A Support Vector Machine-Based Particle Filter Method for Improved Flooding Classification

Patcharin Insom, Chunxiang Cao, Pisit Boonsrimuang, Di Liu, Apitach Saokarn, Peera Yomwan, and Yunfei Xu

Abstract—Support vector machines (SVMs) have been applied to land cover classification, and a number of studies have demonstrated their ability to increase classification accuracy. The high correlation between the data set and SVM training model parameters indicates the high performance of the classification model. To improve the correlation, research has focused on the integration of SVMs and other algorithms for data set selection and SVM training model parameter estimation. This letter proposes a novel method, based on a particle filter (PF), of estimating SVM training model parameters according to an observation system. By treating the SVM training function as the observation system of the PF, the new method automatically updates the SVM training model parameters to values that are more appropriate for the data set and can provide a better classification model than can the original model, wherein the parameters are set by trial and error. Various experiments were conducted using Radarsat-2 synthetic aperture radar data from the 2011 Thailand flood. The proposed method provides superior performance and a more accurate analysis compared with the standard SVM.

Index Terms—Flooding classification, particle filter (PF), Radarsat, support vector machine (SVM).

I. INTRODUCTION

PUBLIC awareness regarding floods has increased in the past few decades. In response, researchers in various fields have attempted to understand the characteristics of floods in an attempt to mitigate this type of natural hazard. The

2009–2010 Data Fusion Contest, which was organized by the Data Fusion Technical Committee of the IEEE Geoscience and Remote Sensing Society, concentrated on the evaluation of existing algorithms for flood mapping through change detection. Supervised and unsupervised evaluations exhibited different performances [1].

A support vector machine (SVM) is an advanced supervised classification technique that outperforms neural network models, particularly when only a small data set is available for training. Therefore, SVMs can be deployed in numerous applications, including classification of high-resolution remotely sensed imagery [2]. A process that integrates SVMs with other techniques can improve classification accuracy. There are two main approaches for joining such processes. First, because the training data set of the SVM training model influences the performance of the classification model, researchers seek for an appropriate sample for the SVM training process with an additional algorithm such as a genetic algorithm [3]. Second, joining processes improves the correlation of the SVM training model parameters with most available data sets. In this manner of joining, parameter estimation is required to enhance the correlation [4]–[6]. In this letter, an alternative approach to the estimation of these parameters based on the state estimation technique is presented. A grid-search algorithm based on k-fold cross validation, in which parameters are established by a human, is frequently applied in SVM land cover classification [7]. A particle filter (PF), which is a state estimation technique, or sequential Monte Carlo is a nonparametric implementation of a Bayes filter, which is one of the most general algorithms for the problem of estimating the state of a dynamical system. In parameter estimation, a PF can adjust the parameter values according to the particle weights, which is a more unbiased method compared with the widely used algorithm.

The remainder of this letter is organized as follows. Section II discusses the background of the SVMs that are joined to develop the proposed method. Section III presents an SVM-based PF (SVM-PF) classification scheme. Section IV describes the data set and presents the experimental results. Finally, conclusions are provided in Section V.

II. SVM

The purpose of an SVM is to search for a hyperplane that completely separates a data set. The construction of an SVM has been described in many publications [8], [9]. The performance of an SVM training model depends on two factors: the applied data set and the parameters of the SVM training model [8], [9]. It can be assumed that the correlation between the

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P. Insom and D. Liu are with the State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences and the University of the Chinese Academy of Sciences, Beijing 100094, China (e-mail: insom.patcharin@gmail.com; liudl@radi.ac.cn).

C. Cao and Y. Xu are with the State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100094, China (e-mail: caocx@radi.ac.cn; xuyf@radi.ac.cn).

P. Boonsrimuang is with the Telecommunication Engineering Department, Faculty of Engineering, King Mongkut’s Institute of Technology Ladkrabang, Bangkok 10520, Thailand (e-mail: kpbrisit@kmitl.ac.th).

A. Saokarn is with the State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences and the University of the Chinese Academy of Sciences, Beijing 100094, China, and also with the Royal Thai Survey Department, Bangkok 10520, Thailand (e-mail: mj_apitach@hotmail.com).

P. Yomwan is with the Bureau of Mapping Technology, Department of Lands, Nonthaburi 11210, Thailand (e-mail: peerayom@hotmail.com).

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SVM training parameters and the data set influence the overall performance of the classification model. A strong correlation results in a highly favorable performance, whereas a weak correlation results in an inadequate SVM model. Parameter estimation is a necessary process for enhancing the correlation. The parameter selection in the SVM-PF scheme was performed by a PF to obtain the following three important parameters of the SVM training model [4]–[6].

1) The kernel function is used to map the nonlinear data into linear aspects. There are many types of kernel functions, including polynomials and hyperbolic tangents. A Gaussian radial basis function kernel is frequently used in several applications, including in this work, and is expressed as

\[ K(s_i, s_j) = \exp\left(-\frac{||s_i - s_j||^2}{2\sigma^2}\right) \]  

where \( s_i \in \mathbb{R}^N \) is an \( N \)-dimensional data vector with each sample belonging to a class labeled as \( y_i \). The parameter that defines the kernel function in this experiment is the standard deviation \( \sigma \).

