specific formulas of foreground and background Gaussian mixture probability model expressed by $Pr(c_i / \theta F)$ and $Pr(o_i / \theta B)$ are shown as follows:

$$Pr(c_i \mid \vartheta_f) = \sum_{j=1}^{k} \pi_j n(c_i; \mu_i, \sum j) \quad (6)$$

$$Pr(c_i \mid \vartheta_b) = \sum_{j=1}^{k} \pi_j n(c_i; \mu_i, \sum j) \quad (7)$$

The histogram probability model formulas of the foreground and background depth information expressed by $Pr(c_i / \theta F)$ and $Pr(o_i / \theta B)$ are shown as follows:

$$Pr(d_i \mid \vartheta_f) = \bar{z}.(\frac{n_1}{E}, ..., \frac{n_k}{E}, ..., \frac{n_c}{E}) \quad (8)$$

$$Pr(c_i \mid \vartheta_b) = \bar{z}.(\frac{n_1}{E}, ..., \frac{n_k}{E}, ..., \frac{n_c}{E}) \quad (9)$$

$\bar{Z}i$ is a unit vector whose dimension is c, assume that the maximum value of the image depth information is D, then D in $\bar{Z}i$ is 1, representing the category of d_i in the histogram, $\frac{nk}{E}$ represents the datum histogram class probability which has been marked by the users, n_k represent the sample number of the k_{th} category, E is the total number of samples. Thus the histogram probability model based on depth can be easily expressed by mathematical formula in the form of sample probability. The above is the complete probability model formula, the color part uses the Gaussian mixture model, actually they have known that it is difficult to construct high dimension probability model by using the histogram through practice, the depth modeling adopts the histogram modeling, because the solve of Gaussian mixture needs to use the EM algorithm, which is loop iteration and has higher time complexity, but the histogram can build the probability model of one-dimension data in a short time, which is proper for the modeling of depth information, besides the depth histogram modeling of this paper is good to determine α, which is determined on the basis of the vector of histogram probability. In conclusion, using histogram to probability modeling takes less time, and it is good to balance the degree of importance between depth information and color information.

B. The Determination of Weight and the Graph Structure

In the graph cut algorithm, every pixel in the image is generally regarded as the node of graph in data structure. According to Markov property of the above Markov Random Field, assume that the label of every pixel is affected only by the labels of its neighboring pixels, this paper uses 8 neighborhood system, so the edge joints of pixels are shown as figure 1:

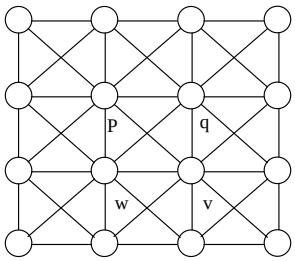


Figure 1. The neighborhood system

On the basis of figure1, add 2 extra nodes, one is the source node, the other is the terminal node, which are called S node and T node for short, S represent the target, T represents the background, and link all the pixel nodes to the two nodes.

In the image model of the graph cut algorithm, every node in the image includes the node which is correspondent to the pixel and a node linked to the terminal node, one is the S node, the other is the T node, S node is also called target node, after finding the minimum segmentation, the node which is still linked to the S node is the extracted target object, the corresponding T node is also called background node, after finding the minimum segmentation by executing the maximum flow algorithm, the node which is still linked to T is the background.

The edges in the image can be divided into two types as previously mentioned, one type is n-link, the connected edge between neighboring pixels nodes in the image, the other type is t-link, the connected edge between the pixel node and the terminal node, figure2 expresses the above nodes and edges:

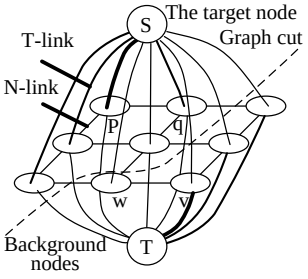


Figure 2. The graph structure of the graph cut algorithm

The two types edges shown in figure2 can be divided into three categories, one is t-link which is linked to S, one is t-link linked to S, the assignment of these two kinds of edges is related to the probability model in section1.2, they adopt similar log-likelihook function, while n-link adopts the ad-hoc function, the introduction of depth information in ad-hoc also adopts the method similar to probability model, it introduces the balance factor α to balance the importance of depth information in the penalty term. The problem remained is how to determine α, because the histogram is introduced to the modeling of depth information, the probability vector made up of the histograms can clearly express the distribution of depth information, the difference between

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the distributions can be expressed by the distance between vectors.

Figure3 is a probability histogram about depth information; the probability histograms of the foreground and background are similar. The following is the probability histogram of foreground depth.

