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IMAGE REGION ASAQUADTREE HYPER GRAPH

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Abstract:
A suitable image illustration induces some smart image algorithms. Hyper graph theory could be a theory of restricted combinatorial sets, modeling a lot of issues of operational analysis and combinatorial improvement. Hypergraphs are at this time employed in several domains like chemistry, engineering and image process. We tend to gift a summary of a hyper graph-based image illustration giving much application in image manipulation nevertheless, the current hyper graph learning methods face issues, i.e., the way to produce hyper edges and the way to handle a large set of hyper edges. We present an summary of a hyper graph-based Image illustration and also the Image region quad tree Hyper graph (IRQH). With the IRQH it's attainable to make a replacement powerful image segmentation activity model. Though the new model is mathematically outlined and no human sensory system model is expressly used, our experiments on varied image distortion types indicate the efficient of proposed model.

Key Words: Hyper Graph, Image Region Quad Tree Hyper Graph (IRQH), Image Region

1. Introduction:

Intuitively, a graph represents a set of elements and a set of pair wise relationships between those elements. The elements are called nodes or vertices, and the relationships are called edges. Formally, a graph G is defined by the sets $G = (v, E)$ in which $E \subseteq v \times v$.We may denote the i-th vertex as $v_i \in v$, and the i-th edge as $e_i \in E$. Since each edge is a subset of two vertices, we may also write $e_{ij} = \{v_i, v_j\}$. In this book we do not consider graphs with self-loops, meaning that $e_{ij} \in$E implies that $i \neq j$. We also do not consider graphs for which there are multiple edges of the same orientation connecting the same node pair. However, for specific graph encodings, self-loops and multiple edges can be useful

Every graph may be viewed as weighted. Given a graph $G = (v, E)$, vertex weighting is a function $\hat{w} : v \rightarrow R$, and edge weighting is a function $\hat{w} : E \rightarrow R$. To simplify the notation, we will use w to refer to both vertex and edge weighting. The weight of a vertex is denoted by $w(v_i)$ or w_i, and the weight of an edgeincident to two vertices is denoted by $w(v_i, v_j)$ or w_{ij}. If $w_i = 1$, $\forall_{vi} \in v$ and $w_{ij} = 1$, $\forall_{eij} \in E$, then we may consider the graph to be unweighted. If not otherwise specified, all node and edge weights are considered to be equal to unity.We treat $w_{ij} = 0$ as equivalent to $e_{ij} \in$E. Intuitively, an edge weight of zero is equivalent to meaning that the edge is not a member of the edge set.

Each edge is considered to be oriented and some edges additionally directed. An orientation of an edge means that each edge $e_{ij} \in E$ contains an ordering of the vertices, $v_i$and v_j . An edge e_{ij} is directed if $w_{ij} \neq w_{ji}$. A graph for which none of the edges are directed is called an undirected graph, and a graph in which at least one edge is directed is called a directed graph or digraph. A directed edge is represented by the notation ei!j . A directed graph is more general than an undirected graph because it does not require that $w_{ij} = w_{ji}$ for each edge. Consequently, all algorithms for directed graphs may also be applied to undirected graphs, but the converse may or may not be true. Therefore, in this chapter we use digraphs to illustrate the most general concepts. The edge orientation of an undirected graph provides a reference to determine the sign of a flow through that edge. This concept was developed early in the circuit theory literature to describe the direction of current flow through a resistive branch (an edge). For example, a current flow through e_{ij} from node v_i to v_j is considered positive, while a current flow from v_j to vi is considered negative. In this sense, flow through a directed edge is usually constrained to be strictly positive. Drawing a graph is typically done by depicting each node with a circle and each edge with a line connecting circles representing the two nodes. The edge orientation or direction is usually represented by an arrow. Edge $e_{ij}$is drawn with an arrow pointing from node v_i to node v_j.

