Multilevel Segmentation of Histopathological Images using Cooccurrence of Tissue Objects: Supplementary Material

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***Abstract*—Digital pathology is becoming an increasingly important tool for automated biopsy analysis. Automated analysis of histopathological tissue images not only increases throughput but also improves reproducibility. The first step of this analysis usually involves the segmentation of a tissue into its homogeneous regions. This technical report contains the supplementary material for the multilevel segmentation algorithm that we developed for the purpose of histopathological tissue image segmentation [1].**

***Index Terms*—Histopathological image analysis, multilevel segmentation, segmentation ensemble, texture, image segmentation**

I. Introduction

In this technical report, we first provide the pseudocodes of our multilevel segmentation algorithm in Sec. II. Subsequently, in order to validate the robustness and stability of the segmentations, we give the visual results of an example image obtained in different runs in Sec. III.

II. Pseudocodes

The proposed approach relies on characterizing a tissue image with high-level texture features and using them in an efficient segmentation algorithm. To this end, it introduces *object cooccurrence features* that quantify the spatial organization of tissue components. These features are extracted by decomposing a tissue image into a set of objects of different types, which approximately represent the tissue components, and calculating the frequency of the cooccurrence of two object types with respect to different distances. The details of this feature extraction are given in [1].

Image segmentation is then achieved by partitioning the objects according to their cooccurrence features. This approach proposes to obtain multiple object partitions (segmentations) and combine them with an ensemble function. For an object partitioning step, a weighted graph is constructed on a selected subset of the objects, with an edge weight being defined as the similarity of its end points with respect to their features, and *a multilevel graph partitioning algorithm* is used to obtain a partition. The main steps of this segmentation algorithm are given in Algorithm 1. The pseudocodes of the subroutines called by this algorithm are also provided in this section.

Algorithm 1 Segmentation

Input: object set O, feature set Φ, number of segmented objects K, number of vertices in the coarsest graph K', sampling ratio $ratio$, number of segmentations M
Output: segmented objects S

$\Psi = \emptyset$
for $i = 1 \rightarrow M$ **do**
  $G^0 \leftarrow$ ConstructSampleGraph$(O, \Phi, ratio)$
  $\Pi'_i \leftarrow$MultilevelGraphPartitioning(G^0, K')
  $\Pi_i \leftarrow$ InducePartition(Π'_i, V^0, O, Φ)
  $\Psi = \Psi \cup \{\Pi_i\}$
end for
$S \leftarrow$ SegmentationEnsemble(Ψ, O, K)

Algorithm 2 ConstructSampleGraph

Input: object set O, feature set Φ, sampling ratio $ratio$
Output: graph G^0

$V = \{v_1, v_2, ..., v_p\} \leftarrow$ RandomSampling$(O, ratio)$
$F = \{\Phi(v_1), \Phi(v_2), ..., \Phi(v_p)\}$
$E = \{e(u, v) \mid u, v \in V\} \leftarrow$ Delaunay(V)
$W = \{w(u, v) = sim(F(u), F(v)) \mid e(u, v) \in E\}$
$G^0 = (V, F, E, W)$

Algorithm 3 MultilevelGraphPartitioning

Input: graph G^0, number of vertices in the coarsest graph K'
Output: partition vector Π'

$[G, T] \leftarrow$ Coarsening(G^0, K')
$\Pi' \leftarrow$ Uncoarsening(G, T)

III. Visual Results

The proposed algorithm involves randomness in obtaining the object partitions, which are then to be combined in an ensemble algorithm. Thus, the segmentation of an image may change from one run to another. In order to validate the robustness and stability of the segmentations found by our proposed algorithm, we conduct the following experiment. For each image, we run the overall algorithm 30 times and calculate the standard deviation of the F-scores over these

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Algorithm 4 COARSENING

Input: initial graph G^0, number of vertices in the coarsest graph K'
Output: graph sequence G, number of levels T

