Tissue Detection in MR Images Using Immune Feature Weighted Support Vector Machines

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Abstract —In brain MR images, the boundary of each encephalic tissue is highly irregular. Owing to its powerful capacity in solving non-linearity problems, Support Vector Machine (SVM) has been widely used in pattern recognition. Traditional SVMs, however, assume that each feature of a sample contributes equally to recognition accuracy, which is not necessarily true in real applications. In addition, the parameters of a SVM and its kernel function also affect recognition accuracy. In this study, Immune Feature Weighted SVM (IFWSVM) method was proposed. Immune Algorithm (IA) was then introduced in searching for the optimal feature weights and parameters simultaneously. IFWSVM was used to detect encephalic tissues in MR images. Theoretical analysis and experimental results showed that IFWSVM has better performance than traditional SVMs.

I. INTRODUCTION

Object detection in medical images is the groundwork for computer-aided medical applications such as the computer-aided diagnosis and the computational modeling of biologic electromagnetic fields. Due to the highly irregular encephalic tissues [1], it is difficult to accurately detect the encephalic tissues. Support Vector Machines (SVMs) have great generalization ability in solving non-linearity problems. Traditional SVMs, however, assume that each feature of a sample contributes equally to the recognition accuracy. Such simplification of the complicated reality is normally not a true representation of real applications where each feature in reality has its own unique contribution. Therefore, the idea of feature weights was proposed inspired by literature [2]. Selecting appropriate feature weights, however, is a complicated issue. Moreover, the parameters of SVM and its kernel function directly affect recognition result as well. Immune Algorithm (IA) has the abilities of learning and self-adaptive adjusting [3]. In this study, IA was introduced in searching for the optimal feature weights and parameters simultaneously. Combining SVM with IA and feature weights, Immune Feature Weighted SVM (IFWSVM) was used to detect encephalic tissues in MR Images.

II. IMMUNE FEATURE WEIGHTED SVMS

In the traditional SVM, any dataset $D=\{x_i, y_i\}_{i=1}^{l}$, $y_i \in \{-1,1\}$, $x_i \in R^d$, can be separated by an Optimal Separating Hyperplane (OSH): $w \bullet x + b = 0$ with the maximum margin between two classes [4].

In the FWSVM, D is transformed to $D' = \{\beta_j x_{ij}, y_i\}$ by the coefficients of feature weights β_j. Let $X_i = (\beta_j x_{ij})_j$. $D' = \{X_i, y_i\}$ can be separated by an OSH: $W \bullet X + b = 0$ with the maximum margin (defined as MG) between the two classes. The classification problem can be solved by maximizing the margin MG.

For the non-linear case, the original problem can be solved by projecting original data space into a high dimensional feature space with a projection φ. Kernel function is used: $K(u,v)=\varphi(u)\bullet\varphi(v)$ in the process of maximizing the margin MG. The Lagrangian dual of the supporting planes yields the following dual QP problem:

$$\text{Minimize } \omega(\alpha)=\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j K(X_i \bullet X_j)-\sum_{i=1}^{l}\alpha_i$$
$$\text{Subject to } \begin{cases} 0 \le \alpha_i \le C, i=1,2,\cdots,l \\ \sum_{i=1}^{l} y_i\alpha_i = 0 \end{cases} \tag{1}$$

Here, a loose variable $\xi_i \ge 0$ and a penalty factor $C \ge 0$ are introduced. α_i is the Lagrange multiplier. Only a small number of $\{\alpha_i\}$ are non-zero, which correspond to Support Vectors (SVs). These SVs determine the OSH. Training FWSVM is equivalent to solving this QP problem and to finding appropriate W and b. So FWSVM is defined by:

$$f(x)=\mathrm{sgn}\left(\sum_{i=1}^{nsv}\alpha_i^0 y_i K(X_i, X)+b\right) \tag{2}$$

In this paper, Radial Basis Function (RBF) is chosen as the kernel function of FWSVM:

$$K(X,X_i)=\exp\left\{-\frac{\|X-X_i\|^2}{2\sigma^2}\right\} \tag{3}$$

In IA, the objective function of the optimization is regarded as an Antigen (Ag); the optimal solution is regarded as an Antibody (Ab). The degree of matching between the antigen and the antibody is described as affinity which reflects the closeness between the objective function and the potential solution. Resemblance among antibodies is described as the similarity which reflects the antibody diversification. The coefficients $\{\beta_j\}$ reflect the contribution of each feature for the recognition accuracy; the parameter C balances the model complexity and the generalization ability; the parameter σ is the width of the RBF which controls the effective range of the kernel function. Different β_j , C and σ affect the recognition accuracy. In this study, IA is introduced to optimize β_j , C and σ simultaneously in order to get the highest Recognition Accuracy (RA) which is the Ag.

