A survey on modified SVM for Image Segmentation

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Abstract: *In image analysis, segmentation is the partitioning of a digital image into multiple regions according to some homogeneity criterion. There are a wide variety of approaches that are used for segmentation and different approaches are suited to different types of images. Segmentation is the process of partitioning an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous. Support Vectors Machines (SVM) have recently shown their ability in pattern recognition and image classification [Vapnik, 1995]. The aim of this paper is to evaluate the potentiality of SVM on image recognition and image classification tasks.*

Keywords: *Image Segmentation, Support vector machine*

I. INTRODUCTION

Depending on the image acquisition model, images can be classified into various types; namely light intensity (visual) images, range or depth images, magnetic resonance images, thermal images. The segmentation is usually the first step of a pattern recognition process. Classification is a central problem of pattern recognition[1] and many approaches to the problem have been proposed, e.g. neural networks [2], Support Vector Machines (SVM) [3], k-nearest neighbors (K-nn) and kernel-based methods. The chosen classifier must either be implemented in low-cost hardware or in optimized software running in real-time. It has been shown that the SVM method gives very good results.

Support Vectors Machines (SVM) have recently shown their ability in pattern recognition and classification, image recognition and image classification tasks. Support Vector Machines are designed for binary classification.

Intuitively, given a set of points which belong to either of two classes, a linear SVM finds the hyperplane leaving the largest possible fraction of points of the same class on the same side, while maximizing the distance of either class from the hyperplane. According to [Vapnik, 1995], this hyperplane minimizes the risk of misclassifying examples of the test set.

The potential of the SVM is illustrated on a 3D object recognition task using the Coil database and on a image classification task using the Corel database. Theimages are either represented by a matrix of their pixel values (bitmap representation) or by a colour histogram. In both cases, the proposed system does not require feature extraction and performs recognition on images regardedas points of a space of high dimension.

II. CURRENT SEGMENTATION TECHNIQUES

In recent years, plenty of efforts have been focusing on the segmentation process. Numbers of differentsegmentation techniques are viewed in the literature, but there is not even a one single method to be considered as a best method for different kind of images, only suitable for one specific type of images. The objective of segmentation is dividing an input image into different regions or edges with similar properties. Many methods have been developed to segment the color images, many of them are based on the basic two properties [4].

A. Thresholding Method

Thresholding is used to separate foreground from background by selecting a threshold value T, any pixel (x, y) is selected as a part of foreground if its intensity is higher than or equal to threshold value i.e $f(x, y) \geq T$, else pixel points to background[5].Method used to select T is by observing histograms of particular image considered for segmentation. Selection of T automatically for each image by system without human involvement is termed as
automatic threshold.
Drawback of this method is time consuming and calculating the meanat every iteration. Dueto this time complexity increases with the size of the image [6].

B. Otsu's Method

This method is used to overcome the drawback of iterative thresholding which is used to calculate the mean after each step. This method identifies the optimal threshold by making use of histogram of the image [7], find the threshold that minimizes the weighted within-class variance. Some assumptions of this method are:

- Histogram (image) is bimodal.
- Assume uniform illumination.
- Theprobabilities of the two classes are separated by threshold and variances of these classes.

C. Segmentation using Watersheds

Watershed techniques considered the gradient of an image (GMI) as a topographic surface. Pixels having the highest GMI correspond to watershed lines, which represents region boundaries [8] some positive points of watersheds are by this method segmentation results are stable, they do not depend on any threshold and secondly the region boundaries are formed naturally out of the process. The boundaries are continuous and there are no gaps. Negative point considered over segmentation [9].

D. Clustering

Clustering is a process of organizing the objects into groups based on its attributes. An image can be grouped based on keyword or its contents. Keyword describes the similar features of an image, whereas content refers to shape, texture etc. Both supervised and unsupervised clustering techniques are used in image segmentation.
Commonly used techniques are:

Log Based Clustering**:**Images can be clustered based on the retrieval system log maintained by an information retrieval process. This technique is difficult to perform in case of multidimensional images [10].

Fuzzy Clustering: In this technique pixel values are divided into clusters on the basis of some similarity criteria and classify pixels values with great extent of accuracy and suitable for decision oriented applications i.etumor detection. It also involves FCM (fuzzy C means) algorithm, GK (Gustafson-Kessel), FCV (Fuzzy C varieties), among all FCM is the most accepted method since it can preserve much more information than other approaches [10].

E. Color Image Segmentation

Three phases in the color images Segmentation are listed below.

Phase 1:Pre-processing:
Morphological methods are applied to remove the noises away from images which applied to smooth some spots on uniformed patterns.

Phase 2:Transformation:
Color space transformed methods are used to transform other color space to RGB. The average intra-cluster distance based method is a traditional method applied for transformation.

Phase3: Segmentation:
We use clustering algorithm like K-means algorithm for finding the appropriate cluster numbers and segment images in different color spaces. The cluster with the maximum average varianceis split into new clusters [4].

