A NOVEL UNIFYING MODULE SUB-MARKOV RANDOM WALK WITH PARAMETRIC IMAGE SEGMENTATION

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Abstract--*Segmentation is typically the first step in object identification in an image. It may also be used in compression to compress different areas, segments of an image, at different compression qualities. So, for segmentation we are developed a novel technique known as sub-Markov random walk (subRW) algorithm with label prior for seeded image segmentation, which is similar to traditional random walk having auxiliary nodes added in it. Under this auxiliary nodes consideration we given uniqueness of proposed work than existing systems. Different methods analyzed and shown that our method is more efficient. The uniqueness will be nothing but adding or changing the auxiliary nodes in segmentation algorithm. We face segmentation problem in existing system if the image is having very thin and elongated parts. To solve this type of problem we implemented proposed work. MATLAB simulation results proved that our proposed subRW is giving better results compare to all other existing RW algorithms for both synthetic and natural images.*

1. INTRODUCTION

Image segmentation will play a major role in image processing. So practically image segmentation algorithm must provide four qualities. Those are 1) fast computation 2) fast editing 3) producing an arbitrary segmentation with enough interaction 4) intuitive segmentations. By using the random walk algorithm we can get all the above desired qualities [1]. By using some methods we can solve the problem of sparse, symmetric positive definite system of linear equations. The random walk algorithm may give good results by taking the solution of previous one as the initialization of an iterative matrix solver. The algorithm formation on a graph allows the application of the algorithm to surface meshes or space-variant images [2], [3].

In K-away image segmentation user defined seeds are given to indicate the regions of the image belonging to K objects. Every seed indicates the location with user defined label. In previously established paper [4] [5] random walker first consider the seed points which exactly equals the solution to the Dirichlet problem [6] and the seed point is fixed to unity remaining are set to zero. To see the more information refers this [7]. Fully discrete calculus [8] development allowed for connection between random walks on graphs [9] and discrete potential theory [10]The solution for dirichlet problem on an arbitrary graph is electric circuits with resistors which should represent the inverse of the weights i.e. conductance and boundary conditions which should represent the voltage sources and fixing the electric potentials at boundary nodes.

The image segmentation work mainly focused on building of possible image models. The parameters for these models are developed based on these algorithms. The synthesis and analysis of image textures mainly depends on frame models. The desired behavior of an algorithm first established in a different line of computer vision research. And also PDE or other physical process also did. In this process the image content is viewed by the metric properties. Here the mainly used algorithms are anisotropic diffusion for image filtering and normalized cuts for image segmentation.

The random walk approach requires some characteristics in interactive segmentation algorithm those are 1) 1) Location of weak (or missing) boundaries, 2) Noise robustness, 3) Ability to identify multiple objects simultaneously, 4) Fast computation (and editing), 5) Avoidance of small/trivial solutions (i.e., an avoidance of a "small cut" phenomenon).

In this paper we propose a sub Markov random walk (subRW). It will have four RW-based algorithms: RW, RWR, LRW and PARW. To solve the twig problem it is extended by adding label prior. In the properties of subMarkov random walk first step is build a subRW framework for image segmentation. First it will leave a graph G from a node i having the probability of c_i and then it will move to the other adjacent nodes in G having the probability of 1-c_i. This random walk is changed to a Markov transition probability ($\sum q(i,j) = 1$) in an expanded graphG_e. This G_e is constructed by adding auxiliary staying nodes connected with seeds and unseeded nodes into graph G are connected with auxiliary killing nodes.

2. A UNIFYING VIEW OF SUBRW

By using the sub-Markov transition probability (subRW) random walk algorithm is proposed for the interactive multi-labeled image segmentation and the analysis was done between the previous and proposed popular RW algorithms such as RW, RWR, LRW, and PARW.

In this approach, user should indicate as multi-labeled seeds on foreground objects and background objects.

A. The Sub-Markov Random

In the random-walk the variables represented, weighted graph G, labeled nodes VM, and unlabeled nodes VU, and VU ∪ VM =V. for the seeded segmentation subRW algorithm is used. To get a graph G and Expanded graph G_e two types of auxiliary nodes are added.

B. The Optimization of SubRW:

subRW algorithm mainly depends on random walks, it can be taken as a general optimization problem. By using the optimization, we can employ the general vision application.

