Image Reconstruction Using Pixel Wise Support Vector Machine (SVM) Classification.

Mohammad Mahmudul Alam Mia, Rashedul Islam, Md. Ferdous Wahid, Shovasis Kumar Biswas

Abstract: Image reconstruction using support vector machine (SVM) has been one of the major parts of image processing. The exactness of a supervised image classification is a function of the training data used in its generation. In this paper, we studied support vector machine for classification aspects and reconstructed an image using support vector machine. Firstly, value of the random pixels is used as the SVM classifier. Then, the SVM classifier is trained by using those values of the random pixels. Finally, the image is reconstructed after cross-validation with the trained SVM classifier. Matlab result shows that training with support vector machine produce better results and great computational efficiency, with only a few minutes of runtime is necessary for training. Support vector machine have high classification accuracy and much faster convergence. Overall classification accuracy is 99.5%. From our experiment, It can be seen that classification accuracy mostly depends on the choice of the kernel function and best estimation of parameters for kernel is critical for a given image.

Index Terms: Neural networks, Classification, SVM, Kernel functions, Training set.

1 INTRODUCTION

Classifying data has been one of the major parts in machine learning [1]. The idea of Support Vector Machine (SVM) is to create a hyper plane in between data sets to indicate which class it belongs to [2]. SVM map a given set of binary labelled training data to a high dimensional feature space and separate the two classes of data with a maximum margin of hyper plane. SVM uses an optimum linear separating hyper plane to separate two sets of data in a feature space. The separating hyper plane is the hyper plane that maximizes the distance between the two parallel hyper planes [3]. This optimum hyper plane is produced by maximizing minimum margin between the two sets. Therefore the resulting hyper plane will only be depended on border training patterns called support vectors. So, Support vectors are the data points that lie closest to the decision surface [4]. Recently several studies have reported that support vector machine (SVM) delivers higher accuracy in terms of data classification compared with other data classification algorithm [5]. However, SVM performance is sensitive to how the cost parameter and kernel parameter are set. As a result, the user normally needs to conduct extensive cross validation in order to figure out the optimal parameter as cost parameter and kernel parameter [6], [7]. This process is known as model selection. We have experimented with a number of parameters associated with the use of the SVM algorithm that can impact the results. These parameters include choice of kernel functions, the standard deviation of the Gaussian kernel, relative weights associated with slack variables to account for the non-uniform distribution of labeled data, and the number of training examples [8],[9]. This paper is organized as follows. In next section, we introduce some related background including some basic concepts of SVM with variable definition, kernel function selection, steps involved in the design of SVM and model selection (parameters selection) of SVM. In the following section, we explain training and tuning algorithm of an SVM classifier and then give all experiment results. Finally, we have some conclusions with future work.

- *Mohammad Mahmudul Alam Mia is a Senior Lecturer at Department of Electronics & Communication Engineering, Sylhet International University, Sylhet-3100, Bangladesh.*
  E-mail: mahmud_ece_ku@yahoo.com
- *Rashedul Islam is a Lecturer at Department of Computer Science & Engineering, Metropolitan University, Sylhet,Bangladesh E-mail: rashed@metrouni.edu.bd*
- *Shovasis Kumar Biswas is a PhD student at McMaster University, Department of Electrical and Computer Engineering. E-mail: biswassk@mcmaster.ca*
- *Md. Ferdous Wahid is a Lecturer at Department of Electronics & Communication Engineering, Sylhet International University, Sylhet-3100, Bangladesh.*
  E-mail: ferdous_ece07@yahoo.com

2 OVERVIEW OF SUPPORT VECTOR MACHINE

SVM utilizes an optimum linear separating hyperplane to separate two data sets in a feature space. This optimum hyperplane is produced by maximizing minimum margin between the two sets [10]. Therefore the resulting hyperplane will only be depended on border training patterns called support vectors. The support vector machine operates on two mathematical operations: (1) Nonlinear mapping of an input vector into a high-dimensional feature space that is hidden from both the input and output. (2) Construction of an optimal hyperplane for separating the features.

