GRAPH BASED SOLUTION FOR SEGMENTATION TASKS IN CASE OF OUT-OF-FOCUS, NOISY AND CORRUPTED IMAGES

Anita Keszler, Tamás Szirányi
Distributed Events Analysis Group, Computer and Automation Research Institute
Hungarian Academy of Sciences, Budapest, Hungary

Zsolt Tuza
Combinatorial Computer Science Research Group, Computer and Automation Research Institute
Hungarian Academy of Sciences, Budapest, Hungary

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Abstract: We introduce a new method for image segmentation tasks by using dense subgraph mining algorithms. The main advantage of the present solution is to treat the out-of-focus, noise and corruption problems in one unified framework, by introducing a theoretically new image segmentation method based on graph manipulation. This demonstrated development is however a proof of concept: how dense subgraph mining algorithms can contribute to general segmentation problems.

1 INTRODUCTION

We introduce a new method for image segmentation tasks by using dense subgraph mining algorithms. Image classification based on the automatically extracted location of the main objects for indexing and retrieval purposes is a still active research area on the different levels of machine vision. We contribute to this problem an automatic method finding image areas out of focus.

The goal in the segmentation is a binary task: discriminate the focused and out of focus areas. The method first builds up a graph, where pixels are the vertices and edges are weighted by the interpixel similarities in a given radius. In image segmentation graph cut and spectral analysis methods (Kim and Hong, 2009)(Shi and Malik, 2000)(Cousty et al., 2009) are the most frequently used solutions, however these methods usually have several drawbacks. The main disadvantage in this type of application is the fixed number of segments these methods give as an output, where this number is often independent of the intput dataset. However, in case of dense subgraph mining algoritmhs there are numerous approaches where we can avoid this problems, although applied for social interaction mining (Du et al., 2007),(Faloutsos et al., 2004)(Mishra et al., 2007).

2 FINDING THE AREA OF FOCUS

This development is however a proof of concept: how dense subgraph mining algorithms can contribute to general image segmentation problems. The present problem, segmenting focused areas was an unsolved one until (Kovacs and Sziranyi, 2007). That paper suggested a solution using localized blind deconvolution, without any a priori knowledge about the image or the shooting conditions and using a new error measure for area classification. Previous methods (Lim et al., 2005) used edges or autocorrelation methods to find sharp areas, but their efficiency was weaker for the real focus detection than that of (Kovacs and Sziranyi, 2007). The focus-map detection methods are usually based on the assumption that pixels are smoothed in out-of-focus areas resulting in lower contrast there. While edge based methods consider the local derivatives to measure smoothness, the blind deconvolution based method (Kovacs and Sziranyi, 2007) makes estimation on the local image content itself. The previous methods do not handle the case when the in-focus condition is evaluated against noisy and corrupted (e.g. scratched or badly transmitted) images.

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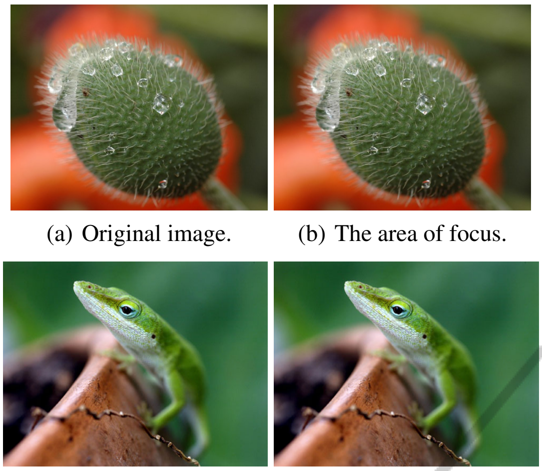


(a) Original image. (b) The area of focus.

(c) Original image. (d) The area of focus.

Figure 1: Test results on images with blurred background.

The present method is also based on the fact that local contrast is weaker in blurred areas, but noise and data corruption is considered on a graph theoretical view-point. However, this procedure is different from conventional morphology or correlation based image corrections, like ones in (Licsar et al., 2010). The main advantage of the present solution is to treat the out-of-focus, noise and corruption problems in one unified framework, by introducing a theoretically new image segmentation method based on graph manipulation.

2.1 Finding the Blurred Area in an Image

The method of blurred area detection is to identify the clusters of pixels corresponding to the blurred areas. The first phase of finding the clusters is to detect the cluster cores (corresponding pixels), then the next step is to classify the remaining pixels (blurred or focused area) depending on their similarities to cluster cores. If a pixel is similar to any of the found cores, it will belong to a blurred area in the image.