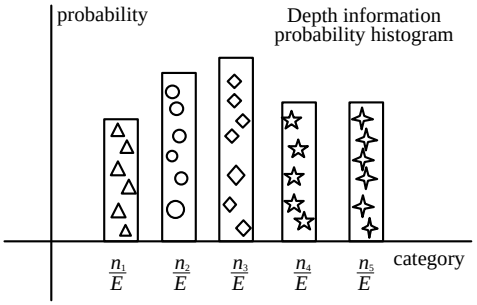


Figure 3. The depth information histogram

Different graphs represent different categories, the height of the columnar represents the size of the probability, then the vector made up of probabilities can show the shape of the histogram completely, the distance between vectors can show the difference between histograms, and it can be used to express αin the probability histogram, that is:

$$a = (\frac{n_1}{E},...,\frac{n_k}{E},...,\frac{n_c}{E})_b \times (\frac{n_1}{E},...,\frac{n_k}{E},...,\frac{n_c}{E})_f$$

According to the above formula, we know 0≤α≤1, and the bigger α is, the larger the difference of depth information between foreground and background is, the target can be segmented effectively only by the depth information.

TABLE I. THE WEIGHTS OF ALL KINDS OF EDGES

Connected with $s\,t-link$:
$In((1-\alpha)\Pr(c_i\|\theta_F)+\alpha P_r(d_i\|\vartheta_F))$
Connected with $s\,t-link$:
$In((1-\alpha)\Pr(c_i\|\theta_F)+\alpha P_r(d_i\|\vartheta_F))$
$n-link$
$\exp\left(\frac{(1-\alpha)(c_i-c_j)^2+\alpha(d_i-d_j)^2}{2\sigma^2}\cdot\frac{1}{dist(i,j)}\right)$

The determination of weight is very important for graph cut, how to use different information effectively, how to combine the information to perform effective image segmentation, the combination of color, paperure, depth and regional boundary, the grasp of the balance, all of those are very important for the image segmentation. As mentioned before, the determination of the values of two kinds of t-link and one n-link has been basically known, t-link adopts the log-likelihoods function, n-link adopts the ad-hoc function, two kinds of t-link both adopt the log-likelihoods function, but their trained parameters of the probability model are different, that means although they have the same probability model, the combination of Gaussian mixture model and histogram model, their prior information is different, the foreground and background pixels have been determined during the users' interaction, so define these two kinds t-link by two different weights, the specific weights are shown as table 1:

The color paperure and depth information can be combined effectively by α, which makes that the image can utilize the difference of depths effectively on the condition that the foreground and background have same color but different depths, namely if the value of α tends to large, tend to use deeply information. This is very effective for automatic image segmentation, it can automatically determine the specific gravity of depth information and color information of the image segmentation, thus the accurate segmentation can be gotten.

C. Hierarchical Algorithm

According to experiments, the solving of the graph cut algorithm is very slow, the most time consuming part is the EM iteration algorithm of Gaussian mixture probability model, it is unacceptable for the waste of time in loop iteration, because in the beginning iterations, the users give foreground and background information, meanwhile, first segmentations do not reach the accurate segmentation, the goal is to get the ideal segmentation at the last step, after knowing that, because in most cases according to experiments, the graph cut algorithm can meet the ideal requirements the users want after three to four times iterations, many scholars in our country adopt multi-scale method to accelerate the process of EM probability modeling after knowing that, building a three to four layers image-pyramid, making the number of iterations is equal to that of the graph cut algorithm, thus it can reduce the time of getting ideal segmentation effectively, and it definitely does not reduce the segmentation accuracy, because the graph cut algorithm takes most of its time in probability modeling, while it does not need accurate probability model at the beginning. The method of multi-scale can reduce the number of samples, thus it can reduce the time segmentation takes effectively.

There is an algorithm researching on the acceleration algorithm of the iterative graph cut through multi-scale, the upper probability modeling is performed by selecting the maximum in 4 neighborhoods as the pixel of the pyramid's upper layer, this method is very bad to the condition when there are noises in the image, their segmentation acceleration algorithm ignores the condition of image noises, and even without noises, the algorithm is also far-fetched. This paper adopts their multi-scale thought, but with larger magnitude, it extracts the typical sample effectively by bucket sort during the large magnitude extraction of 4 neighborhoods rather than extract the image pixels by 4 neighbors, thus it has avoid the noise point and unimportant sample point, the other reason is that the depth information often has many noise points, the depth information of these points can not be extracted for its transparency or other reasons, if using the sample points without the biggest and smallest points which is typical in color and depth, then using the depth information of the sample points to exchange the information of those noise points whose depth information can not be extracted, it's really " kill two

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birds with one stone". After scanning the small samples once, those noise points can be excluded and it has little effect on the segmentation time, although it can also segment images, the watershed transform is unfit for the depth images.