III. Experiment and Analysis

MR images were acquired using a 3D T2 weighted fast-spin echo pulse sequence with the voxel size of $1\times1\times1$ mm^3 with a matrix size of $256\times256\times150$. Five objects in the brain MR images including the Background (BG) and 4 kinds of encephalic tissues, i.e., Osseous Compact Substance (OCS), Cerebral Spinal Fluid (CSF), Cerebral Gray Matter (CGM) and Cerebral White Matter (CWM) were detected using the multi-class IFWSVM.

From the MR images, 57 features were extracted. The ground truths of the 5 objects were marked by medical experts on the MR images. The 120^{th} slice, which clearly showed all of the 5 objects, was selected to construct 5 IFWSVM classifiers with one-against-rest strategy. By comparison, Immune SVM (ISVM) algorithm without feature weight and Logistic Regression (LR) algorithm were also implemented. Four slices were randomly picked for testing. The RAs of 4 slices using the 3 different algorithms are shown in Table I.

TABLE I
THE RECOGNITION ACCURACY FOR THE 3 ALGORITHMS

Slice	Algorithm	RAs (%)				
		BG	OCS	CSF	CGM	CWM
90	IFWSVM	97.07	93.14	98.05	92.60	94.94
	ISVM	94.38	90.63	96.65	90.33	92.10
	LR	96.59	87.29	91.30	81.34	93.31
112	IFWSVM	97.45	95.25	98.58	92.71	92.22
	ISVM	93.29	93.10	95.23	90.68	90.04
	LR	96.72	88.08	90.62	77.52	87.87
116	IFWSVM	97.42	95.18	98.55	92.72	92.16
	ISVM	94.21	92.11	96.10	90.41	90.95
	LR	95.89	85.83	89.96	78.99	85.35
137	IFWSVM	96.50	95.45	99.37	96.58	93.42
	ISVM	92.58	92.41	96.47	93.39	90.20
	LR	96.34	86.81	95.78	77.39	89.67

The 116^{th} slice is taken as an example. Fig. 1 shows its recognition results of 2 objects using IFWSVM.

(a) CWM (b) CSF

Fig. 1. The recognition result of the 116^{th} slice

For the IFWSVM, the smallest coefficient is β_{15}^* and the biggest coefficient is β_8^* . This means that the 15^{th} feature is the weakest relativity to the recognition accuracy and the 8^{th} feature is the strongest relativity to the recognition accuracy. In this way, the IFWSVM can obtain the recognition accuracy by different contributions from different feature weights. As shown in Table I, the recognition accuracies of IFWSVM surpass the recognition accuracies of ISVM. It means that optimal feature weights have a positive effect on the recognition accuracy. The LR can also adjust feature weights to improve recognition accuracy. However, it depends linearly on predictors x_1 to x_d and can not work well in solving the non-linearity problem. From Table I, in several cases LR outperforms ISVM, which is clearly attributed to the fact that the LR adjusts the feature weights in the training process. It clearly demonstrates IFWSVM, with optimal feature weights in the SVM framework, has superior performance.

IV. Conclusion

Due to the highly irregular each encephalic tissue in brain MR images, it is difficult to accurately detect the encephalic tissues. As a powerful machine learning method, SVM has good performances in solving the non-linearity problem. The traditional SVMs, however, assume that each feature of a sample contributes equally to the recognition accuracy. The introduction of the feature weight can generates higher recognition accuracy by suppressing the features that are weakly related to the final result and by strengthening the features that are strongly related to the final result. IA was introduced in searching for the optimal feature weights, parameters of SVM and the kernel function. In this study, IFWSVM was successfully implemented to detect 5 different encephalic tissues. The introduction of IFWSVM breaks the limitation of traditional SVMs and improves the performance of the SVM method.

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V. References

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