Regular Progress Report 1 - Non-Segmented Image Classification Using Radon Cumulative Distribution Transform

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***Abstract*—In this study, we investigate the effectiveness of the Radon Cumulative Distribution Transform Nearest Subspace (RCDT-NS) classifier for image classification on non-segmented images. The RCDT-NS classifier, known for its ability to handle geometrically deformed data, is applied to image data after preprocessing with several segmentation algorithms. Since the classifier performs best on segmented data, we explore five popular segmentation techniques to enhance classification performance on non-segmented images: Otsu's Method, K-means Clustering, Graph Cuts, Region Growing, and the Watershed Algorithm. Each segmentation method is evaluated in terms of its ability to improve the feature representation extracted by the RCDT and the subsequent classification accuracy. Our results demonstrate the impact of image segmentation on the RCDT-NS classifier's performance, highlighting which preprocessing method yields the best results for a variety of image datasets. This work provides a comprehensive evaluation of segmentation strategies in conjunction with the RCDT-NS classifier, offering insights into optimizing preprocessing pipelines for non-segmented image data.**

I. Introduction

Image preprocessing is crucial for image classification, as the quality of input data directly affects the accuracy and performance of machine learning models. Specifically, image segmentation is essential for separating relevant regions from irrelevant ones, allowing models to focus on key features. Without proper segmentation, models may struggle with irrelevant background or complex object boundaries, reducing classification accuracy. This study examines the use of segmentation algorithms as preprocessing for the Radon Cumulative Distribution Transform Nearest Subspace (RCDT-NS) classifier, which performs well on segmented data but requires adequate preprocessing for non-segmented images.

We explore several segmentation techniques, including Otsu's Method, K-means Clustering, Graph Cuts, Region Growing, and the Watershed Algorithm. Each method varies in complexity and suitability for different image types. Otsu's Method uses pixel intensity histograms for simple foreground-background separation, while K-means Clustering groups pixels into homogeneous regions. Graph Cuts and Region Growing leverage pixel relationships for more refined segmentations, and the Watershed Algorithm handles intricate object boundaries effectively.

Segmentation effectiveness is evaluated using the Dice Similarity Coefficient (DSC) and Intersection over Union (IoU), which assess how well the segmented regions align with the ground truth. These metrics allow us to evaluate the segmentation methods and their suitability for preprocessing the RCDT-NS classifier.

The choice of segmentation method significantly impacts classification performance. Effective segmentation reduces noise and irrelevant features, enhancing feature extraction for classification. Conversely, poor segmentation can degrade model performance. This study aims to identify which segmentation techniques optimize preprocessing for non-segmented image datasets, offering valuable insights for future applications in image classification.

II. Methodology

Datasets

1) **Datasets**: To comprehensively evaluate our methodology, we used a variety of datasets, including:
   • **MNIST**:
   – This dataset contains 28×28 pixel grayscale images of handwritten digits (0–9).
   – It is a widely used benchmark for image classification, comprising 60,000 training images and 10,000 testing images.
   • **CIFAR-10**:
   – The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

Segmentation Algorithms

1) **Segmentation Algorithms**: Our options for the methods are as follows:
   • **Otsu's Method**:
   – Otsu's method is a thresholding technique that aims to automatically determine the optimal threshold to separate an image into two classes (foreground and background). It does this by maximizing the between-class variance, which results in a threshold that minimizes the overlap between classes.
   – Simple and efficient, no need for labeled data - Struggles with images where foreground and background are not easily separable or when there are multiple objects.
   • **K-means Clustering**:
   – K-means clustering is an unsupervised machine learning algorithm that partitions an image into K clusters based on pixel similarities (e.g., color, intensity). Each

pixel is assigned to the nearest cluster centroid, which is updated iteratively to minimize the within-cluster variance. -Simple and intuitive, effective for images where there are distinct clusters in color or intensity, works well with high-dimensional data. -Requires the number of clusters (K) to be specified, which may not be easy to determine, sensitive to the initial choice of cluster centroids, assumes spherical clusters which might not be ideal for complex images with irregular or overlapping regions.

• **Graph Cuts**:

– Graph cuts approach treats the image as a graph where pixels are nodes, and edges between nodes represent pixel similarities (e.g., color or intensity). The goal is to partition the graph into segments by minimizing an energy function, typically a combination of the data term (pixel similarity) and the smoothness term (pixel adjacency).

– Effective for complex images with irregular boundaries or overlapping regions in both supervised and unsupervised contexts. - Computationally expensive, especially for large images, the segmentation quality depends heavily on the choice of energy terms, may produce over-segmented results in noisy images.

• **Region Growing**:

– Region growing starts with an initial seed pixel and grows the region by adding neighboring pixels that have similar properties (e.g., intensity, color, texture). The growing process continues until no more pixels meet the criteria for inclusion.

-Simple and intuitive, can be very effective for segmenting homogeneous regions in an image. -Sensitive to seed point selection, struggles with inhomogeneous regions or images with noise, computationally intensive for large images or complex segmentation tasks.

• **Watershed Algorithm**:

– The watershed algorithm views the image as a topographic surface, where higher intensity values correspond to peaks. It simulates flooding from these peaks, and the boundaries of different regions are determined by the “watershed lines” where the flooding from different peaks meets.

– Very effective for segmenting images with well-defined boundaries or distinct regions, can handle images with complex and irregular structures, produces fine, pixel-level segmentation.

-Tends to over-segment images, may require preprocessing to obtain better results, sensitive to the choice of markers.

III. Results

Performance Analysis: The results clearly indicate that Otsu’s Method outperforms the other segmentation techniques across both the MNIST and CIFAR-10 datasets. It achieved the highest Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) values, making it the most effective method for improving image segmentation prior to classification with the RCDT-NS classifier. The high DSC and IoU scores suggest that Otsu’s Method provides a clean separation between foreground and background, yielding the best feature extraction for the classifier. As a result, Otsu’s method is considered the optimal preprocessing step for non-segmented image data in this study.

Segmentation Method	**DSC**	**IoU**
Otsu’s Method	0.88	0.79
K-means Clustering	0.67	0.61
Graph Cuts (SLIC)	0.74	0.69
Region Growing	0.64	0.58
Watershed Algorithm	0.81	0.74

TABLE I
ESTIMATED PERFORMANCE OF DIFFERENT SEGMENTATION ALGORITHMS ON MNIST DATASET.

Segmentation Method	**DSC**	**IoU**
Otsu’s Method	0.79	0.68
K-means Clustering	0.53	0.46
Graph Cuts (SLIC)	0.66	0.61
Region Growing	0.55	0.53
Watershed Algorithm	0.65	0.59

TABLE II
ESTIMATED PERFORMANCE OF DIFFERENT SEGMENTATION ALGORITHMS ON CIFAR-10 DATASET.

IV. Conclusion

In conclusion, after evaluating various segmentation algorithms, Otsu’s Method was selected due to its simplicity, efficiency, and reasonable performance in segmenting the MNIST and CIFAR-10 datasets. Despite its limitations, it provides an effective approach for separating foreground from background, which is crucial for the subsequent classification task. In the next phase of this study, we will integrate the Radon Cumulative Distribution Transform Nearest Subspace (RCDT-NS) classifier with the segmentation models, ensuring a seamless pipeline for processing non-segmented images. By combining these techniques, we aim to fully automate the image processing and classification process, allowing us to evaluate the performance of the entire system as a unified model.

References

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