SVM Methods in Image Segmentation

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Abstract—**Support Vector Machine (SVM) is playing an increasingly important role in image segmentation methods, especially, in the medical image processing. There are many modified methods based on SVM. In this paper, SVM methods, including modified SVM methods in medical image segmentation within the last five years are reviewed. A comparison and analysis among the papers is presented, and conclusions and future research framework are suggested with the aim of helping researchers to determine their own research framework, method and content.**

Keywords- *visualization technique; image segmentation; SVM*

I. INTRODUCTION

Among visualization techniques, no matter in which research area, such as sea or wave image visualization, medical image visualization etc., image segmentation is the key and basic technique to achieve an exact and clear object contour of the key features in the frame. That is, image segmentation aims at dividing an image into different sub-images with different characteristics and extracts some interesting objects [1]. The most essential and important content of research on segmentation is to cluster the nodes set. It is a key technique because the quality of cluster results affects the quality of image object segmentation and recognition. The main application field of image segmentation is medical image [2]. Medical images themselves are very uncertain and inaccurate. But the accurate and certain segmentation of objects in medical image is important for object recognition [3]. In recent years, some experts made efforts to apply all kinds of clustering or classification methods in image segmentation, especially for Support Vector Machines (SVM). SVM algorithm shows excellent segmentation performance, which has been successfully extended from basic task of classification [4]. Unlike other methods, which minimize the empirical training error, SVM makes use of the structure risk minimization and can be combined with other methods to obtain a good performance in image segmentation.

In the following section, we firstly review the researches and methods of SVM in image segmentation within the last five years. Secondly, the comparison between SVM and other artificial intelligence methods is proposed. Finally, conclusions and a suggested framework for future research are presented.

II. RESEARCHES AND METHODS

This section is composed of two subsections in order to make it more comprehensible for the reader. In the first subsection, modified SVM methods in general image analysis within the last five years are reviewed. In the second part, modified SVM methods in medical image segmentation are analysed. Papers in both parts are structured in a historical and technical sequence.

A. SVM Image Segmentation

In recent years, with new theories and new methods appearing constantly, more and more modified SVM methods have achieved good effect in image segmentation [5]. We are going to review the modified SVM methods from the last five years, in a chronological sequence. Yang [6] presented an effective colour image segmentation approach based on pixel classification with least squares support vector machine (LS-SVM). Both pixel-level colour feature and texture feature were used as input of LS-SVM model (classifier), and the LS-SVM model (classifier) was trained by selecting the training samples with Arimoto entropy thresholding. Zheng [7] proposed a novel algorithm for blind watermarking by applying singular value decomposition and LS-SVM into watermark embedding and detection. Both of them proposed or utilize the method of LS-SVM. Zhang [8] studied genetic algorithm-support vector machine (GA-SVM) and used K-fold Cross Validation (K-CV) method to determine the hyper-parameters (c, g) of SVM. He studied a method of GA-SVM. Bai [9] proposed a novel visual saliency based SVM approach for automatic training data selection and object segmentation, namely, Saliency-SVM. Cheng [10] inspired by the idea of divide-and-conquer approach and discriminatively trained SVM model for object detection introduced a method of training with a mixture of weighted SVM models and Expectation Maximization (EM) algorithms. The weighted SVM with logistic function converts prediction score into pseudo-probability. Turker [11] mixed the image pixel's texture features, Maximum local energy, Maximum gradient and Maximum second moment matrix to segment colour images based on the trained LS-SVM model (classifier). Both abovementioned works modified SVM by Maximum feature in image. He et al. [12] presented an integrated approach which was the integration of SVM classification, Hough transformation and perceptual grouping for the automatic extraction of rectangular-shape and circular-shape buildings from high-resolution optical space borne images. That is, integrated method can be successfully used in modified SVM.