$G =< G^0 >$
$t \leftarrow 1$
$G^1 = G^0$
$currVertexNo \leftarrow |V^0|$
while $currVertexNo > K'$ **do**
  for each randomly visited vertex v in V^t **do**
    if v is not $merged$ with any other vertex **and** $currVertexNo > K'$ **then**
      $U = \{u \mid u, v \in V^t$ and $e(u,v) \in E^t\}$
      $u^* \leftarrow \underset{u \in U}{\operatorname{argmax}}\ w(F^t(u), F^t(v))$
      merge vertices u^* and v
      update F^t, E^t, and W^t
      mark u^* and v as $merged$
      $currVertexNo = currVertexNo - 1$
    end if
  end for
  $G =< G, G^t >$
  $G^{t+1} = G^t$
  $t = t + 1$
end while
$T \leftarrow t - 1$

Algorithm 5 UNCOARSENING

Input: graph sequence G, number of levels T
Output: partition vector Π'

$P^T \leftarrow$ labels of V^T
for $t = T - 1 \rightarrow 0$ **do**
  $S \leftarrow$ super-vertices of V^t
  $P^t \leftarrow P^{t+1}(S)$
  $B^t \leftarrow \{u \mid \exists v \in V^t$ s.t. $e(u,v) \in E^t$ and $P^t(u) \neq P^t(v)\}$
  $iterNo \leftarrow |B^t|$
  repeat
    {This for loop is called a $pass$}
    for $i = 1 \rightarrow iterNo$ **do**
      $b \leftarrow$ randomly select an unvisited vertex in B^t
      if b is not $moved$ in this $pass$ **then**
        move vertex b to its most similar region
        update P^t and B^t
      end if
    end for
    find newly emerged $parts$
  until $parts$ remain unchanged
end for
$\Pi' \leftarrow P^0$

runs. We then use the average of these standard deviations over the test set images to examine the robustness and stability of the segmentations. The average F-scores are found to be 1.58, 2.00, 1.74, and 1.26 percents for $K = 2$, 3, 4, and 5, respectively. The results indicate that the segmentations slightly change from one run to another. The visual results also support this finding. In Figs. 1 and 2, we provide the visual results of an example image obtained over these 30 runs for $K = 2$ and 3, respectively.

Algorithm 6 INDUCEPARTITION

Input: partition vector Π', selected object set V, object set O, feature set Φ
Output: new partition vector Π

$\mathcal{E} = \{e(u,v) \mid u, v \in O\} \leftarrow$ DELAUNAY(O)
$\mathcal{W} = \{w(u,v) = sim(\Phi(u), \Phi(v)) \mid e(u,v) \in \mathcal{E}\}$
for each object o_i in O **do**
  if $o_i \in V$ **then**
    $\Pi(o_i) = \Pi'(v_i)$
  else
    $U = \{u \mid u \in V$ and $e(o_i, u) \in \mathcal{E}\}$
    $u^* \leftarrow \underset{u \in U}{\operatorname{argmax}}\ w(\Phi(o_i), \Phi(u))$
    $\Pi(o_i) = \Pi'(u^*)$
  end if
end for

Algorithm 7 SEGMENTATIONENSEMBLE

Input: partition vector set Ψ, object set O, number of segmented objects K
Output: segmented objects S

$G_b \leftarrow$ CONSTRUCTBIPARTITEGRAPH(Ψ, O)
$S \leftarrow$ GRAPHPARTITIONING(G_b, K)

REFERENCES

[1] A. C. Simsek, A. B. Tosun, C. Aykanat, C. Sokmensuer, and C. Gunduz-Demir, "Multilevel segmentation of histopathological images using cooccurrence of tissue objects,", submitted, 2012.