The mining of the cluster cores is an essential part of numerous dense subgraph mining algorithms. A core is a set of vertices that is sufficiently dense compared to the average density of the graph. Especially in a large graph it is a hard task to find a fast way of recognizing the cores. In (Mishra et al., 2003) the authors present a theoretical approach to solve this problem for bipartite graphs in $O(|V|)$ time, mining ε-bicliques. $|V|$ denotes the number of objects to be clustered. Although the running time is linear in the number of nodes, it is exponential in the parameter showing how close we are to the complete bipartite subgraphs. Another disadvantage is that it is only applicable if the size of a cluster is also $O(|V|)$, and as it is based on random sampling, it only finds the clusters with a given probability.

In our solution, the running time of the core finding FINDCORES() algorithm is $O(|V|^2)$ for an arbitrary graph. However, it is suitable for any cluster size, and finds all cluster cores parallelly. Besides this, if the input graph is sparse ($E = O(V)$), the running time is $O(V)$. Since in case of graphs of images, where only the neighboring pixels are connected, we have a sparse graph, we get a linear running time in the number of pixels. We work with a modified minimum weight spanning tree algorithm, and we use the Kruskal-algorithm as a basis.

Since we do not need to have a subgraph without circles, we only use the idea that the order of connecting vertices depends on how similar they are. An obvious problem is to define the stopping conditions of the algorithm. We will use d_{limit} as a threshold to ensure that in each cluster core the nodes are similar enough. In each step, when the Kruskal-algorithm decides whether an edge should be a part of the spanning tree, we also check the diameter of the evolving component. Let P be the pixel set of the image, and let M be the feature matrix, where each μ_i row is the corresponding feature vector of pixel $v_i \in V$. The steps of the algorithm are the following:

Algorithm [ClusterCores]=**FINDCORES**(M, d_{limit}).

1. Compute the distance between feature vectors
2. Increasing order of the distance values: $Dist_{order}$
3. Inicialization: Let $G = (V,E)$ be a graph, E'=$\{\}$; $i = 1$;
4. $x = Dist_{order}(i)$;
5. if $x < d_{limit}$ $E = E \cup x$; $i = i+1$; else discard x;
6. If there are edges left, go to step 4.
7. ClusterCores = Connected components

The focused areas of the images are more detailed than the blurred ones, hence differences between neighboring pixels tend to be higher. On the other hand the components we get as an output (ClusterCores) contain the pixel-sets with the smallest differences. These pixel-sets correspond to the blurred areas of the image. Since we only need to make a difference between focused and blurred parts, as it was mentioned before, the pixels corresponding to any of the ClusterCores, will belong to the blurred area. The d_{limit} is the maximum weight of the edges we choose

(a) (b) (c) (d) (e)

Figure 2: (a) Original image. (b) MSE-based method. (c) PSF-based algorithm. (d) Localized blind deconvolution algorithm. (e) The presented method.

for the cluster cores and is set based on the distribution of edges. The algorithm will stop when adding the edges corresponding to weight of d_{limit} results in the smallest changes in the output.

2.2 Test Results

We present two results for the FINDCORES() algorithm for detecting blurred regions on several images on Fig. 1: (a), (c) show the original images. The pixels of the ClusterCores were masked and the remaining ones are selected as focused area, presented on (b) and (d).

We have compared our results to other methods, see Fig. 2. Fig. (a) shows the original image, (b) is an MSE distance-based extraction algorithm (Kovacs and Sziranyi, 2005), (c) PSF-based method, while (d) is the method presented in (Kovacs and Sziranyi, 2007). Compared to the focus map the other algorithms present (b)(c)(d), one should notice that the proposed algorithms (e) detects the area in focus and gives an output with a higher (pixel-level) resolution with a small running time.

3 FINDING THE AREA OF FOCUS IN A NOISY IMAGE

Handling noisy input data is an important task in focus detection as well. The proposed method can also be applied as a preprocessing step for image restoration algorithms, since selecting the area of focus in noisy images offers the opportunity of applying different deblurring methods for areas of different contrast levels. Fig. 3 (a) and (b) present an example of the original and noisy images. If we use the RGB codes of the neighboring pixels as feature vectors, the output of the FINDCORES() algorithm will become almost unusable (Fig. 3 (c)). Since the algorithm works on pixel-level, noisy pixel features might result in high edgeweights, or on the contrary we might connect pixels that should be separated in the clean image. To overcome this problem we extend the feature vectors of the vertices with the features of the neighboring pixels (8-connection). With this, we get a more robust method in case of pixel-level noises (Fig. 3 (c)).

4 FINDING THE AREA OF FOCUS IN CASE OF PARTIALLY MISSING INFORMATION

Several problems occur for videos in online transmission when some portion of the image is missing (lines or blocks). Since we do not have the data needed to calculate the distance of these damaged pixels with the former methods, we need a different model to make use of the available information.