It is worthwhile to highlight the several desirable aspects of hyper graph based image segmentation: (1) different fromcommonly used pixel-wise similarity, hyper graphs consider patch based homogeneity, which is arguably more meaningful;(2) hyper graphs enable a user to directly specify softconstraints to be considered as edges (called hyper edges);(3) hyper graphs are suited to super pixels which are not definedon a uniform grid, and they two combined togetherboth have favorable computational efficiency and enable ahierarchical segmentation scheme.

2. Hyper Graph in Image:

In this section we introduce hyper graphs, a natural generalization of graphs, and describe our procedure for constructing hyper graph based image models, followed by the hyper graph Laplacian matrices, which play a similar role for hyper graphs as the role of the graph Laplacian matrices for traditional graphs.

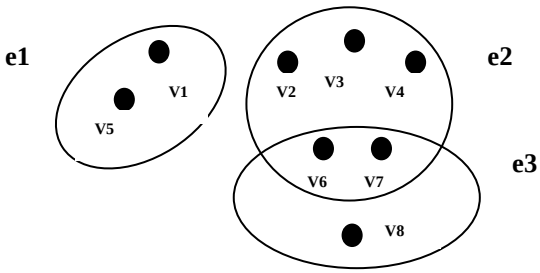


Figure 1: An example hyper graph with8 vertices and 3 hyper edges. V = {v1, v2, v3, v4, v5, v6, v7, v8}, E = {e1, e2, e3} = {{v1, v2}, {v2, v3, v4, v6, v7}, {v6, v7, v8}}.

3. Hyper Graph:

A hyper graph generalizes a graph. In a hyper graph, edges can connect any number of vertices. Formally, a hyper graph is a pair *(V,E)*, where *V* is a set of vertices, andE is a set of non-empty subsets of *V* called hyper edges. Therefore, *E* is a subset of *P(V)*, where *P(V*) is the power set of *V*. We present several useful definitions as follows. A hyper graph *G* can be represented by *a* $|V| \times |E|$ matrix *H* called the incidence matrix of G with $H(v, e) = 1$ if$v \in e$ and $H(v, e) = 0$ if otherwise. A hyper graph *G* can be a weighted one, where an edge e has a weight *w(e)*,and *W* is a diagonal matrix containing the weights of hyper edges. For a vertex $v \in V$, its degree is defined as $d(v) = \sum_{\{e \in E | v \in e\}} w(e)$. D_v is the diagonal matrix containingthe vertex degrees. For a hyper edge $e \in E$, its degreeis defined as $\delta(e) = |e|$, which is the cardinality ofe as a finite set. D_e is the diagonal matrix containing the hyper edge degrees.

Thus, we see that hyper graphs go beyond traditional graphs in that an edge in a traditional graph defines a binaryrelation between two vertices, while a hyper edge defines are lation among a number of vertices. In image segmentation, a traditional graph edge models pair wise pixel similarity, while a hyper edge corresponds to an image patch.

4. Hyper Graph as Image Model:

Graph-based image segmentation methods are dependent on neighborhood graphs constructed from images based on the pairwise (distance, brightness, color) similarity. In our hyper graph-based approach, several hyper edges are constructed for each pixel containing nearby pixels and their weights are assigned based on the homogeneity of pixel colors in the hyper edge.

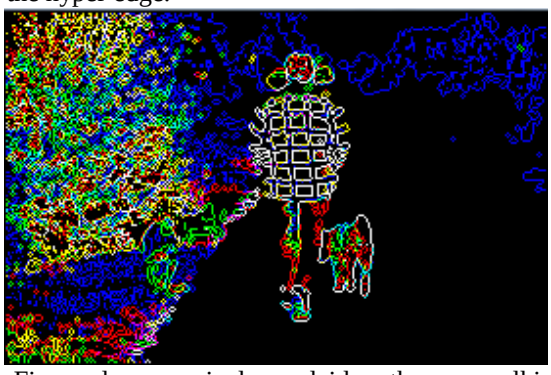


Figure 2: Fine scale super pixels overlaid on the man walking image

Our hyper graph image model utilizes the concept of *super pixels* from the computer vision literature, which are formed in a preprocessing stage to group pixels into larger sets, which are local, coherent, and preserve most of the structure necessary for segmentation at the scale of interest.

