Exploring Uncertainty in Image Segmentation Ensembles

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Abstract

Finding the most accurate image segmentation involves analyzing results from different algorithms or parameterizations. In this paper, we identify different types of uncertainty in this analysis that are represented by the results of probabilistic algorithms, by the local variability in the segmentation, and by the variability across the segmentation ensemble. We propose visualization techniques for the analysis of such types of uncertainties in segmentation ensembles. For a global analysis we provide overview visualizations in the image domain as well as in the label space. Our probability probing and scatter plot based techniques facilitate a local analysis. We evaluate our techniques using a case study on industrial computed tomography data.

CCS Concepts

•***Computing methodologies*** → *Image segmentation; Uncertainty quantification;*

1. Introduction and background

In image segmentation, there is no single best method, as for each application scenario, algorithm adaptation and parameter tuning is needed. For this purpose, methodical sampling of one or more algorithms is required [SHB*14], resulting in a set of slightly different segmentations, a *segmentation ensemble*. Torsney-Weir et al. [TWSM*11] target finding suitable parameters when an objective quality measure is available. Pretorius et al. [PMTR12] suggest to analyze segmentation ensembles using a tree-based visualization. Fröhler et al. [FMH16] propose methods utilizing hierarchical clustering and aggregated visualizations. These tools do not utilize *uncertainty* information, but Saad et al. [SMH10] show that it can provide valuable insights in this context. More recently, Summa et al. [STP17] proposed a method to find alternative segmentations using uncertainty information. Their methods are limited to analyzing a single probabilistic segmentation. Al-Taie et al. [ATHL14a] introduce an ensemble segmentation method utilizing the variability in the ensemble in a rule-based combined classification. However, they do not visualize the variability in relation to other uncertainty information. The contribution of our work lies in

- Identifying types of uncertainty in segmentation ensembles
- Techniques for the systematic exploration of this uncertainty
- A case study showing the usefulness of these techniques.

2. Uncertainty types in segmentation ensembles

Probabilistic segmentation algorithms, such as the Random Walker [Gra06], compute the probability for each pixel x of belonging to each label l as $a_x(l)$. a_x is a probability distribution over the set L of all labels in the segmentations. Figure 1(a) shows a sample algorithm probability distribution for pixel x of the first member in the small ensemble in (b). The *neighborhood variability* of a pixel in a segmentation is indicating uncertainty, as segmentation algorithms often have problems to delineate borders accurately. The labels in a pixels neighborhood are considered as a distribution $n_x^m(l) = c(N_x^m, l)/|N_x^m|$ for pixel x in member m, where N_x^m is the set of labels of the pixels in the neighborhood of x in member m. $c(N_x^m, l)$ yields how often l occurs in N_x^m, and $|N_x^m|$ is the size of the set N_x^m. Figure 1(c) shows the neighborhood distribution for pixel x. The *ensemble variability* can also be considered as a measure for the uncertainty. We establish the probability distribution e_x for a pixel x as $e_x(l) = c(M_x, l)/|M_x|$. M_x is the set of labels for pixel x in all ensemble members, $|M_x|$ thus is the number of members. This concept is visualized in Figure 1(d) for the pixel marked with x, y and z in the respective members in (b). Note that in contrast to a_x^m and n_x^m, which are defined for each pixel x and every member m, there is only a single e_x for one pixel x across all members of the whole ensemble.

3. Uncertainty determination and visualization

Inspired by the information-theory based measures for uncertainty introduced by Potter et al. [PGA13] and Al-Taie et al. [ATHL14b], we use a normalized entropy in the range $[0, 1]$ as measure of uncertainty for the distributions defined above. We refer to the uncertainties computed from a_x^m as *algorithm uncertainty*, from $n_x^m(l)$ as *neighborhood uncertainty*, and from e_x as *ensemble uncertainty*,