This paper adopts 2×2 blockette as the extraction unit of the upper layer image pixel, find the absolute value of color in 2×2 pixels and the biggest as well as the smallest pixels, find the point with the largest depth information, the point with the smallest depth information, exclude the above points, if there are point left, then use them to represent the four points, if no ,then ignore the points with the largest and smallest depth information, take two points left by the color information as the sample points to construct the upper image, the sample pixel points gotten by this method can fully represent the essential information of the image, while it is free of the effects of noise points and points whose depth information can not be obtained.

D. Energy Minimization

For the graph cut algorithm, the graph structure and the determination of edge weight are the most important; it can adopt the maximum flow/ the minimum segmentation algorithm to solve. The experimental research has been performed to the maximum flow/ the minimum segmentation algorithm of the graph cut solving, an algorithm which is higher in time complexity $o(ne2)$ than the common maximum flow algorithm theoretically is invented, its theoretical largest complexity is $o(|C|ne2)$,c is the number of segmentations, but in actual experiments, this algorithm can save times of time than other algorithms because of the particularity of the image in graph cut algorithm, it increases channels in the image by constructing trees, expanding and adopting the orphaned nodes, finally solve the maximum flow.

III. Implementation Process of Graph Cut

The method of this paper combines the deep hierarchical graph cut algorithm, the essence of this algorithm is to use histogram in the depth information modeling, it introduces the balance factor αto balance the color paperure and the depth information, when there is obvious difference between the foreground and background depth information, factor αis close to 1,which means it can segment the target in the image only by the depth information, when there is no big difference between the foreground and background depth information, factor a_{is} close to 0, then segment the image by color and paperure information. Other than the depth information, the introduction of the hierarchy also accelerate the process of graph cut algorithm, because as the document [11] has mentioned, the graph cut can get its accurate segmentation at its final loop, the beginning layered extractions of the foreground and background do not affect the final segmentation structure.

The overall process of this algorithm is elaborated as follows, firstly, the user uses the mouse to drag out a rectangle, pixels in the rectangle are the probable foreground, but take them as the foreground during the probability modeling, at least it includes the pixels of the foreground, during the loop iteration, take last segmentation result as the next probability modeling basis, thus it can be close to the probability model the user wants. The pixels out of the rectangle is the absolute background, take them as the sample data of the background probability modeling. Take the user's rectangle and image as the input of this algorithm, then implement this algorithm, the first basic initialization of this algorithm is to construct a three-layered pyramid, take 2×2 as the basic unit of pixel extraction, extract the sample pixels in the unit of 2×2 on the basis of original images, can the four pixels, find the pixels with the largest and smallest color absolute value, meanwhile scan the depth image and find the maximum and minimum of the depth, on the basis of removing these four pixels, randomly select a pixel as the upper layer probability modeling sample of multi-scale image segmentation in the left pixels by random algorithm, this is same to the three layered image pyramid. According to the same principle, we can extract one image and build the image pyramid with three floors. After preparing the initialization well, in the upper layer the color is modeled the Gaussian mixture by EM algorithm, and build the depth information histogram after one scanning, the probability vector, at the same time combine the rectangle the user gives, of course the rectangle is narrowed in the upper layer of the pyramid, construct the foreground and background probability models, construct the graph structure of the graph cut algorithm by combining the probability models and table 1-1. Although there are only three layers multi-scale combination, it is very proper for the combination of iterative graph cut algorithm, because a lot of experiments show that in most cases three to four implementations of graph cut can get an ideal segmentation result, the following is the process of this paper in a more simple description and process:

a. For the image pixel, the user gets the probable foreground and absolute background by framing a rectangle.

b. Construct a three-layered image pyramid by 2×2 sample, the extraction method is as mentioned before, remove the outliers and select algorithm randomly.

c. Perform EM Gaussian mixture and histogram probability modeling in the upper layer image, then get the foreground and background probability model, the formula the probability model is as follow:

$$(1-a)\Pr(c_i|\theta)+a\Pr(d_i|\vartheta) \qquad (10)$$

d. build the graph structure of the graph cut and implement the improved maximum flow algorithm.

e. Perform the mapping of edges to the second layer and continue the probability modeling.

f. build the graph structure of the graph cut and implement the improved maximum flow algorithm.

g. Segment the structure and build probability model on the original image.

h. Implement step 6 until the idea segmentation.