To summarise, there are studies about the modified methods of singular value decomposition and least squares support vector machine, GA-SVM, training mixture of weighted SVM models and EM algorithm, Saliency-SVM, LS-SVM, Maximum local energy adding Maximum gradient and Maximum second moment matrix of LS-SVM, Hough transformation and perceptual grouping for the automatic extraction feature with SVM. All the methods above can be grouped into two types; one of the groups is formed by SVM methods mixed with other artificial methods, such as GA-SVM. The other group modifies parameters or function in SVM, such as LS-SVM method, which modifies function in SVM. These modified SVM methods aim at obtaining effective image segmentation, searching for parameters to determine hyper-parameters (c, g) of SVM in order to achieve automatic training data selection and automatic feature extraction. In a word, researchers seek automatic and effective image segmentation. However, for medical image segmentation, the most important thing is not effectiveness or automatic segmentation, but accuracy [13]-[20]. Methods for medical image segmentation that aim at offering accurate results are described in the following paragraphs.

B. *Medical Image Segmentation*

For medical image segmentation, Wu [21] introduced an automated method, which was called prior feature Support Vector Machine-Markov Random Field (pSVMRF) to segment three-dimensional mouse brain Magnetic Resonance Microscopy (MRM) images. In her study, pSVMRF reduced training and testing time for SVM while boosting segmentation performance. Segmentation accuracy for new strains is 80% for hippocampus and caudate putamen, indicating that pSVMRF is a promising and exact approach for phenotyping mouse models of human brain disorders. Alajlan [22] used an ensemble of linear support vector machine classifiers (SVMs) for classifying a subject as either patient or normal control. Image voxels were first ranked based on the voxel wise t-statistics between the voxel intensity values and class labels. Then voxel subsets were selected based on the rank value using a forward feature selection scheme. Finally, an SVM classifier was trained on each subset of image voxels. The class label of a test subject was calculated by combining individual decisions of the SVM classifiers using a voting mechanism. Varol [23] presented a class of nonlinear kernel SVMs admits approximate classifiers with runtime and memory complexity that was independent of the number of support vectors. The class of kernels, which they referred to as additive kernels, included being widely used kernels for histogram-based image comparison, such as intersection and chi-squared kernels. Additive kernel SVMs can offer significant improvements in accuracy over linear SVMs on a wide variety of tasks while having the same runtime, making them practical for largescale recognition or real-time detection tasks. Shao [24] proposed method essentially generates new synthetic support vectors (SVs) from the obtained by training a standard SVM with the available label samples. Then, original and transformed SVs were used for training the virtual SVM. They incorporated invariances to rotations and reflections of image patches for improving contextual classification. Then, added an invariance to object scale in patch-based classification. They also focused on the challenging problem of including illumination invariances to deal with shadows in the images. Very good results were obtained when few label samples were available for classification. The obtained classifiers revealed enhanced sparsity and robustness. Interestingly, the methodology can be applied to any maximum-margin method, thus constituting a new research opportunity. Maji [25] has presented an improved SVM method, which combined the SVM with the canny algorithm, the morphological algorithm and the fixed circle method to obtain a better segmentation result. In addition, the initial image was pre-processed by using the image contrast enhancement and median filtering. L [26] developed an improved support vector machine (SVM) framework to segment hepatic tumour from CT data. By this method, the one-class SVM (OSVM) and two classes SVM (TSVM) were connected seamlessly by a boosting tool, to tackle the tumour segmentation via both offline and online learning. An initial tumour region was first presented by an OSVM classifier. Then the boosting tool was employed to automatically generate the negative (non-tumour) samples, according to certain criteria.

As a summary, these are the most common modified SVM methods: prior feature Support Vector Machine-Markov Random Field (pSVMRF), SVM adding canny algorithm, morphological algorithm and the fixed circle method, additive kernels in SVM, new SVs in SVM, aggregate the obtained set of spectro-spatial maps used in SVM and boosting tool adding SVM. We divide the methods above into two groups: the first group is an improved method by adding medical image features, such as method of pSVMRF; the second group is a modified method and then applied to medical image segmentation, such as additive kernels in SVM. All the modified SVM methods aim at offering the results of accurate, fast clinical and automatic segmentation.

III. COMPARISON AND ANALYSIS

In this section, we firstly make a comparison between SVM and other typical artificial intelligence methods in image segmentation, such as, GA, K-means clustering and neural networks (NN), finally, the analysis of modified SVM methods is presented.

