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NOVEL WATERSHED SEGMENTATION METHOD FOR STUMPY BOUNDARY DETECTION FOR IMAGE CLASSIFICATION

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Image segmentation is one of the important areas of current research. This paper presents a novel approach for creation of topographical function and object markers used within watershed segmentation. Typically, marker-driven watershed segmentation extracts seeds indicating the presence of objects or background at specific image locations. The marker locations are then set to be regional minima within the topological surface and the watershed algorithm is applied. In contrast, our approach uses two classifiers, one trained to produce markers, the other trained to produce object bound-aries. As a result of using machine-learned pixel classification, the proposed algorithm is directly applicable to both single channel and multichannel image data. Additionally, rather than flooding the gradient image, we use the inverted probability map produced by the second aforementioned classifier as input to the watershed algorithm.

Keywords: Machine-learned pixel classification, regional minimum, Bayesian perspective, Markov Random fields and watershed.

1. Introduction

The two key operations in computer vision are segmentation and pixel grouping. While many image segmentation algorithms exist, when objects of the same predefined class are in close proximity to one another, pixel grouping is necessary to cluster the classified pixels into objects. The watershed algorithm [2,4,5] is commonly used within the unsupervised setting of segmenting an image into a set of non overlapping regions. The framework of mathematical morphology considers grayscale images to be sets of points in a 3-D space, with the third dimension constituting gray level image intensity [1, 8]. This topographical analogy respectively considers light and dark image areas as the hills and valleys of an image landscape. To segment a given image the "landscape" is flooded, whereby water flows from high altitude areas along lines of steepest descent until it reaches some regional minimum. The watersheds or catchment basins of the image are the draining areas of its regional minima. These areas are separated by lines called watershed lines. Unfortunately, the segmentation produced by a naive application of the watershed algorithm is oftentimes inadequate: the image is usually over-segmented into a large number of mi-nuscule regions. The most common remedy is to use markers for identifying relevant region minima (e.g., [3, 4, and 7]). By setting marker locations as the only local minima within the watershed image, the number of regions can be automatically controlled. Unfortunately, finding markers can be problematic and is one of the focal points of this paper. A particular approach to finding and utilizing markers can be found in [10], where researchers used a naive Bayes classifier to classify pixel groups as internal markers. In turn, those markers together with the magnitude of the gradient image were used by the watershed algorithm to identify and delineate colored cell nuclei unfortunately the algorithms presented in the aforementioned publications are specific to RGB color space and may not generalize to other image modalities. In contrast, the proposed watershed segmentation algorithm works on images with arbitrary number of channels- and, hence, is applicable to grayscale, color, and hyper-spectral data. In more detail, this paper extends the previously aforementioned work on machine learned marker selection and watershed segmentation in the following ways.

Rather than using the raw pixel values to train classifiers, as was done in [6, 10], we expand the feature space by creating feature maps using standard image processing techniques. In turn, the use of an extended feature set results in very high pixel classification accuracy.

Two distinct sets of classifiers are trained to specialize in (a) marker identification and (b) object-background boundary delineation.

A probability map produced by the object-background classifier, rather than the conventional intensity or gradient magnitude image, is first seeded with the output of the classifier trained to identify markers and subsequently used as the topographic function within the watershed segmentation.

Experimental results demonstrate that the proposed algorithm outperforms the state-of-the-art algorithms as well as simpler variants of novel.

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2. Pixel Classification

While the aforementioned approaches have merits, they are primarily designed for a specific domain. In contrast, our goal is to develop a more general solution, applicable to many image processing domains. One data-driven image segmentation approach is to machine learn a pixel classifier that assigns the probability of a pixel belonging to a given class. Formally, let *(i, j)* index a discrete set of sites on a spatially regular lattice

$$S = \{(i, j) \mid 1 \le i \le N, 1 \le j \le M\} \tag{1}$$

For an input image I and corresponding image labeling L, let $I(i, j)$ and $L(i, j) \bullet (0,1\}$ respectively denote the (grayscale) values of image pixels and corresponding (binary) labels. To elaborate, label $L(i, j) = 0$ denotes that the image pixel $I(i, j)$ is labeled as background, while $L(i, j) = 1$ denotes a pixel belonging to the target object class. In general, our goal will be to produce a probability map P

$$P(i, j) = P[L(i, j) = 1 \mid I(i, j)] \forall (i, j) \in S \tag{2}$$

Unfortunately, as a result of the intensity overlap between classes, using just raw pixel values for classification in (1) results in very poor segmentation. Hence, for most segmentation applications it is insufficient to simply treat individual pixels as independent identically distributed. As a result, feature extraction techniques are needed to produce a set of feature maps describing local image features.