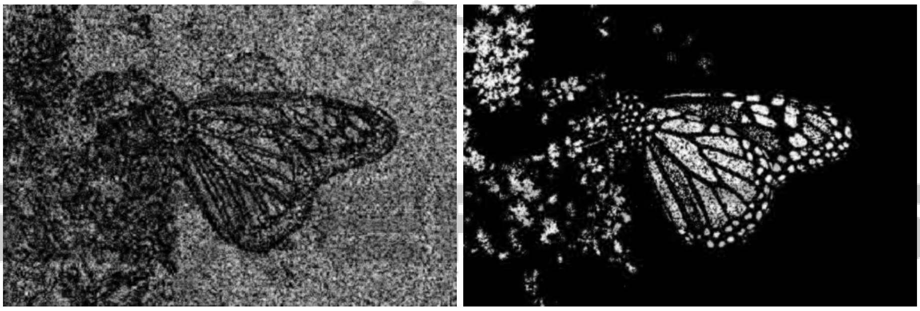
The role of the graph in the former section was to find the cluster cores corresponding to the blurred areas in the image. We will use a bipartite graph to model and cluster the pixels of the cluster cores and the pixels with damaged feature vectors. An important improvement of this structure is applying a bipartite graph model complemented with a standard model, leading to a new way of handling missing data. The idea is to cluster the damaged feature vectors and the corresponding pixels based on the available information by finding the dense bipartite subgraphs they belong to. The cores of these dense bipartite subgraphs are the cluster cores of the FINDCORES(algorithm). The proposed method has the following steps:

Algorithm [MV]=**CLUSTER**(M_{comp}, M_{dam}, ε)

1. $[ClusterCores]$ =FINDCORES(M_{comp},d_{limit})
2. $[C_{ClCore}]$ =CALC-CORECHAR(ClusterCores,ε)
3. $[MV_{matrix}]$ =COMPUTE-MV(M_{comp},M_{dam})

(a) Original image.

(b) Noisy image with random noise of 30%.



(c) Output of the single-pixel based version of the algorithm.

(d) Output of the neighborhood-based version of the algorithm.

Figure 3: Result of the focus-detection in a noisy image using different versions of the algorithm.

(a)

(b)

Figure 4: (a) Original test image. (b) Noisy image with missing pixels of 10%.

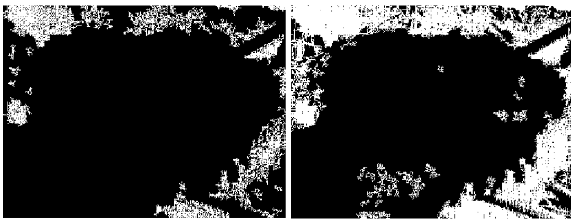


Figure 5: Inner steps of the core finding algorithm. The white areas present the most strongly connected pixels in the image.

The FINDCORES() subalgorithm is applied to detect the cluster cores, based on the pixels with complete feature vectors (M_{comp}). The CALC-CORECHAR() method calculates a characteristic vector for each cluster core, using the feature vectors to select the relevant cluster-dependent features. The pixel feature vectors are compared to the gained characteristic vectors by the COMPUTE-MV() subalgorithm, which gives the membership values of each pixel concerning each cluster as an output. This function calculates the membership values for pixel with complete (M_{comp}) and incomplete or damaged (M_{dam}) feature vectors as well.

4.1 Calculating Characteristics using a Bipartite Graph

In the bipartite graph, the gained ClusterCores of the FINDCORES() subalgorithm form dense bipartite subgraphs, where the density definition is the same as in (Mishra et al., 2003): Let $G = (A, B, E)$ a bipartite graph and $0 \leq \varepsilon \leq 1$. A $G' = (A', B', E')$ subgraph is an ε-quasi-biclique, if

$$\forall v_i \in A', |N'(v_i)'| \geq (1-\varepsilon) \cdot |B'|, where N'(v_i) \in B'$$

The ε parameter can be bounded from below using the d_{limit} parameter from the FINDCORES() subalgorithm. Although these cores are dense compared to the average density of the graph, if $\varepsilon \geq \varepsilon_{desired}$ then to get better results the most weekly connected nodes should be removed. As a result we get the relevant features for each cluster core, see Fig. 6.