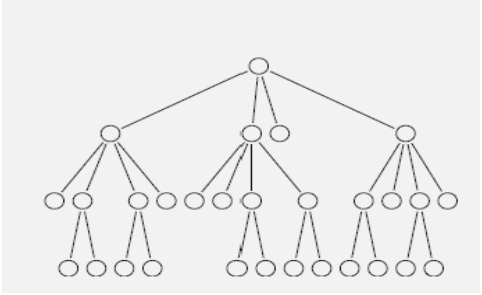
The motivations of this grouping are: (1) pixels are merely a consequence of the discrete representation of images; (2) the number of pixels is typically very high, which makes optimization on the level of pixels intractable. The normalized cuts algorithm is used to produce the super pixel map. In Figure 2, fine scale super pixels are plotted on top of the original image using the code available on line1. We observe from this example that the super pixels are roughly homogeneous in size and shape, which makes a *hierarchical* treatment of image segmentation possible, from the finest scale pixels to super pixels (hard label constraints) and then to hyper edges (soft label constraints) which merge the super pixels and finally to the learned meaningful segments. Although some structures may get lost when we use super pixels, they are usually minor details. The critical aspects of a hyper graph are the construction of hyper edges and the weight of each hyper edge. Ideally, hyper edges correspond to the set of super pixels that we want to combine together. We derive our image model by constructing multiple hyper edges at each super pixel, and assigning a weight to each hyper edge based on patch homogeneity such that the image dependent constraints for combining super pixels are incorporated in a systematic way to our hyper graphic image model. Our model has an advantage over the Image region quad tree Hyper graph (IRQH) proposed, since IRQH considers only one hyper edge at each location, which is more

prone to segmentation errors; our model, however, has multiple hyper edges at each location (super pixel) and assigns a weight to each hyper edge making the resulting segmentation more stable.

5. Image Region Quad Tree Hyper Graph (IRQH):

Image data is almost always sampled in a regular, rectangular lattice that is modeledwith the graphs in the previous section. However, images are often simplified priorto processing by merging together regions of adjacent pixels using an untargeted imagesegmentation algorithm. The purpose of this simplification is typically to reduceprocessing time for further operations, but it can also be used to compress the imagerepresentation or to improve the effectiveness of subsequent operations. Whenthis image simplification has been performed, a graph may be associated with thesimplified image by identifying each merged region with one node and defining anedge relationship for two adjacency regions. Unfortunately, this graph is no longerguaranteed to be regular due to the image-dependent and space-varying merging ofthe underlying pixels. In this section we review common simplification methods thatproduce these irregular graphs.

One very well-known irregular image tessellation is the Image region quad tree Hyper graph (IRQH). A region quadtree is a hierarchical image representation that is derivedfrom recursively subdividing the 2D space into four quadrants of equal size untilevery square contains one homogeneous region (based on appearance properties ofevery region of the underlying rectangular grid) or contains a maximum of one pixel.

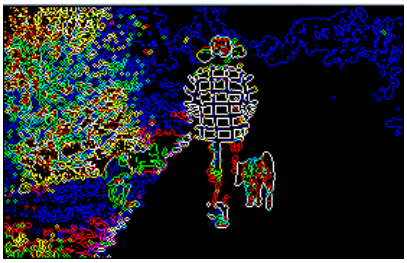


(a)