F. Neural Network

A simple view of Neural networks (NN) is as a massively parallel computing system consisting of large number of processors (nodes) with many interconnections. NN models have nodes (neurons) and directed edges (with weights) between neuron outputs and neuron inputs. NN can learn complex nonlinear input-output relationships. Commonly used NNs are the multilayer perceptron (MLP) and Radial-Basis Function (RBF) NN. Self-Organizing Map (SOM) or Kohonen-Network is another popular NN mainly used for data clustering and feature mapping. NN learning/training involves using data examples (and teaching signals) in updating and optimization of the architecture and weights to efficiently perform good classification later. For a specific selected architecture, training involves optimization of the weight parameters. NN training uses empirical risk minimization which stops training once learning error is within a specified margin. This leads to non-optimal model and the solution is often plagued by local minimum problems. Also different training session lead to different NN weights parameters.

III. PROPOSED SEGMENTATION TECHNIQUES

A. SVM for image classification

SVM has been used in recent years as an alternative to NN. SVM, unlike NN, takes into account learning examples as well as structural behaviour. It achieves better generalization due to structural risk minimization (SRM). SVM

formulation approximates SRM principle by maximizing the margin of separation. Basic SVM is linear but it can be used for non-linear data by using kernel function to first indirectly map non linear data into linear feature space. Basic SVM is also a two class classifier however; with some modification, multiclass classifier can be obtained.

Our goal is to evaluate the accuracy of a performingclassifier such as Support Vector Machine on object recognition and image classification. Support Vector Machines are designed for binary classification.

The main idea of SVM is to separate the classes with a hyperplane surface so as to maximize the margin among them. The SVM is used during a first step, pre-processing the training set and thus rejecting any ambiguities. Here, a novel training method is proposed to improve the efficiency of SVM classifier, by selecting appropriate training samples. The basic idea of our training method is to eliminate the redundant training vectors, such that only few training vectors are enough to train the SVM.

B. Problems with huge training sets in SVM

Recently SVMs have shown promising performance in many applications. However, they require the use of an iterative process such as quadratic programming to identify the support vectors from the labeled training set of samples. When the number of samples in the training set is huge, sometimes it is impossible to use all of them for training; otherwise heuristic methods have to be used to speed up the process.

One such heuristic approach is to use chunks of samples. A chunk is a pre-defined small number of samples, which is much less than the total number of samples in the whole training set. Each chunk of samples is used to iterate for support vectors, and the samples, which are support vectors are kept for further training[3] . Samples, which cannot be support vectors, are simply discarded. The process continues with different chunks until all training samples are being used. Although this is a feasible way of avoiding memory capacity and cost problems, it is still very time consuming for huge data sets.

C. Proposed solution

Although SVMs have shown attractive potential and promising performance in classification, they have the limitation of speed and size in training large data sets. The hyper plane constructed by SVM is dependent on only a fraction of training samples called support vectors

that lie close to the decision boundary (hyper plane). Thus, removing any training samples that are not relevant to support vectors may have no effect on building the proper decision function[4]. If it is possible to identify such non-relevant samples from the training set, it is possible to reduce the computational cost, and in turn allow us to use complex kernels that can increase the accuracy of the classification results. The redundant training vectors are eliminated by Gaussian mixture model.

The problem to be solved here is how the non-relevant samples in the training data set can be identified. If it is possible to identify such non-relevant samples from the training set, it is possible to reduce the computational cost, and in turn allow us to use complex kernels that can increase the accuracy of the classification results. The problem to be solved here is how the non-relevant samples in the training data set can be identified.

D. Fast Support Vector Machine approach

Given the set of training vectors , the objective of the fast support vector machine approach(FSVM) is to (i) eliminate the redundant training vectors and (ii) train the classifier by the remaining training vectors. In other words, the difference between FSVM and the existing SVM approaches is that FSVM focuses on reducing the number of redundant training vectors.

FSVM algorithm:

Thesteps to eliminate training vectors are as detailed below:

Step1. Use all the training samples to train an initial SVM, resulting in $l1$ support vectors $\{SV^{In}_i , i = 1, 2, . . . , l1\}$

Step2. Eliminate the redundant training vector , whose projections on the hyperplane have the largest curvatures:
2a: For each support vector SV^{In}_i, find its projection on the hyperplane, $p(SV^{In}_i)$, along the gradient.
2b: For each support vector SV^{In}_i, calculate the generalized curvature of $p(SV^{In}_i)$on the hyperplane, $c(SV^{In}_i)$.
2c: Sort SV^{In}_i in the decrease order of $c(SV^{In}_i)$, and exclude the top n percentage of support vectors from the training set.

Step 3: Use the remaining samples to re-train the FSVM, resulting in $l2$ support vectors$\{SV^{Re}_i , i = 1, 2, . . . , l2\}$ andthe corresponding decision function d2(_x). Notably, $l2$ isusually less than $l1$.

Step 4: Use the *l2* pairs of data points {SV^{Re}_i , d2(SV^{Re}_i)} to finally train the FSVM, resulting in *l3* support vectors {SV^{Fl}_i , *i*=1, 2, . . . , *l3*} and the corresponding decision function d3(_x). Notably, *l3* is usually less than *l2*.

IV. CONCLUSION

This paper addresses the training method and eliminating the redundant training vectors to increase the efficiency of SVM for fast classification, without system degradation.The proposed approach can reduce the number of input training vectors, while preserving the support vectors, which leads to a significant reduction in the computational cost while attaining similar levels of accuracy.

FSVM shows a better performance in image classification by structural risk minimization (SRM) as compared to other segmentation technique.

Among most learning techniques, SVM can be trained even if the number of examples is much lower that the dimensionality of the input space.

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