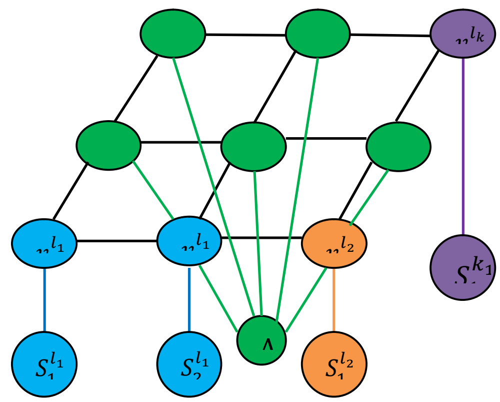

Figure.1. The nodes graph of a subRW. The ellipse nodes denote the original nodes in V and the circle nodes are the newly added auxiliary nodes. The green ellipses are the unseeded nodes and the others are the seeded nodes.

C. Relations with Other Well-Known RW Algorithms:

The proposed results are compared with the conventional popular algorithms to see the performance. RW, RWR, LRW, and PAPW.

1) Relations with RW:

For the segmentation, Grady proposed random walk algorithm with a Markov transition probability. This can be taken as a special case of subRW. In this algorithm it places a random walker at each unlabeled node then calculates all the labeled nodes. This calculation is not practical.

2) Relations with RWR:

In this for each node assigned a steady state probability and it develops a seeds.

3) Relations with LRW:

In super pixel segmentation has been done by using the lazy random-walk algorithm and multi labeled segmentation problem is removed by using this algorithm. In this random walker will stay in the present position and walk out with an arbitrary edge.

4) Relations with PARW:

Ranking, clustering, and classification were done by using the partially absorbing random walks (PARWs). The PARW starts at current node i with the probability λ_i and walk out of it having a random edge with probability 1-λ_i.

3. LITERATURE SURVEY

For the segmentation of medical images so many approaches have been proposed. These approaches generally grouped into two main categories. Those are semi-automatic and fully automatic method. Random walker algorithm will come under as semi-automatic method. It is proposed by grady2 and other methods based on graph-cuts (e.g., see FunkaLea et al.3), for the segmentation of regions user should provide seed points. By using all these methods the final segmentation and results are obtained. When a large batch of images is there for segmentation these methods are practically not used. In automatic methods, it does not require any manual interaction. So many conventional methods have been proposed in the past years. Those methods based on clustering (e.g., Sikka et al.4), level-sets (e.g., Liu et al.5) and active contours (e.g., Gao et al.6). in the recent years many proposals have done for the development of atlas-based methods, in this for the segmentation of one new image one or several pre-labeled templates used. In these approaches the methods will be based on least square support vector machines (e.g., Kasiri et al.7), intensity classification (e.g., Sdika et al.8), Markov random fields (e.g., Bauer et al.9), decision fusion (e.g., Rohlfing et al.10) and graph cuts (e.g., Lotjonen et al.11). to get more information about atlas-based segmentation, refer Cabezas et.al.1

And also for the segmentation of medical images many histogram-based methods have been proposed because of their greater efficiency. For the segmentation of brain MR volumes a simple method based on Otsu's thresholding technique 13 by Shan et al.14 proposed. For instance, to segment the liver tissues Seo et al.15 proposed a method i.e. tail threshold the histogram of intensities. And for the segmentation of brain images Nakib et al.16 proposed in this 2D histograms (intensities and their spatial correspondences). Lastly to segment the brain MRI images Dou et al.17 fuzzy-clustering algorithm on the histograms used. In this paper also histogram is used to get a fast automatic segmentation of images. Little parameter tuning and class membership probabilities are additional benefits.

4. PROPOSED METHOD

An object with twigs is usually consists of two parts: one is main branch and the other one is twig part. Actually, the twig part and the main part are similar to each other. There are so many RW- based algorithm have been proposed to omit the twig part. In this paper, some appropriate user-specified scribbles on the main object have included enough information for segmenting out the twig part. To achieve this, we need to add label prior to the scribbles into the sub RW which are used to segment out the twig part efficiently.

A. Added Label Prior

In an object usually two types of nodes are available. One is seeded node and the other one is unseeded node. Prior will work only at seeded node and there will not be prior at unseeded node. All the new nodes V present in an object are labeled as new label prior, which as less exact than user scribbles but can be used for unseeded nodes. As shown in figure, a label l_k has intensity distribution H_k for each and every node. Each prior node is connected with all nodes in V and weight w_{ih_k} of an edge between a prior node h_k and a node $vi \in V$ is proportional to probability density u_k^i , i.e., $w_{ih_k} \propto u_k^i$.