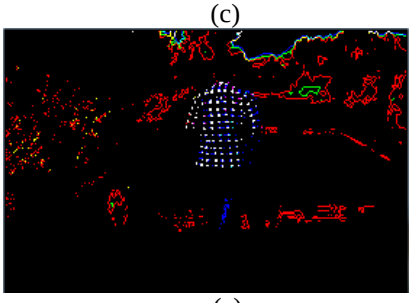
0	1	0	0	7	7	7	7
1	0	2	2	7	7	7	7
0	2	2	2	7	7	7	7
4	4	2	2	7	7	7	7
0	0	1	1	3	3	7	7
1	1	2	2	3	7	7	7
2	4	3	0	5	7	7	7
2	3	3	5	5	0	7	7

(b)

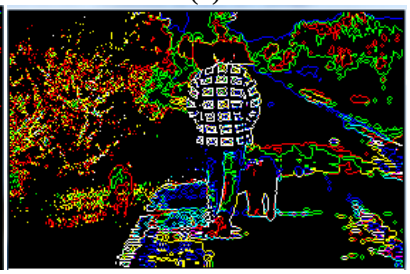
(c)



(d)



(e)



(f)

Figure 3 (a) An image with the quad tree tessellation, (b) the associated partition tree, (c) areal image (d) the region adjacency hyper graph associated to the quad tree partition, (e) and (f) two different irregular tessellations of an image

An Image region quad tree Hyper graph (IRQH) can be easily represented by a tree where each nodeof the tree corresponds to a square. The set of all nodes at a given depth provides agiven level of decomposition of the 2D space. Figure 3 presents a simple exampleon an image (Figure 3(a)) with the associated tree (Figure 3(b)), as well as anexample on a real image (Figure 3(c)). Quad trees easily generalize to higher dimensions.For instance, in three dimensions, the 3D space is recursively subdividedinto eight octants, and thus the tree is called an octree, where each node has eightchildren.

Finally, any partition of the classical rectangular grid can be viewed as producingan irregular tessellation of an image. Therefore any segmentation of an image canbe associated with a region adjacency graph. Figure 3(d) presents the regionadjacency graph associated to the partition depicted in 3(c). Specifically, givena graph $G = \{V, E\}$where each node is identified with a pixel, a partition into Rconnected regions $V1 \cup V2 \cup \ldots \cup VR = V$, $V1 \cap V2 \cap \ldots \cap VR =$; may be identifiedwith a new *graph* $\tilde{G} = \{\tilde{V}, \tilde{E}\}$where each partition of V is identified with a nodeof $\tilde{V}$, that is, $V_i \in \tilde{V}$,. A common method for defining $\tilde{E}$ is to let the edge

weightbetween each new node equal the sum of the edge weights connecting each originalnode in the sets, that is, for edge $e_{ij} \in \tilde{E}$

$$w_{ij} = \sum_{eks,uk \in Vi, vs \in Vj} wks$$

Each contiguous V_i is called a super pixel. Super pixels are an increasingly populartrend in computer vision and image processing. This popularity is partly due to thesuccess of graph-based algorithms, which can be used to operate efficiently on theseirregular structures (as opposed to traditional image-processing algorithms which requiredthat each element is organized on a grid). Indeed, graph-based models (e.g., Markov Random Fields or Conditional Random Fields) can provide dramatic speedincreases when moving from pixel-based graphs to super pixel-based graphs due to the drastic reduction in the number of nodes. For many vision tasks, compact and highly uniform super pixels that respect image boundaries are desirable. Figure 2 (e) and (f) presents some irregular tessellations based on super pixel algorithms.

Table 6: Log-average miss rate (%) on Caltech-Test of upper, left and full body parts with respect to data volume. All results are obtained by fine-tuning from NN which adopted image-level pre-training strategy

Fine-Tuning Data	Upper	Left	Full
Every 30th image	41.19	46.96	33.01
Every 10th image	38.25	46.36	30.45
Every 5 th image	36.63	41.59	23.83
Every 3 rd image	34.60	39.69	23.18
Every image	34.11	37.83	21.19

- ✓ Reasonable subset. Pedestrians are larger than 49 pixels in height and have at least 65 percent visible body parts. Reasonable subset is considered as a more representative evaluation than overall performance on all pedestrians and is the most frequent evaluation setting. Without special illustration, we use Reasonable as our default setting to compare performance.
- ✓ Partial and heavy occlusion subsets where pedestrians are larger than 49 pixels in height and have 1−35 and 36− 80 percent occluded body parts, respectively.