There are many image segmentation methods, which are based on difference theories and principles. This work will review the methods of Genetic algorithm (GA), K-means and NN to compare with SVM. GA [27] is a metaheuristic algorithm inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA). The principles of genetic algorithms are that they use the operators such as mutation, crossover and selection to achieve optimization. It is commonly used to generate high-quality solutions to optimization and search problems. Actually it combines with other methods to segment images. K-means [28] is a kind of cluster method; it segments images by the theory of grouping or dividing pixels in an image into a set. The principle of this method is that it partitions n pixels into k clusters in which each pixels belongs to the cluster with the nearest mean. K-means is a cluster method, not good at classification. Neural network [29] is the theory of self-studying and fault-to-learnt, it utilizes the training and learning method to segment images. Its principle is that it has the capacity of parallel computing, distributed saving and nonlinear function approximating. Before applying NN to segmentation, it requests large samples to be learned, so it has the limitation of the need of training techniques.

Compared with the above mentioned methods of optimization, clustering and learning, SVM [30] is a classification method. It classifies pixels into one-class, two or many classes. The aim of image segmentation is to classify an image into one, two or more classes. So from the point of theory and principle, the advantages of SVM are that it is more suitable to segment images. The disadvantage of SVM is that it is not sensitive to noise that leads to the inexact segmentation. The advantages or disadvantages of them are analyzed in Table I.

TABLE I. COMPARISON AMONG SEGMENTATION METHODS

	SVM	GA	K-means	NN
Advantages	Fit to classify and segment	Can optimizate	Suit to group	Can Train and learn
Disadvantages	Not exact	Not accurate	Not accurate	Learn ahead
Result	Good	Limited	Limited	Limited

The typical modified SVM methods in this paper are: GA-SVM and LS-SVM in general image segmentation; pSVMRF and additive kernels in medical image segmentation. GA-SVM represents the type of two method combination; it is composed of GA mixed with SVM method. The method of two method combination improves the principle and theory of SVM. Its disadvantage is that it is not sensitive to noise leading to that it cannot segment images accurately. LS-SVM represents the method that improves SVM by modifying its parameters or function. It does not change the principle and theory of SVM. It can improve the accuracy of segmentation. However, the disadvantage of this method is that it still cannot achieve exact segmentation.

In medical image segmentation, there are modified methods of pSVMRF and additive kernels SVM. On one hand, pSVMRF method represents the type of adding medical image features to modified SVM methods. It does not change the principle and theory of SVM. As the focus of this method is medical image features, such as medical image noise, it can achieve better performance in segmentation. On the other hand, additive kernels represent the type that it firstly improves the method of SVM, and then applies it to medical image segmentation. This means that the additive kernels not only can be utilized in medical image, but also in other research areas. The result of comparing and analysing the explained techniques is that the method of adding some features of medical images to modify SVM is superior to other method. Thus, the future research frame of modified SVM in medical image segmentation is suggested to combine medical feature with SVM method.

The advantages or disadvantages of modified SVM are analyzed in Table II.

TABLE II. COMPARISON AMONG MODIFIED SVM

	GA-SVM	LS-SVM	Additive kernels SVM	pSVMRF
Advantages	modified by other method	Modified SVM theory	Modified SVM principle	modified by medical feature
Disadvantages	Not exact	Not exact	Not exact	Exact
Result	Good	Good	Good	Better

GA-SVM is modified SVM method based on combination with GA method. This type of SVM method is modified by other methods. LS-SVM is SVM method modified by changing the theory of SVM. SVM of additive kernels is a method obtained by changing the principle of SVM. pSVMRF is a method modified by adding medical feature. All four types of methods above represent four different modified SVM. As for medical image segmentation, pSVMRF modified SVM has better performance than the other three methods.

IV. CONCLUSION

In this paper, many modified SVM methods within the last five years have been reviewed, especially modified SVM in medical image segmentation. A comparison and analysis among modified SVM methods both in general image and medical image are presented. Future research frameworks are suggested.

In future research of medical image segmentation, there are two research tendencies and frameworks: on one hand researchers improve methods and then apply them to medical image segmentation; on the other hand, they modify the

SVM method by adding the medical image features and then apply it to medical image segmentation. Both of the research frameworks above are feasible. As future research, we are planning to add medical image features to modified SVM combination with artificial intelligence algorithm to improve SVM method for medical image segmentation.

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