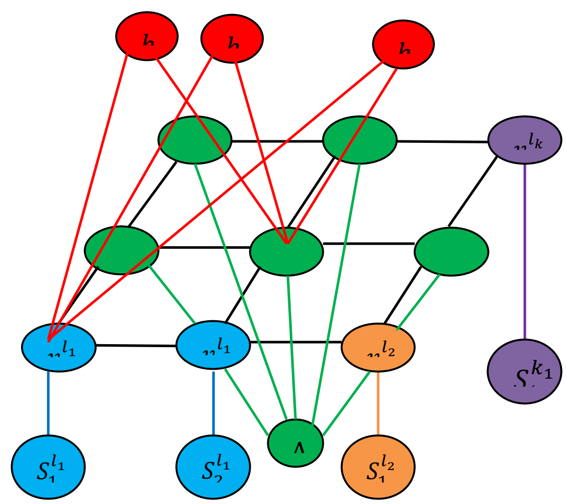

Figure.2. The nodes graph with prior nodes of a subRW. The red circle nodes represent the prior nodes, which should be connected with all the original ellipse nodes. We only show two edges for each prior node for simplification. One edge connects a seeded node, and the other connects an unseeded node. Except for the red circle nodes, the other nodes are defined as the same as the nodes in Fig. 1.

In this paper, we set weight w_{ih_k} as:

$$w_{ihk} = (1 - c_i) \lambda\, u_i^k \quad (1)$$

where λ is a regularization parameter, which measures the importance of the prior distribution.

Then the transition probability is expressed as

$$\bar{q}(i,j) = \begin{cases} c_i & if\ i \in V,\ if\ j \in \{\Delta\} \cup S_M \\ (1-c_i)\,\frac{\lambda u_i^k}{d_i + \lambda g_i},\ if\ i \epsilon V, j = h_k \\ (1-c_i)\,\frac{w_{ij}}{d_i + \lambda g_i},\ if\ ji \epsilon V \cup S_M \cup H_M \\ 1 & if\ i = j\ \ \epsilon \{\Delta\} \\ 0 & otherwise \end{cases} \quad (2)$$

Hence, a transition probability $\bar{q}$ on a graph with prior $\bar{G}$, the probability r_{im}^{-lk} the random walker from one node position reaches to the m th staying node S_m^{lk} with label l_k or prior node h_k, is expressed as follows$r_{im}^{-l_k} = (1 - c_i) \sum_{j \sim i} \frac{w_{ij}\, r_{im}^{-l_k}}{d_i + \lambda g_i} + (1 - c_i) \frac{\lambda u_i^k}{d_i + \lambda g_i} + c_i\, b_{im}^{l_k}$ (3)

The present prior node h_k is seen as a new staying node with label l_k. So, the reaching probability of h_k is to be considered by the vector as

$$\bar{r}_m^{l_k} = (\mathrm{I}\text{-}D_c)\, \bar{p}\, \bar{r}_m^{l_k} + (\mathrm{I}\text{-}D_c)\, \bar{u}^k + D_c b_{im}^{l_k}$$

$$= (\mathrm{I} - (\mathrm{I} - D_c)\, \bar{p}\,)^{-1} ((\mathrm{I}\text{-}D_c)\, \bar{u}^k + D_c b_{im}^{l_k}) \quad (4)$$

$$= \bar{E}^{-1} ((\mathrm{I} - D_c) \bar{u}^k + D_c b_{im}^{l_k})$$

The modified vector notation $\bar{r}_m^{l_k}$ can be formulated as

$$\bar{r}^{l_k} = \frac{1}{Z_k}\, \bar{E}^{-1} \left((\mathrm{I} - D_c) \bar{u}^k + \frac{1}{M_k} D_c b^{l_k} \right) \quad (5)$$

The final labeling (segmentation) result with a label prior is obtained as follows:

$$\bar{R}_i = \arg\max_{l_k} \bar{r}_i^{l_k} \quad (6)$$

Where $\bar{R}_i$ represents the final node for each pixel of an image.

B. The Optimization Explanation

Similar to the subRW, we can also give the optimization explanation for the subRW with label prior. Suppose $\forall i, 0 < ci < 1$, then the objective function is as follows:

$$\bar{O}^{l_k} = \frac{1}{2} \sum_{i=1}^{N} \sum_{i=1}^{N} w_{i,j} (r_{im}^{-l_k} - r_{jm}^{-l_k})^2 + \frac{1}{2} \sum_{i=1}^{N} \frac{(d_i + \lambda g_i) c_i}{(1 - c_i)}\, w_{i,j} (r_{im}^{-l_k} - r_{im}^{-l_k})^2 + \frac{1}{2} \sum_{i=1}^{N} \lambda\, u_i^k\, (r_{im}^{-l_k} - 1)^2 + \frac{1}{2} \sum_{t=1, t\neq k,}^{N} \sum_{i=1}^{N} \lambda\, u_i^t\, \bar{r}_{im}^{l_k\,2} \quad (7)$$

