ISSN 2277 – 5528
Impact Factor- 4.015

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & MANAGEMENT

COMBINATORIAL APPROACH FOR IMAGE SEGMENTATION

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ABSTRACT

A novel algorithm called sub-Markov random walk (subRW) algorithm is used for image segmentation along with prior nodes. Various random walk methods are used for clustering of objects and a combination of certain random walk methods will produce the sub-Markov random process. It is used to solve twigs segmentation problem by adding auxillary nodes along with label prior. The random method solves certain segmentation issues among thin and elongated objects. The proposed method solves the complex texture issues in natural images. It performs better than other random walk algorithms

Keywords*: sub-Markov, random walk, label prior, complex texture.*

I. INTRODUCTION

Image segmentation is the process of partitioning an image into set of pixels. The set of pixels will represent the interested region or boundary. It is used to locate objects in the entire image. It is mostly useful for applications like image compression or object recognition in certain image analysis techniques. The image segmentation carried on the basis of color, texture, object etc., It involves various thresholding and clustering methods. Region based segmentation algorithms works better than other segmentation methods.

Random walk (RW) has been widely used for many different tasks in computer vision and machine learning such as segmentation [20], [23], [28], [35], clustering [19], [25], ranking [13], [31], classification [10], [41] and the other applications [1], [13], [18], [22], [26], [33]. Grady and Funka-Lea [15] first proposed the RW for medical image segmentation and extended it in [20] for general image segmentation. The random walk method is to make unseeded pixels into the region through labeling unseeded pixels. The process is worked out by considering image as graph which is complete and undirected. The algorithm works as follows:

- Allocate region seeds s_i for each region i
- Calculate $u_i(x,y)$: the probability of first arriving s_i for a random walker starting from (x,y)
- Assign (x,y) to Label k if $u_k(x,y)$ is the largest among $u_i(x,y)$ for i= 1…N
- Identify the probability of each node to reach seeded pixel targeted than other non-targeted pixel.
- Select the probability based on adjacency and degree of the node (i.e) pixel.
- The transition matrix to be $P=D^{-1}W$ except for labeled nodes.

where P = probability matrix
D^{-1} = degree matrix

After introducing multilabeling concept for medical applications [15], many related and important methods based on RW [17], [23], [34], [35] multilabel random walker method [17] have been proposed, the Random Walk has been extended to segment out disconnected objects by using prior models without labeling each objects as the user only needs to indicate labels on some objects and the other similar objects will be segmented out the interested region. Sinop and Grady [23] proposed a common framework to unify the previous methods such as Random Walk, graph cuts and shortest path algorithms for interactive segmentation. Furthermore, they added the popular watershed segmentation algorithm to this common framework [35] and made the analysis for the connections between these algorithms theoretically. This unified framework brings out some advantages and it opens new possibilities for using unary terms in traditional watershed algorithms to optimize more general models.

Recently, some researchers [27], [40] have turned their attention on segmenting natural images with complex textures by extending the RW algorithm and obtain better performance for these challenging images. They considered images to be graphs for solving the complex texture problem. Kim *et al.* [27] proposed a random walker with a restarting probability (RWR) for segmentation. It means that this random walker will return to the starting node with a probability c at each step, and walk to other adjacent nodes with probability $1 - c$. Shen *et al.* [40] have developed the lazy random walk (LRW) for superpixel segmentation. A LRW will stay at the current node with a probability $1 - \alpha$ and walk out along the edges connected with the current node with probability α. The compute time [14] is calculated between unlabeled and seed node. Wu *et al.* [37] proposed another similar RW algorithm called partially absorbing random walk (PARW) for applications based on cluster, such as ranking and classification. In PARW, a random walker is absorbed at current node i with a probability αi and follows a random edge out of it with probability $1 - \alpha i$. And they analyze the relations between PARW and other popular ranking and classification models, such as PageRank [7], hitting and commute times [32] and semi-supervised learning [11], [16]. Comparing the above three RW-based algorithms, we can conclude that they all satisfy the subMarkov property [30], i.e., the sum of transition probabilities $q(i, j)$ that a random walker starts from a node to other adjacent nodes is less than or equal to 1. The problem is to have a unified framework. The other problem is how to segment objects with thin and elongated parts (twig problem) in natural images, which is difficult for most RW-based algorithms. This unified framework brings some benefits, including opening new possibilities for using unary terms in traditional watershed algorithms to optimize more general models.