2.1 Variable Definition

1. Let x denote a vector drawn from the input space, assumed to be of dimension m_o.
2. Let $\{\varphi_j(x)\}$ for j=1 to m_1, denote a set of nonlinear transformations from the input space to the feature space [8].
3. m_1 is the dimension of the feature space.
4. $\{w_j\}$ for j=1 to m1 denotes a set of linear weights connecting the feature space to the output space.
5. $\{\varphi_j\ (x)\}$ represent the input supplied to the weight w_j via the feature space.
6. b is the bias.
1. 7.α_i is the Lagrange coefficient.
7. d_i corresponding target output.

2.2 Kernel Selection of SVM

Training vectors x_i are mapped into a higher (may be infinite) dimensional space by the function φ. Then SVM finds a linear separating hyperplane with the maximal margin in this higher dimension space. C > 0 is the penalty parameter of the error term [11]. Furthermore, $K(x,x_i) = \varphi^T(x)\varphi(x_i)$ is called the kernel function. There are many kernel functions in SVM, so how to select a good kernel function is also a research issue. However, for general purposes, there are some popular kernel functions [12], [6]:

1.Linear kernel:

$$K(x,x_i) = x^T x_i$$

2. Polynomial kernel:

$$K(x,x_i) = (\gamma x^T x_i + r)^d, \gamma > 0$$

3. RBF kernel:

$$K(x,x_i) = \exp(-\gamma \|x - x_i\|^2), \gamma > 0$$

4. Sigmoid kernel:

$$K(x,x_i) = \tanh(\gamma x^T x_i + r)$$

Here, γ, r and d are kernel parameters. In these popular kernel functions, RBF is the main kernel function because of following reasons [12], [13]:

1. The RBF kernel nonlinearly maps samples into a higher dimensional space unlike to linear kernel.
2. The RBF kernel has less hyper parameters than the polynomial kernel.
3. The RBF kernel has less numerical difficulties. The type of activation function is sigmoid.

2.3 Steps Involved in the Design of SVM

1. Hyperplane acting as the decision surface is defined as

$$\sum_{i=1}^{N} \alpha_i d_i K(x,x_i) = 0$$

Where

$K(x,x_i) = \varphi^T(x)\varphi(x_i)$ represents the inner product of two vectors induced in the feature space by the input vector x and input pattern xi pertaining to the ith example. This term is referred to as inner-product kernel [4], [8].

Where

$$W = \sum_{i=1}^{N} \alpha_i d_i \varphi(x_i)$$

$$\varphi(x) = [\varphi_0(x), \varphi_1(x), \dots\dots.., \varphi_{m_1}(x)]^T$$

$\varphi_0(x) = 1$ for all x

w_0 denotes the bias b

2. The requirement of the kernel $K(x,x_i)$ is to satisfy Mercer's theorem [14] . The kernel function is selected as a polynomial learning machine.

$$K(x,x_i) = (1 + x^T x_i)^2$$

3. The Lagrange multipliers $\{\alpha_i\}$ for i = 1 to N that maximize the objective function Q(α), denoted by α_0,i is determined.

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j K(x,x_i)$$

Subject to the following constraints:

$$\sum_{i=1}^{N} \alpha_i d_i = 0$$

$0 \le \alpha_i \le C$ for *i* =1,2,…., *N*

4. The linear weight vector w_0 corresponding to the optimum values of the Lagrange multipliers are determined using the following formula:

$$w_0 = \sum_{i=1}^{N} \alpha_{0,i} d_i \varphi(x_i)$$

$\varphi(x_i)$ is the image induced in the feature space due to x_i .

w_0 represents the optimum bias b_0.