The vector formation of above equation is given as

$$\bar{O}^{l_k} = \frac{1}{2} \bar{r}_m^{l_k T} (D - W) \bar{r}_m^{l_k} + \frac{1}{2} \left(r_m^{-l_k} - b_m^{l_k} \right)^T (\mathrm{I} - D_c)^{-1} (D + \lambda D_g) D_c \left(r_m^{-l_k} - b_m^{l_k} \right) + \frac{\lambda}{2} \left(r_m^{-l_k} - e \right)^T D_u^k \left(r_m^{-l_k} - e \right) + \frac{\lambda}{2} \sum_{t=1, t\neq k,}^{K} r_m^{-l_k\,T} D_u^t r_m^{-l_k} \quad (8)$$

By taking the partial derivative of $\bar{r}_m^{l_k}$, we have

$$\frac{\partial \bar{O}^{l_k}}{\partial r_m^{-l_k}} = (D - W) \bar{r}_m^{l_k} + D_\eta^{-1} D_a D_c (r_m^{-l_k} - b_m^{l_k}) + \lambda \left(D_u^k r_m^{-l_k} + \sum_{t=1, t\neq k,}^{k} D_u^t\, r_m^{-l_k} - u^k \right)$$

$$= (D_a - W)\, r_m^{-l_k} + D_\eta^{-1} D_a D_c \left(r_m^{-l_k} - b_m^{l_k} \right) - \lambda\, u^k$$

$$= D_\eta^{-1} D_a \left[(D_\eta + D_c - D_a^{-1} D_\eta W) r_m^{-l_k} - D_c b_m^{l_k} - D_a^{-1} D_\eta \lambda\, u^k \right] = D_\eta^{-1} D_a \left[\bar{E}\, r_m^{-l_k} - (D_\eta \bar{u}^k + D_c b_m^{l_k}) \right] \quad (9)$$

Algorithm 1 segmentation by subRW with label prior

Input: an image V (v_i) and K kinds of user scribbles V_M={$V^{l_1}, V^{l_2}, \ldots. V^{l_k}$}, the parameters $D_c = diag(c_1, c_2, \ldots c_N)$,$\lambda.\gamma$:

Output: The segmentation result $\bar{R}_i$ for each pixel:

1: Obtain the indicating vectors b^{l_k},k=1: K of scribbles:

2: Define an adjacency matrix W=$[w_{ij}]_{N\times N}$ with neighbors graph structure by (1);

3: Generate the GMMs with five components from all scribbles and then get the probability density u_i^k:

4: Scale probability: $u_i^k \leftarrow \max(100 + \log(u_i^k), 10^{-10})$:

5: **if γ = 1 then**

6: obtain coarse segmentation result C$R_i = arg \, {}^{max}_{k} \, u_i^k$;

7: get the candidate vector cr^k from CR_i;

8: reset the prior vector $u^k \leftarrow u^k \odot cr^k$;

9: **end if**

10: Set$g_i \leftarrow g_i^k$, where $u_i^k + {}^{max}_{t\neq k} u_i^k$;

11: Compute the transition probability matrix $\bar{P}$ and the vector $\bar{u}^k$ by (37) and (38);

12: solve linear equations:$\bar{E}\bar{r}^{l_k} = (I - D_c)\bar{u}^k + \frac{1}{M_k} D_c b^{l_k}$;

13: Normalize the reaching probabilities:$\bar{r}^{l_k} \leftarrow \frac{1}{Z_k}\bar{r}^{l_k}$:

14: Obtain segmentation result$\bar{R}_i = argmax l_k \bar{r}_i^{l_k}$;

We can find that it comprises of three segments. The initial two segments are the smooth term and the unary term, which are like the parts in (10). The last component relates to the label prior. By limiting this component, the achieving likelihood $r_m^{-l_k}$ will be reliable with the label prior.

C. Noise Reduction

Adding the label prior to each node of a pixel may produce some noise. This noise may produce some distortions. To avoid this one of the solution is to decrease parameter λ. If the value of λ is too small, the twig part may get lost. We need to some other strategies to reduce noise like combining label prior value for each node. Coarse segmentation is achieved to avoid lose of twig part. Coarse segmentation is represented as

$$CR_i = \arg\max_k u_i^k \quad (10)$$

As we know there will be much noise in the coarse segmentation, it mostly does not connected with the main part of an object. So, we can choose the connected regions with seeds from the coarse segmentation as the candidate regions. Next we will every label prior into these candidate regions, which helps to keep the prior information of twig part as well as noise get removed. Furthermore, the candidate regions are dilated to add more prior information into the boundary regions. Since the contrast of the prior information near boundaries is high, it will help to find correct boundaries.