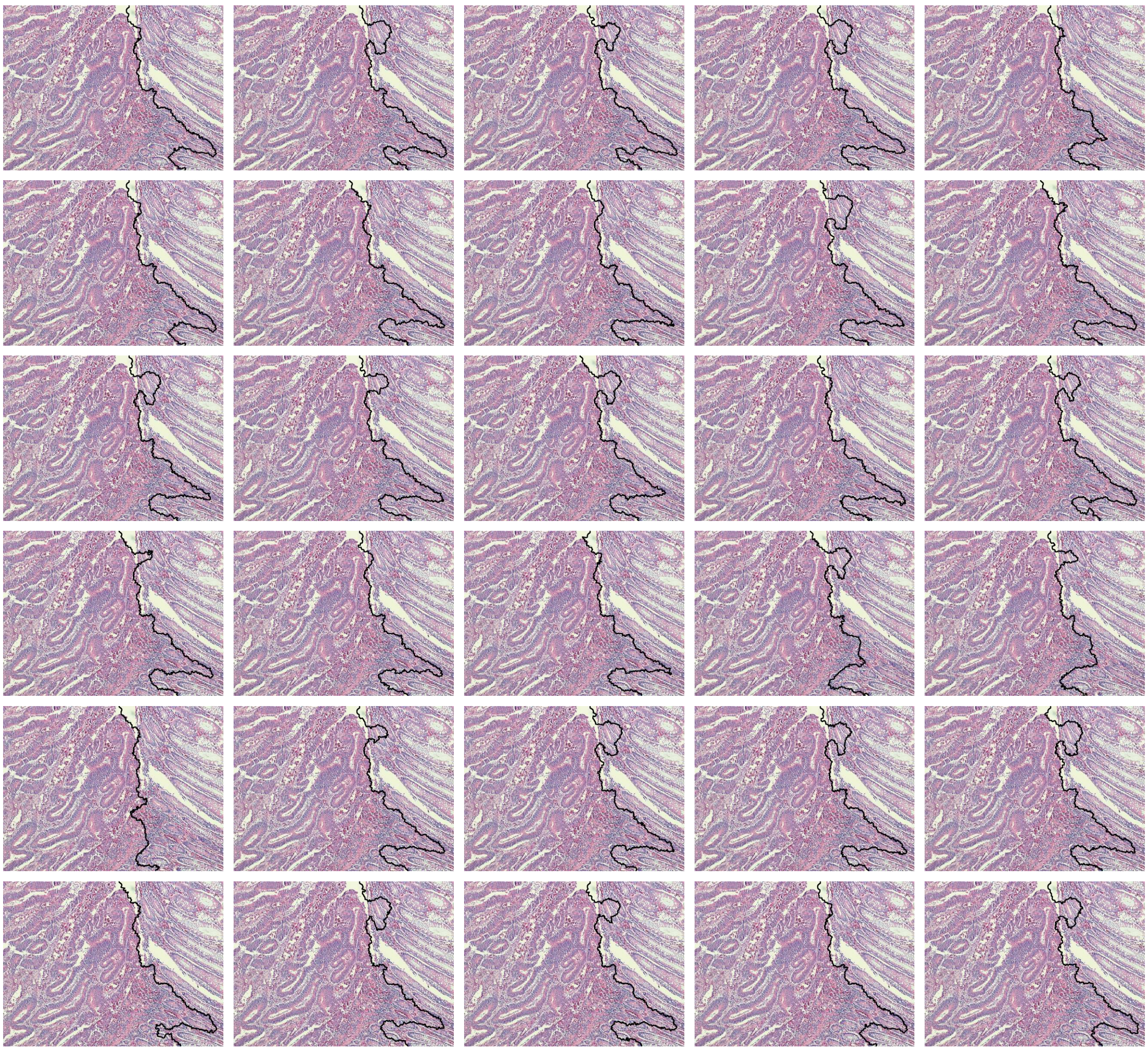

Fig. 1. The visual results of an example image obtained over 30 runs for $K = 2$.