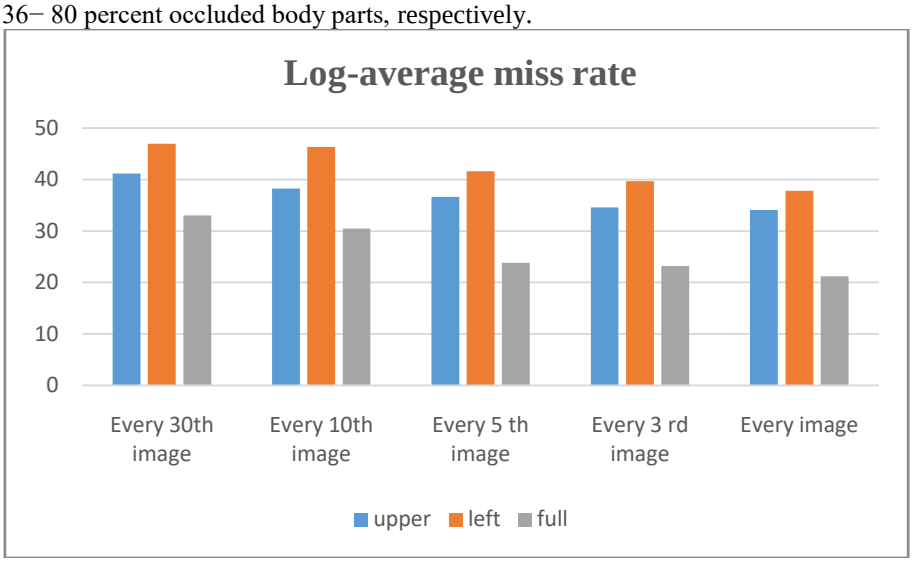


Figure 4: Graph for Log-average miss rate

5. Discussion:

First, our Image region quad tree Hyper graph (IRQH) method addresses two kinds of constraints: the hard ones are modeled by upper pixels, where we require that constituent pixels take the samelabel; the soft ones are modeled by hyper edges, where label consistency is encouraged. Based on our method, onecan build an interactive interface, where a user supplies softconstraints (regions likely to come from an object) and thesystem takes them into consideration by adding new hyper edges in addition to those constructed a priori.Second, it is possible to combine active learning, whichis the framework that allows the learner to ask for informative examples and in our case seeds, with hyper graph-based image region. There are sometimes regions in an imagewith varied texture and color, which can be very hard tosegment given only few labeled pixels. Allowing a user tointeractively provide some segment labels at critical pointscould greatly enhance the region quality. Third, the efficiency of our approach comes from the combination of quad tree and hyper graphs. The majorityof computational time is spent on calculating a fine scale super pixel map, which there are methods in the literature toaccelerate. Suppose N is the number of super pixels. The time needed for hyper graph construction is O(N), and thelinear coefficient is bounded by the maximum number of hyper edges at one super pixel, which is typically a smallnumber. Empirically, the segmentation process when super pixels are available

takes from 0.5 to 2.5 minutes on a1.5 GHz Pentium machine. The computation time dependson the size and the texture content of an image.

6. Conclusion:

In this paper, we have demonstrated the effectiveness of learning Image region quad tree Hyper graph (IRQH). In particular, we use hyper graph based interpolation and showits equivalence to an iterative procedure based on random walks on hyper graphs. Experimentally, we have achievedcompetitive results on the image with our method.We are planning to use more sophisticated probabilisticmodels to address the natural hierarchy of hard and soft constraintsin image region.

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