2.4 Model Selection of SVM

SVM have shown good performance in data classification. Its success depends on the tuning of several parameters which affect the generalization error. We often call this parameter tuning procedure as the model selection. If you use the linear SVM, you only need to tune the cost parameter C. Unfortunately, linear SVM are often applied to linearly separable problems. Many problems are non-linearly separable. Therefore, we often apply nonlinear kernel to solve classification problems, so we need to select the cost parameter (C) and kernel parameters (γ, d) [12]. We usually use the grid-search method in cross validation to select the best parameter set. Then apply this parameter set to the training dataset and then get the classifier [6]. After that, use the classifier to classify the testing dataset to get the generalization accuracy.

2.5 SVM Program Procedure

Step 1: Read the Image and convert to the Binary Image.
Step 2: Read 5000 random pixel of Binary Image and keep the pixel value (1 for white, 0 for black).
Step 3: Train the SVM and show the output.
Step 4: Consider the RBF kernel.
Step 5: Classify an observation using a Trained SVM Classifier.
Step 6: Use cross-validation to find the best parameter rbf_sigma and boxconstraint.
Step 7: Use the best parameter rbf_sigma and boxconstraint to train the whole training set.
Step 8: Test and Evaluate the performance of the classifier.

3 EXPERIMENT

Our given image is RGB image. For our work, we first convert RGB image to gray scale image and then gray scale image to binary image.

Step 1: Boundary Determination and Curve Fitting

In this section, two classes of training data are determined and the boundary is set up. The goal of this task is and just is to test and justify the classification accuracy of the given picture which is shown in figure 2. We divide the picture into two classes. The wooden part of the door with frame represents as Class 1 and rest of the picture is treated as Class 2. In order to classify these two classes clearly, twenty boundary lines are needed. The specific data coordinate point is obtained by using data cursor, which can be found in the MATLAB figure toolbar. The data cursor sets up the zero point (0, 0) inherently at the top left corner of the given picture. The (0, 0) point in the matlab simulation output of our project should be the bottom left corner. In order to produce the boundary lines effectively and efficiently, curve fitting is employed.