Based on the feature vectors of the nodes in each core, we get the cluster characteristics. A weight vec-

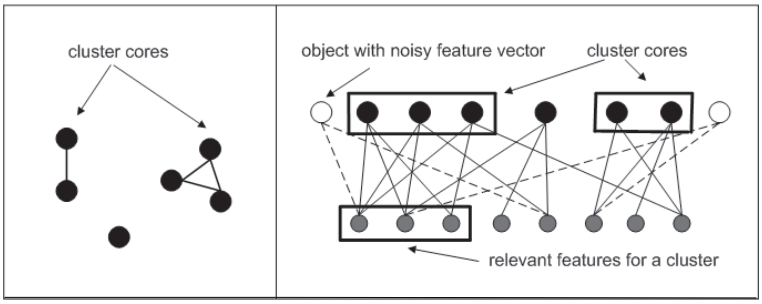


Figure 6: Cluster cores of the standard graph (left) found by the FINDCORES() method. Bipartite graph model: we determine the relevant features for each cluster core; Pixels with incomplete feature vectors will be clustered based on the similarities between their non-missing features and the relevant feature sets of the clusters.

tor is calculated as an average of the feature vectors in each cluster core and the disparity vector as well. If the disparity is low, the feature is relevant for the given cluster. The feature relevance is important also among the cluster cores. If the disparity within the clusters is low for a given feature, then it is not suitable to make a distinction between the clusters.

The cluster characteristics consist of a characteristics value, derived from the two disparity values, and a weight value. The steps of the CALC-CORECHAR() algorithm for calculating the characteristics are as follows: (The $f()$ function is for normalizing the characteristics.)

In this case, it is an apparent overcomplication to select relevant features, since now we work with low dimensional feature vectors. However, the presented test results were only an illustration of the capacities of the algorithm. The algorithm is capable of handling high dimensional feature vectors, for example if the SIFT features of the pixels are used.

Algorithm $[c_{ClCore}, w_{ClCore}]$ = **CALC-CORECHAR** (ClusterCores).

1. For each core c_i in ClusterCores
2. $w_{ClCore}(i,k)$ = avg(μ_{jk}) if $v_j \in c_i$
3. $\sigma_{cl}(i,k)$ = disp(μ_{jk})
4. For each feature F_k $\sigma_{ClCores}(k) = disp(w_{ClCore}(i,k))$
5. For each core c_i in ClusterCores $c_{ClCore}(i,k) = f(\sigma_{ClCores}(k)/\sigma_{cl}(i,k))$

4.2 Clustering the Nodes

By clustering one usually means deciding to which cluster core the given node belongs to. Here to each object we calculate a membership-value, how strong the connection to each core is, and a confidence value, representing the reliability of this strenght value.

Algorithm $[MV_{matrix}]$=COMPUTE-MV (M_{comp}, M_{dam}, c_{ClCore}, w_{ClCore}).

1. For each v_i in M_{comp} and M_{dam}
2. For each c_j cluster core if $m_{ij} \neq 0$
3. $diff(i,j)$ = abs$(m(i) - w_{ClCore}(j))$
4. $d(i)$ = norm$(diff(i))$
5. $MV(i,j,k) = d(i) \cdot c_{ClCore}(j)$
6. $MembValue(i,j) = sum_k[MV(i,j,k)]$
7. $Confidence(i,j) = sum(m_{ij})/F$ if $m_{ij} \neq 0$

We compare the $m(i)$ feature vector of each vertex v_i with the cluster weight vector $w_{ClCore}(j)$, and we apply normalization (step 4). The previously calculated characteristics will be used as relevance measure weights. The membership values are derived from the non-missing elements of the feature vectors. The confidence value represents the ratio of the available information.

Let us notice that every node is re-clustered, even the ones, we used for finding the cluster cores. If more membership values are high in case of a given node, it means the node belongs to both clusters. This way the algorithm can be used even if the dataset contains overlapping clusters.

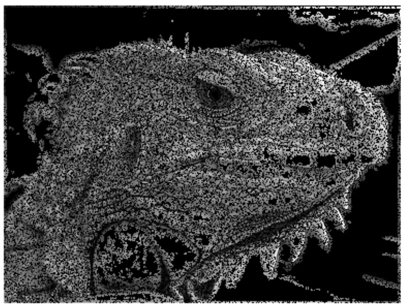


Figure 7: The foreground part of the image selected by the algorithm.

5 CONCLUSIONS

We have implemented a theoretically new image segmentation algorithm, based on graph core mining in the structure of bipartite graphs. This approach makes it possible to involve image reconstruction-like operations into the same framework: focus-detection, denoising and patching. This paper is only a posing of a greater framework, where the method will be developed by: multi-level clusters, multi-scale evaluation, texture-analysis and semantic level evaluation. The above results encourage us to exploit the potential of graph clustering in more complex image understanding tasks. The algorithm can also be applied as a preprocessing step for image restoration methods.

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