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The above is the overall process of the depth image hierarchical segmentation this paper has mentioned, its advantage is that it uses the histogram to model the depth information, introduces the balance factor α to make a choice between the color paperure information and the depth information, it also uses the layered extraction to avoid the noises and accelerates the time the graph cut algorithm takes. It has made great progress, the way it improves is the introduction of depth information, after having more information to segment images, it is key to balance the importance between the introduced information and original information, while researches before just regarded it as the new one dimension information and added it to the Gaussian mixture model to build the four dimensions Gaussian mixture model, although it has certain effect, the introduction of the balance factor is more effective. Then the experimental result and its analysis will be given in the following chapter.

IV. EXPERIMENTAL RESULTS

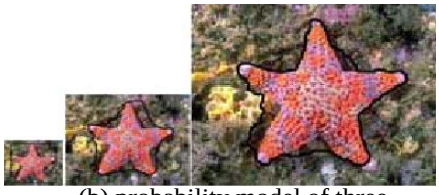
This chapter uses the algorithm of this paper to segment the images, compared with the standard graph cut algorithm in time and process, it reduces the time largely on the condition that the segmentation accuracy remains the same, and it can segment images when the color information can not be distinguished correctly.

Because this algorithm implements the segmentation of depth images, the standard images of some graph cut algorithm does not have depth information, this paper adopt the method of randomly generated gray-scale image to generate the depth information automatically to segment the standard images, because it is randomly generated, the depth information histograms of the foreground and background , the probability vector, are basically the same, which leads that the balance factor a_{is} very small, essentially the important part is color paperure information, so it does not influence the segmentation accuracy, then apply this method to the standard image of the graph cut algorithm, compare the time and segmentation result, the aim is to reduce the time without the decrease of accuracy.

From the figure, on the condition that the original image in figure 4(a) and the user rectangle are input, the algorithm of this paper can build image pyramid model, the image in every layer is the input of former segmentation result, the first input is the user's rectangle, from figure4(b)the probability model of the image is on the basis of the image pyramid, every segmentation result is expressed by a black line, the pixel sample of the foreground probability model is within the black line, the pixel sample of the background probability model is out of the black line, because the depth information adopts the gray-scale image which is randomly generated, there are three results showing that α is very small, $\alpha \leq 0.01$, it is useless, we can see it is the color Gaussian mixture model that plays an key role, but time it takes is shorter, the following is the time consuming ratio of three iterations.



(a) The source image and input from the user



(b) probability model of three layers of the pyramid image



(c) three times of iteration method



(d) iterative graph cut algorithm three iterations

Figure 4. Comparison in the accuracy of the algorithms

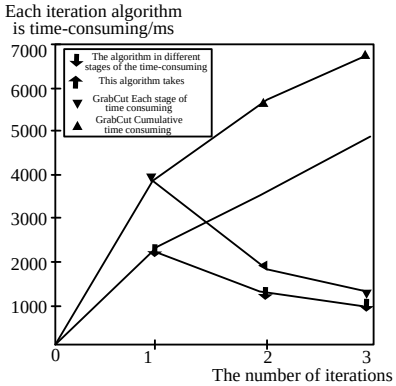


Figure 5. Comparison in time of the algorithms

TABLE II. TIME CONSUMING RATIO OF THE ALGORITHMS

The number of iterations	GrabCut Time consuming/ms	This algorithm is time-consuming/ms	Ratio of time consuming
first	3946	2252	57.1
second	1908	1423	74.6
three	1012	1125	111.1
cumulative	6866	4800	69.9

From figure5 and table 2, time this algorithm takes in the beginning part reduces almost a half, and 30% in the whole, but the segmentation accuracy is not affected.

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Then take real depth image as the input, compare the performance of two algorithms.



Figure 6. The left is RGB image, the right is depth image



Figure 7. Comparison in the segmentation results of depth image

The left of figure7 is the segmentation result of iterative graph cut(the depth information is just the 4thdimension information)the right is the segmentation result of this algorithm, experiments show that the present depth information plays a crucial role, this is true, according to the value of α, it is larger than 0.7 during three iterations, thus the depth information can be the basis of image segmentation, from figure7, it is impracticable to add the depth as the fourth dimension to the Gaussian mixture model, which can not show the importance of the depth information. According to experiments this algorithm can segment depth images correctly by automatically judge the importance the depth information, use the depth information when it is obvious, if not, use the color information to segment images.

V. CONCLUSION

Although this paper has improved the execution efficiency of the iterative graph cut algorithm, and used the depth information of the depth image effectively, there is also limitations, it does not give the calculation formula of ϕ clearly, in the iterative graph cut algorithm the value of θ_{is} solved by using the matrix, this paper just add the depth information and solves the value of θ_{by} using 4 dimensions matrix , later this part will be improved to better understand the significance and performance of the graph cut algorithm.

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