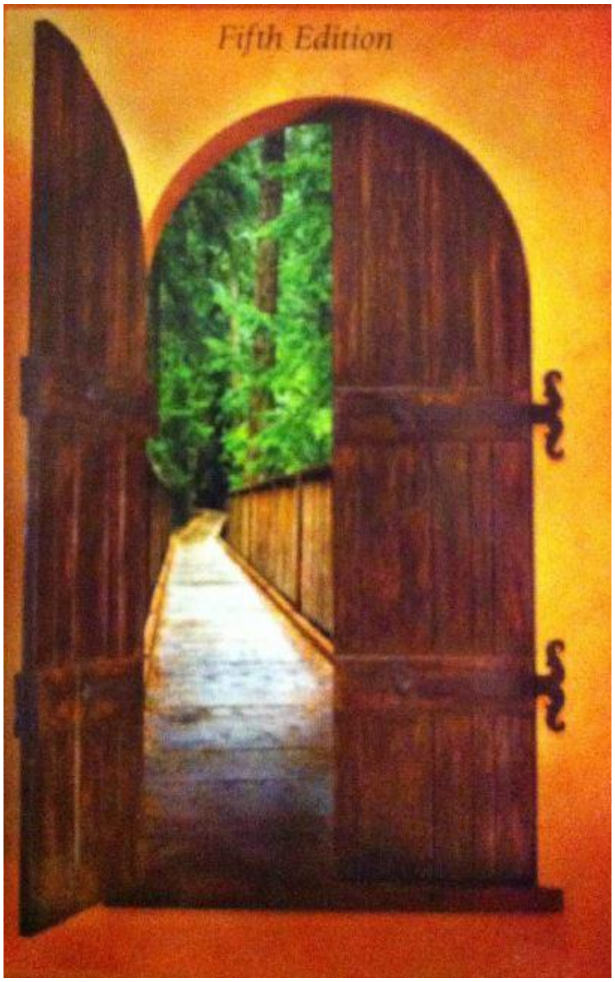

Fig. 2. *Given Picture.*

Step 2: Training Data Set and Testing Data Set Determination

After we have the boundaries of the wooden part of the door with frame, the next step is to obtain points from the original picture and sort the points by colour (black and white). First of all, 252353 points are obtained uniformly from the picture with a resolution of 409×617 pixels. Then, all the points in the wooden part of the door with frame is set as "0" and the colour is set as black. Similarly, all the rest points are set as "1" and the colour is set as white. So after this procedure, a 252353×3 matrix is generated as the database for our test. The first two columns represent the X co-ordinate and Y co-ordinate of a certain point. The third column of the matrix represents the colour of the certain point. For training data set we randomly select 7000 points from 252353 points. The testing data set has 2100 points that are selected from the whole picture randomly.

Step 3: Simulation Results

In MATLAB software, we used 10-fold cross-validation to find the best parameter rbf_sigma and boxconstraint. At first, we take 7000 samples, divide them into 10 groups of 700 samples each. Then train the network with 9 groups (6300 samples) and test with 1 group (700 samples). This is repeated ten times in matlab simulation, with each group used exactly once as a test set. Finally the 10 results from the folds are averaged to produce a single output. The results confirmed that the