3. Novel Water Shed Method

For each lattice site we denote by $f(i, j)$ the extracted feature vector and attempt to train a classifier to produce a probability map conditioned on the feature vectors rather than just the raw grayscale values

$$P(i, j) = P\left[L(i, j) = 1 \middle| f(i, j)\right] \forall (i, j) \in S \tag{3}$$

The form $p[y = 1|x]$ in (3) defines an arbitrary binary proba-bilistic discriminative classifier. One particular choice for mod-eling the aforementioned class conditional, commonly used in statistics, is the generalized linear model [9]. To model the conditional likelihood that a pixel belongs to a target class, we use the logistic link function within the generalized linear model defined as

$$p\left[y = 1 \middle| x\right] = \frac{1}{1 + e^{-(w_o - w_1^{Tt} x)}} = h_w(x) \tag{4}$$

where $w = \{w_0, w_1\}$ are the model parameters, which can be estimated by maximizing the likelihood of the training data using standard nonlinear optimization routine h_w denotes the trained pixel classifier. From a Bayesian perspective, ideally one would want to integrate over the model parameters using some prior distribution. However, this usually interact able and is approximated in practice. In this work, bagging [6] is used, whereby we simply draw n samples from the underlying probability distribution by learning a set of classifiers, $\Omega = \{h_{w1}, \ldots h_{wn}\}$, each optimized over a different subset of the training data. The outputs of each classifier are subsequently merged by uniform averaging

$$H_\Omega(x) = \frac{1}{n} \sum_{x}^{n} h_{w_k}(x) \tag{5}$$

Using (4) and (5) to model the probability map elements in (3), we get

$$\begin{aligned} P(i.\ j) &= p\ [L(i, j) = 1 | f(i, j)] \\ &= \frac{1}{n} \sum_{x}^{n} h_{w_k}(f(i, j)) \\ &= H_\Omega(x)\ (f(i, j)) \end{aligned} \tag{6}$$

To simply the notation, we will refer to H_Ω simply as h in the remainder of the paper.

For most nontrivial domains, the outlined data-driven approach can usually outperform unsupervised segmentation algorithms, provided (a) relevant features have been identified, and (b) the machine learning technique utilized to build the conditional probability model in (3) is capable of utilizing the extracted features. Unfortunately, even if the method exhibits good generalization performance on images unseen during the training phase, objects of the same class that are in close spatial proximity, to one another will be merged together into a single object. Hence, while the machine learned classifier may have a high pixel classification score, due to the unresolved object-object boundaries, the resulting object labeling can still be very poor.

4. Modified Novel Watershed Method

A popular approach to resolve object-object boundaries is to use region growing methods such as watershed. However, to be effective these methods require object markers. Using *ad hoc* rules to extract markers requires *a priori* knowledge of either, (a) the number of objects within an image, (b) specific image properties, or (c) object locations. In either case, the parameters governing, marker extraction tends to vary from image to image, again motivating the use of machine learning approaches for robust identification of object markers. To improve the situation, we proposed training a marker identification classifier, h_{marker} on ground truth modified by morphological erosion. Let

$$L_{eroded} = L \Theta B \tag{7}$$

Denote the erosion of label image *L by* a suitably chosen structural element *B*. The output of h_{marker} denoted as $P_{\text{marker.}}$ is given by

$$\begin{aligned} P_{marker}(i, j) &= P[L_{\text{eroded}}(i, j) | f(i, j)] \\ &= h_{\text{marker}}(f(i, j)) \end{aligned} \tag{8}$$