5. SIMULATION RESULTS

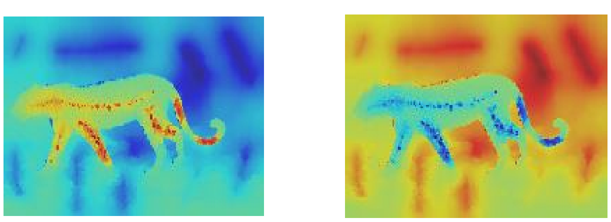

Figure.3. the image is shown in two different color spaces

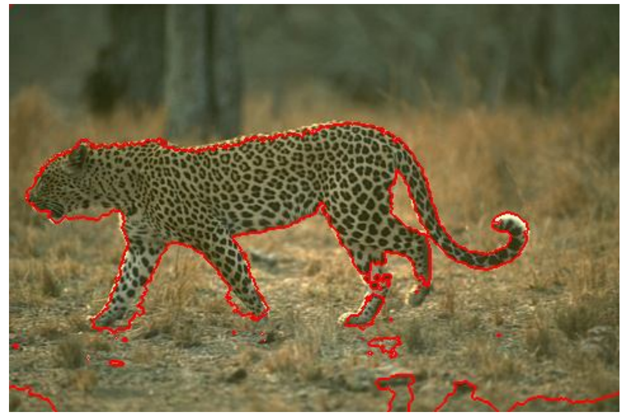

Figure.4. separation of both background and foreground regions

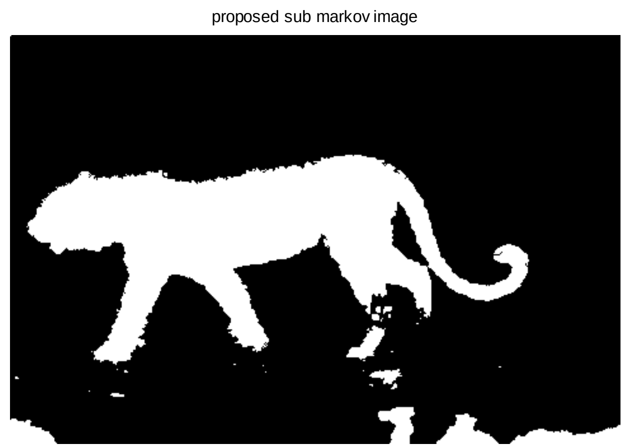

Figure.5. shows the resultant image using sub markov random model

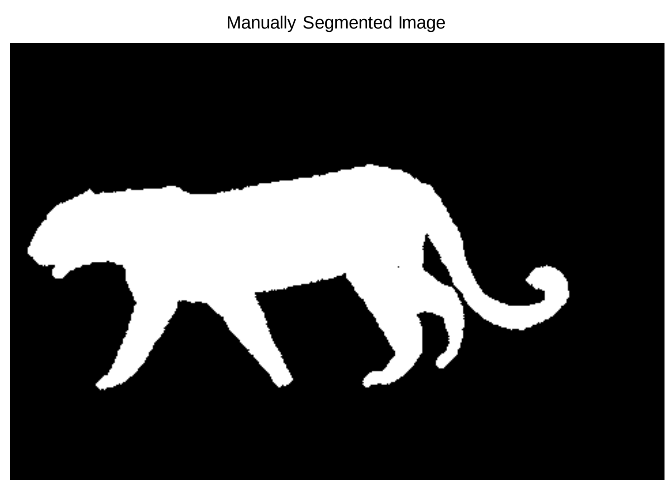

Figure.6. extension result

6. CONCLUSION

We have conferred a completely unique framework supported the subMarkov random walk for interactive seeded image segmentation in this work. This framework are often explained as a traditional random walker that walks on the graph by adding some new auxiliary nodes, that makes our framework simply interpreted and a lot of versatile. Below this framework, we unify the well-known RW-based algorithms that satisfy the subMarkov property and build bridges to create it simple to remodel the findings between them. What is more, we've got designed a novel subRW with label before solve the twigs segmentation problems by adding previous nodes into our framework. The experimental results have shown that our algorithmic outperforms the progressive RW-based algorithms. This also proves that it's practicable to style a replacement subRW algorithmic program by adding new auxiliary nodes into our framework. In the future, we'll extend our algorithmic program to a lot of applications, such as center line detection at 3D medical pictures and classification.

In the extension work, some of the parameters of an algorithm have been changed to reduce the noise of an image as well as to extract the particular region of an image with perfect edges and flexibility.

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