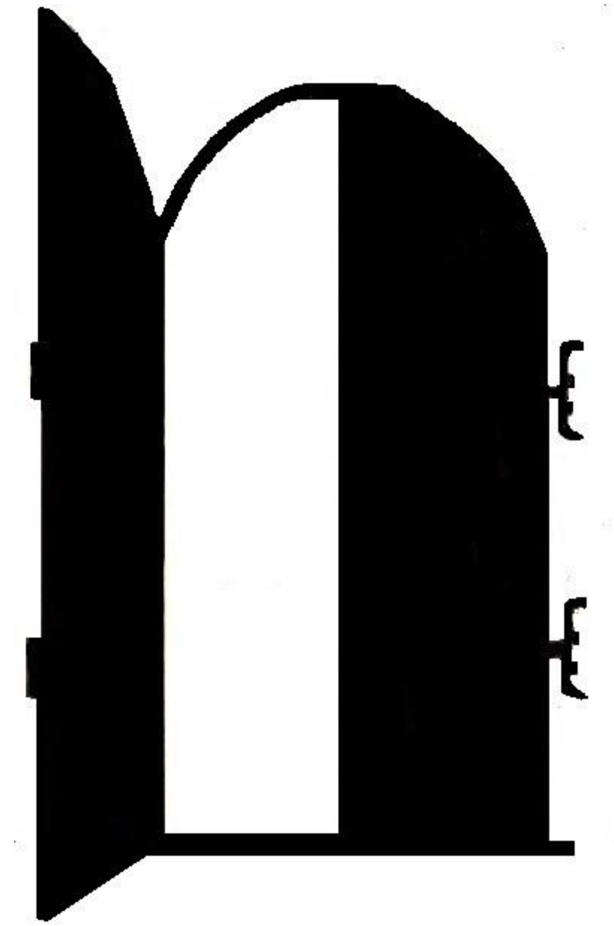

Fig. 3. *Image divided by colours 'black' and 'white'.*

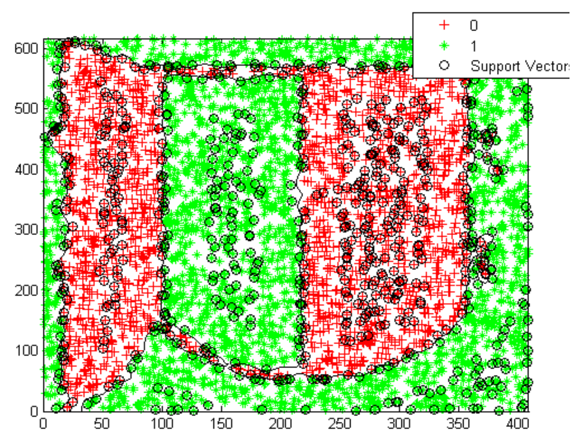

Fig. 4. *Output of the SVM after 10 Cross Validation.*

Classification precision of the SVM with radial function (RBF) kernel function was as high as 99.5% when rbf_sigma and boxconstraint where 0.1005 and 62.1672. Then we used the best parameter rbf_sigma and boxconstraint to train the whole training set.

The outputs from Matlab software are:

Classification Accuracy = 99.5%

4 Conclusion

A support vector machine is a robust tool for many aspects including classification, regression and outlier detection. In this paper, we studied support vector machine (SVM) for classification issues. The SVM utilizes measurable learning hypothesis to look for the best parameters with fminsearch that fits the accessible data well without over-fitting. The SVM has very few free parameters (rbf_sigma and boxconstraints), and these parameters can be optimized using cross-validation. By utilizing this strategy, we get the best parameters for trained the SVM. In our experiment, we get the value for rbf_sigma and boxconstraints is 0.1005 and 62.1672 respectively. Overall classification accuracy is 99.5%. So, the exactness is high, however the execution time need to enhance, particularly when we work with large dataset. This requires a large number of random data points from whole dataset for making kernel matrix.

References

[1] Kim, Sangwook, et al. "Deep learning of support vector machines with class probability output networks." Neural Networks (2014).

[2] Srivastava, Durgesh K., and Lekha Bhambhu. "Data classification using support vector machine." (2010).

[3] Wong, Wai-Tak, and Sheng-Hsun Hsu. "Application of SVM and ANN for image retrieval." European Journal of Operational Research 173.3 (2006): 938-950.

[4] Foody, Giles M., and Ajay Mathur. "The use of small training sets containing mixed pixels for accurate hard image classification: Training on mixed spectral responses for classification by a SVM." Remote Sensing of Environment 103.2 (2006): 179-189.

[5] Lima, Ana Carolina ES, and Leandro Nunes De Castro. "A multi-label, semi-supervised classification approach applied to personality prediction in social media." Neural Networks 58 (2014): 122-130.

[6] Hsu, Chih-Wei, and Chih-Jen Lin. "A comparison of methods for multiclass support vector machines." Neural Networks, IEEE Transactions on 13.2 (2002): 415-425.

[7] Wong, Wai-Tak, and Sheng-Hsun Hsu. "Application of SVM and ANN for image retrieval." European Journal of Operational Research 173.3 (2006): 938-950.

[8] Ng, Jeffrey, and Shaogang Gong. "Composite support vector machines for detection of faces across views and pose estimation." Image and Vision Computing 20.5 (2002): 359-368.

[9] Schmidhuber, Jürgen. "Deep Learning in Neural Networks: An Overview." arXiv preprint arXiv:1404.7828 (2014).

[10] Tokan, Nurhan TÜRKER, and Filiz Gunes. "Analysis and Synthesis of the Microstrip Lines Based on Support Vector Regression." Microwave Conference, 2008. EuMC 2008. 38th European. IEEE, 2008.

[11] Haykin, Simon S., et al. Neural networks and learning machines. Vol. 3. Upper Saddle River: Pearson Education, 2009.

[12] Byun, Hyeran, and Seong-Whan Lee. "A survey on pattern recognition applications of support vector machines." International Journal of Pattern Recognition and Artificial Intelligence 17.03 (2003): 459-486.

[13] AR, Vanitha L. Venmathi. "Classification of Medical Images Using Support Vector Machine." Proceedings of International Conference on Information and Network Technology (ICINT 2011). 2011.

[14] Fausett, Laurene V. Fundamentals of neural networks. Prentice-Hall, 1994.