where, h_{marker} is derived in the manner analogous to (6). To make the notational distinction more pronounced, we henceforth denote by h_{region} and P_{region} the classifier trained on the standard ground truth and the resulting probability map. As the experimental results will demonstrate, the h_{marker} classifier is overly conservative and produces superior object markers as compared to thresholding P_{region} using higher values of T. Having described both P_{region} used to delineate object-background boundaries, and P_{marker} used to identify object markers, we turn our attention to the topological surface utilized by the watershed algorithm. However, since the probability maps themselves form a topological surface. We can once again utilize a machine learning approach. Intuitively, the highest intensity values within P_{region} image correspond to pixels with the highest probability of being part of the target class, hence using the inverted probability map, $1-P_{region}$, can be advantageous because the aforementioned high probability regions will be flooded first. Since we use multiresolution features, these high probability peaks occur near the object center. Unfortunately, more than one local maximum may be present within large sized objects, thereby motivating the need for markers. To produce a topology amenable to the watershed algorithm, we invert the probability map P_{region} and set the regional minima to correspond with marker locations extracted from the P_{marker} probability map by hard thresholding.

5. EXPERIMENTAL RESULTS

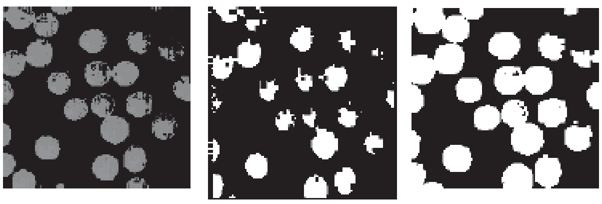


Figure 1: Original bmp - Novel Water Shed -Modified Novel Watershed

Figure 2: Original bmp - Novel Water Shed - Modified Novel Watershed

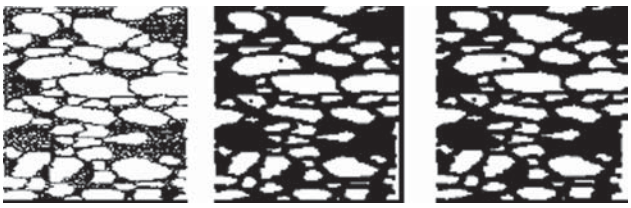
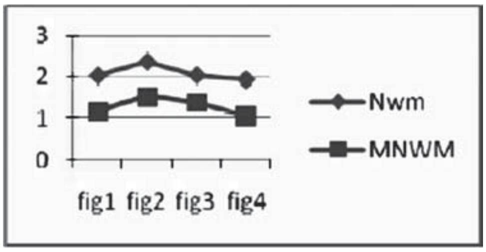


Figure 3: Original bmp - Novel Water Shed - Modified Novel Watershed

Figure 4: Original bmp - Novel Water Shed - Modified Novel Watershed

Table1
Comparison of Novel Watershed Method and Modified Novel Water Shed

Images	novel water shed	Modified Novel watershed
fig1	2.0201	1.1648
fig2	2.3656	1.5236
fig3	2.0295	1.3786
fig4	1.9241	1.0569



Graph1: NWM (Novel Watershed Method)

6. CONCLUSIONS

Novel Watershed Segmentation proposed a principled approach, based on machine learned pixel classification, for extracting: (a) object markers, (b) object-background region boundaries, and (c) topological surface used by the novel watershed algorithm. We demonstrated that while region classifiers produce probability maps which successfully identify pixels belonging to objects of interest, there is not enough information to group the classified pixels into objects. As a result, the object labeling is poor when objects of the same class are in close proximity to each other. In other words, simply thresholding the probability map is not sufficient to delineate the individual objects of interest. To improve the pixel grouping process we turned our attention to watershed segmentation, which requires markers in order to be successful. Extracting internal markers from the aforementioned region probability map by using higher thresholds still results in a poor object labeling.

The first contribution of this approach was to expose the benefits of ground truth manipulation. By training a classifier using eroded ground truth, the resulting probability maps produce superior object markers. By seeding, the probability map produced by a region classifier and using the resulting inverse for watershed segmentation state-of-the-art performance was achieved. Hence, the second contribution of this paper is to demonstrate the use of the inverted probability map for flooding via the watershed as an alternative to the gradient image. This method is tested on multiresolution images and obtained better results than conventional watershed methods. However this method is not suitable for uniform textured images like sand, cloth textures, leather and tree barks.

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