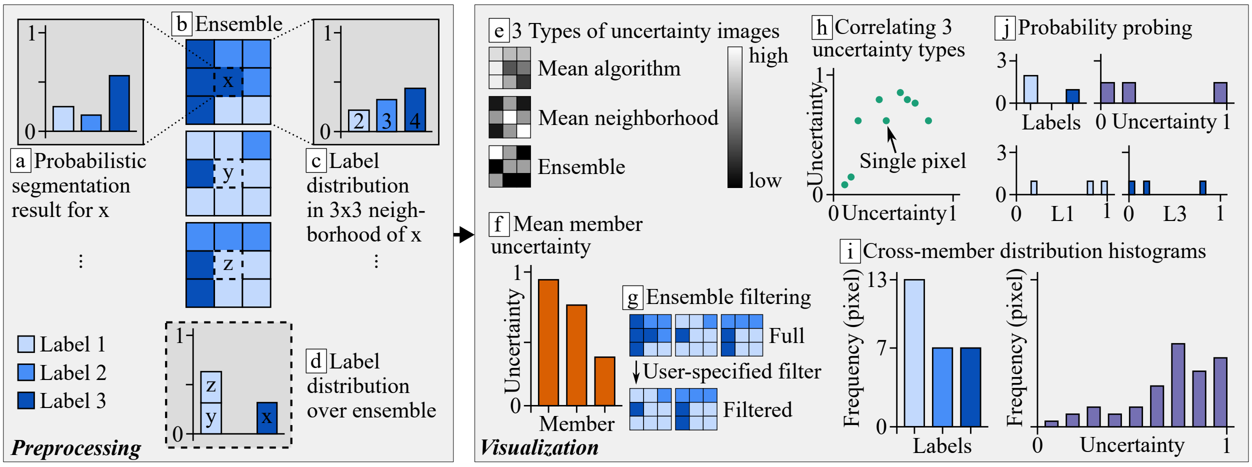

Figure 1: *Workflow for a segmentation ensemble with three 3x3 images. (a) Label probabilities for pixel x from a probabilistic segmentation algorithm. (b) Segmentations computed from (a) by maximum probability rule. (c) Neighborhood distribution for pixel x. (d) Ensemble distribution for all middle pixels. (e) Uncertainty images. (f) Mean member uncertainty. (g) Filtering for interesting members. (h) Scatter plot correlating between uncertainty types. (i) Label/Uncertainty distribution for all ensemble members and pixels. (j) Probability probing.*

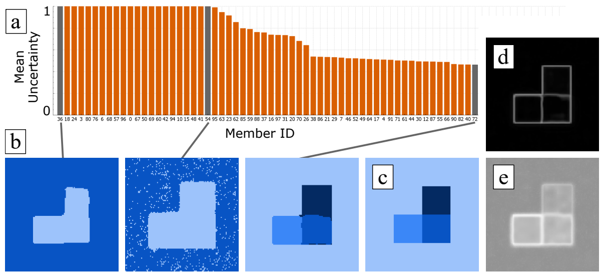

Figure 2: *(a) Mean member uncertainty. (b) Selected members. (c) Ground truth. (d) Neighbourhood uncertainty image. (e) Mean algorithm uncertainty image.*

respectively. We compute mean algorithm, mean neighborhood and ensemble *uncertainty images* and visualize these using a gray scale color mapping (see Figure 1(e)). The *mean member uncertainty* bar chart, showing the mean algorithm uncertainty across all pixels for each member, provides a member overview (see Figure 1(f)). To remove unsuitable results from analysis, the user can either filter for members in the mean member uncertainty chart or employ a result-based filtering inspired by Zhu et al. [ZLE14] (see Figure 1(g)). For a localized analysis, correlations of the different types of uncertainties are visualized in scatter plots (see Figure 1(h)). Our *probability probing* technique is based on the work by Potter et al. [PKXJ12]. For the current pixel we show the label and uncertainty distribution in the ensemble as a histogram of label occurrences and histograms of the probabilities from the probabilistic segmentation algorithm (see Figure 1(j)).

4. Evaluation and results

We evaluate our methods on a synthetic computed tomography (CT) dataset. Figure 2(a) shows a part of the distribution of mean member uncertainties. In (b) we see the segmentations of three members which are selected in (a). The first two on the left have high mean member uncertainty. A visual inspection shows that these are unsuitable results. The third selected segmentation, with lower mean uncertainty, is close to the expected result, in this case a manually labeled ground truth, shown in (c). This tells us that for this ensemble there is a close relation between algorithm uncertainty and segmentation quality. An analysis of the mean neighborhood uncertainty, visible in (d), tells us that when considering the local variability of each member, the uncertainty is very high at the borders between the different labels (white indicates high uncertainty, black a low one). The mean algorithm uncertainty, shown in (e), also indicates this, and the grayer overall look tells us that the algorithm uncertainty is in general higher than the neighborhood uncertainty in (d). The algorithm uncertainty further tells us that the region with highest uncertainty is the rectangular region on the lower left. We can thus focus our further refinement of the algorithm on this region. Details on the dataset, the segmentation algorithm we used, as well as a further case study using the other techniques described above, can be found in the appendix.

5. Conclusions and future work

We have systematically categorized the uncertainty information available in a segmentation ensemble into *algorithm*, *neighborhood* and *ensemble uncertainty*. We propose techniques for analyzing this information, and discuss how these techniques can be utilized to gain insights on the performance of segmentation algorithms. We are currently looking into further ways how the available information could be used to refine the segmentations.

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