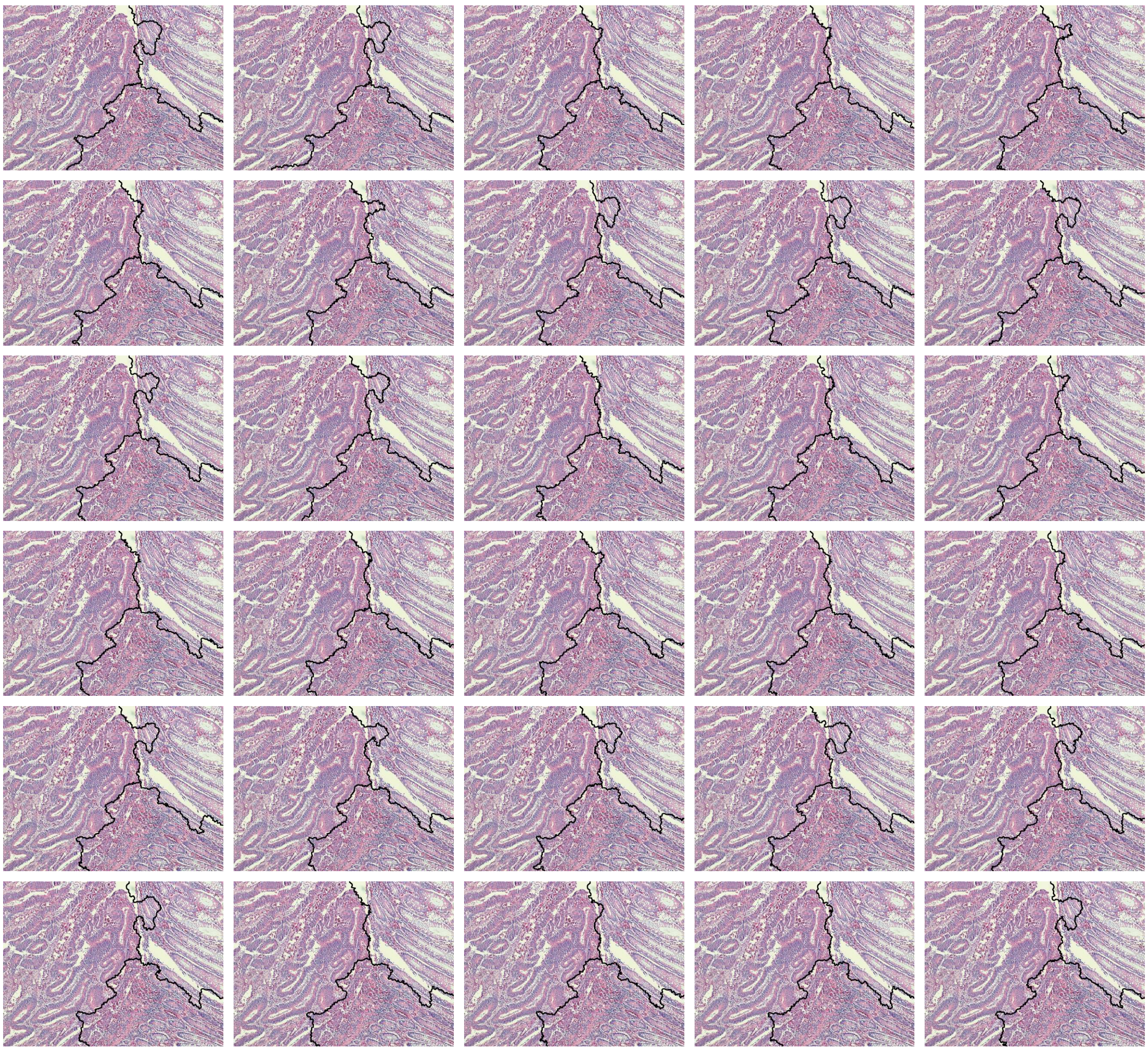

Fig. 2. The visual results of an example image obtained over 30 runs for $K = 3$.