Recently, some researchers [27], [40] have focused on segmenting natural images with complex textures. They extend the RW algorithm and obtain better performance for these challenging images

II. SUBRW WITH LABEL PRIOR FOR SEEDED IMAGE

Segmentation

In this paper, we proposed a novel subMarkov random walk (subRW) framework to unify four RW-based algorithms: RW, RWR, LRW and PARW, and extend it by adding label prior to solve the twig problem. First, according to the subMarkov property, we build a subRW framework for image segmentation.

In subRW, a random walker will leave a graph G from a node i with probability c_i and walk to the other adjacent nodes in G with probability $1 – c_i$. This random walker can be transformed to a random walker with Markov transition probability ($\sum q(i,j) = 1$) that walks in an expanded graph Ge. This graph is constructed by adding auxiliary staying nodes connected with seeds and auxiliary killing nodes connected with unseeded nodes into graph G. In order to further understand the subRW, we give a detailed optimization explanation. Then we unify the subRW and the aforementioned four RW-based algorithms in the expanded graph. After analyzing the connections between them, we design a new RW-based algorithm by changing edges or adding auxiliary nodes. According to this idea, we introduce a novel subRW with label prior to solve the twig problem. This label prior can be viewed as global 'seeds' connected with all nodes. Each global 'seed' corresponds to a label.

Adding some prior nodes connected with all nodes into graph G_e to build a new expanded graph G_p. Then we compute the probability that a random walker starting from each node reaches the staying nodes or the prior nodes in graph Gp, as the likelihoods probability of corresponding labels. In other words, we want to compute the probability of reaching the user specified seeds plus the probability of reaching the global 'seeds'. These global 'seeds' will help to segment out the twig parts.

The popular random walk with Markov transition probability is first added into our unified optimization framework, which makes this framework more complete. Considerable new theoretical analysis and proofs are added into the initial subRW algorithm such as the uniqueness and a new optimization explanation[29],[34] for subRW with label prior, which make it applicable for more vision applications based on optimization. The optimization framework and explanation improves the initial algorithm to be more suitable for multi-label segmentation. We also extend the original experiments from 2-label segmentation to multilabel segmentation.

The main contributions are summarized as follows:

- A novel random walk (subRW) with label prior is proposed for unifying well-known RW-based algorithms, such as RW [20], RWR [27], LRW [40] and PARW [37], which all satisfy the SubMarkov property, making it easier to convert the intrinsic findings between them.

- The subRW is interpreted as a general optimization problem, which makes it easier to find the latent problem of the subRW for different vision applications.
  For example, from the optimization explanation of subRW with label prior, we find the consistence between label prior and reaching probability may be violated in multi-label segmentation and we successfully solve this problem.

- We further introduce a novel subRW algorithm by adding auxiliary nodes into the original graph.
  According to this idea, a novel subRW method with label prior is proposed to solve the twig segmentation problem with thin and elongated objects.

A. The Sub Markov Random Walk

Given a weighted graph *G*, a set of labeled nodes *VM* and a set of unlabeled nodes *VU*, where $VU \cup VM = V$, the multilabeled image segmentation can be formulated as a labeling problem, where each node $vi \in V$ should be assigned with a label from set *LS*. This problem can be solved by comparing the probability rlk_i of each node belonging to a label *lk* in our algorithm. As mentioned in the graph segmentation process[20],[21],[27] and [40] weight of an edge is calculated as

$$w_{ij} = \exp((\| I_i - I_j \|)^2 / \sigma)+\epsilon \qquad (1)$$

where I_i = denotes intensity of pixel i
σ= controlling parameter
ϵ = constant

Before computing this probability, we define the subMarkov transition probability *q* on *V* as follows:

Definition 1*:* *q* denotes a subMarkov transition probability if for each node *vi*

$$\sum q(i,j) \leq 1 \qquad (2)$$

According to [30], a subMarkov transition probability has the following property:
Property 1: Through adding an auxiliary node , a sub- Markov transition probability *q* on *G* can be made into a (Markov) transition probability on $V \cup \{\_\}$ by setting $\sum q(i,j) = 1$. The steady state probability equations are solved by using [3]-[5] techniques.

The probability can be viewed as a probability that a random walker leaves graph *G*. According to the above property, we can design different subMarkov random walk algorithms by adding different auxiliary nodes. The other advantage of a subMarkov transition probability is that it will help to improve segmentation performance in images with complex texture. The laplacian matrix(2) is obtained by using diagonal and weighted matrix as mentioned in [6].

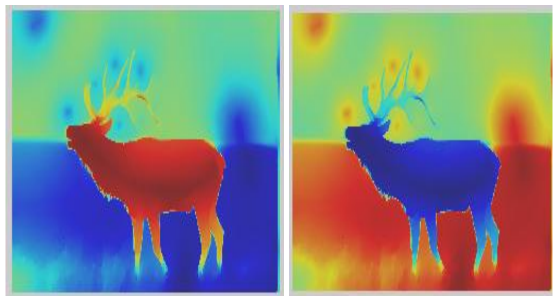
$$L=D-W \qquad (3)$$

An object with twigs can be separated into two parts: main branch object and twig part. Usually, the twig part is similar to the main object, so appropriate user-specified scribbles on the main object have included enough information for segmenting out the twig part. But most RW-based algorithms do not make full use of this information and often omit the twig part. In this section, we want to add a label prior constructed by these scribbles into the subRW to help segment out the twig part.

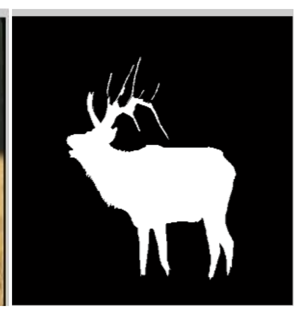
B. Adding Label Prior & auxiliary nodes

In general, user-specified scribbles are considered as exact label prior. The auxiliary nodes are added to the graph so as to obtain the target segment. Unfortunately, this prior only works at the seeded nodes and all unseeded nodes do not have this prior. Therefore, we want to give all nodes in V a new label prior, which maybe less exact than user scribbles, but can be used for unseeded nodes. This label prior is constructed by the user scribbles, i.e., the seeded nodes. We can use probability distributions to build the prior model. Assume a label l_k has an intensity distribution H_k for each node, where $u^k{}_i$ denotes the probability density belonging to H_k at node v_i . The probability distribution follows Gaussian mixture model[24], [36] and [38].

III. RESULT



a) Red and blue for background and foreground indications in the images



b) Proposed result image ***c) Segmented image***

IV. CONCLUSION

We have presented a novel framework based on the sub- Markov random walk for interactive seeded image segmentation in this work. This framework can be explained as a traditional random walker that walks on the graph by adding some new auxiliary nodes, which makes our framework easily interpreted and more flexible. Under this framework, we unify the well-known RW-based algorithms, which satisfy the sub-Markov property and build bridges to make it easy to transform the findings between them. The experimental results have shown that our algorithm outperforms the state-of-the-art RW-based algorithms. The performance results has been measured by using normalized score. The metric limitation [39] was overcome by error rate (i.e) percentage of wrongly labeled nodes. This also proves that it is practicable to design a new subRW algorithm by adding new auxiliary nodes into our framework. The proof of matrix follows the theorem in [2]. In the future, we will extend our algorithm to more applications, such as centerline detection at 3D medical images [42] and classification [41]..

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