2) \( \varepsilon \), which is the insensitive loss function \( (|\xi|_{\varepsilon}) \), is related to the approximation accuracy. The loss is equal to zero if the forecast value is within the \( \varepsilon \)-tube depicted in (2) and Fig. 1. Thus

\[ |\xi|_{\varepsilon} = \begin{cases} 0, & |\xi| \leq \varepsilon \\ |\xi| - \varepsilon, & \text{otherwise.} \end{cases} \]  

3) The regularization parameter \( (C) \) defines the tradeoff cost between minimizing the training error and the model’s complexity.

Normally, these parameters are selected by trial and error or are user defined. Another method for defining these parameters is a grid-search approach [7] based on a \( k \)-fold cross-validation method. Because the grid-search technique also selects the parameter values based on user settings, the parameters of the SVM training model may not provide the best SVM model performance. Using different values for each parameter produces a wide range of performances [8], [9]. Therefore, the coarse setting of the parameters must be corrected to increase the classification model performance.

III. Method

Parameter value selection using a PF can avoid a biased setting and produce rationally selected parameter values based on the particle weights that result from the probability density function (pdf) calculation. Frequently, a PF is implemented in a dynamic system to estimate the states. A PF consists of two important processes, i.e., predicting and updating, and functions as an iterative technique. Using these two processes, a state vector composed of the estimated parameters can update its value during each iteration based on the weight of each particle that is calculated using the pdf of the output of the prediction process and a true measurement value from an observation system.

To implement a PF for an estimated parameter, we can create the true measurement sequence for the updating process by imitating an observation value that is equal to 1 (100%). The final updated state vector will be the input of the training process of the SVM. The SVM-PF-improved flood classification approach beginning with a PF is implemented to estimate the SVM training parameters by retaining the SVM training function as the measurement model and using a normal distribution that describes the fluctuations of the SVM parameter values as defined in the system model. Every iteration of the PF process provides updated parameters to obtain reasonable values. Finally, the SVM-PF classification model results from the SVM training process input based on the updated parameters. To estimate the parameters of the SVM training model via the PF, the system and measurement model are defined as follows:

\[ x_{k+1} = x_k + w_k \]  
\[ y_k = h_k(x_{k}^{k-1}) + v_k \]  

where \( x_k = [\sigma_k, C_k, \varepsilon_k] \) represents the state vector at time \( k \). \( w_k \) is nonlinear noise with zero mean and variance \( Q \), which explains the fluctuations of the SVM parameters. \( y_k \) is the true measurement vector or an accuracy value associated with the SVM training function \( h_k \), and \( v_k \) is the nonlinear prediction error with zero mean and variance \( R \). A flowchart of the SVM-PF method is depicted in Fig. 2, and the main steps are as follows.

1) The initial values of the SVM parameter vector elements are set as \( x_0 \). “n” particles are set, and their weights are initialized as \( \{x^n_i = x_0, \omega^n_0 = 1/n\}_{i=1}^n \).

2) For \( k = 1, 2, 3, \ldots \)
   - Use the particle set \( \{\hat{x}_k^{i-1}, 1/n\}_{i=1}^n \) from previous time \( k - 1 \) with the equation of system model (3).
   - Predict the SVM output measurement \( \hat{y}_k^{i-1} \) by training the SVM with the state vector \( \hat{x}_k^{i-1} \) using (4).
   - Create the true measurement sequence \( y_k \) by duplicating the observation value of the SVM training model performance \( y_k = 1 \).
   - Using the true measurement \( y_k \) value, update each particle’s weight as \( \omega_i^k = p(y_k | \hat{x}_k^{i-1}) \).
   - Normalize the particle weights as \( \omega_i^k = \omega_i^k / \sum_{j=1}^n \omega_j^k \).
   - The particles will be retained or rejected depending on their weight \( (\omega_i^k) \) following processing by a resampling algorithm.
3) Obtain the output parameter estimate at time $k$ as

$$\hat{x}_k = \frac{1}{n} \sum_{i=1}^{n} \hat{x}_i^k.$$ 

4) Train the SVM model with the updated parameter vector $\hat{x}_k$ to obtain the prediction of $\hat{y}_{k+1}$.

5) Check the condition for stopping the iteration based on the minimum error values.

The updated parameters or state vector at the last iteration will be used as an input of the SVM training model, which generates the SVM-PF classification model. The stopping criterion of the PF can be defined using various techniques, such as a minimum error setting, as implemented in this work. Additionally, the correlation in this study at any iteration time between the SVM training model parameters and the data set is represented by a term representing the average value of every particle’s weight at that time, which is expressed as follows:

$$\text{corr}_k(\text{parameters, data set}) = \frac{1}{n^2 - n} \sum_{i=1}^{n} \omega_i^k. \quad (5)$$

### IV. Experiments and Discussion

#### A. Study Area and Data Sets

Thailand faced its most severe flood disaster in 50 years during the monsoon season in 2011. Radarsat-2 synthetic aperture radar (SAR) imagery with a 50-m resolution and using the ScanSAR narrow mode (acquired on December 4, 2011) is used in this study. The imagery covers the Ayutthaya province and has an image size of $3129 \times 3517$ pixels [see Fig. 3(a)].
Preimage processing was provided by the Geo-Informatics and Space Technology Development Agency (GISTDA), Thailand. A sampling data set for the training model was selected using visual interpretation to generate a sample size of 888,960 pixels (i.e., 95,104 flood pixels and 793,856 nonflood pixels) based on the flood map reference provided by GISTDA [10] (see Fig. 3(b)). The sampling data were equally divided into training and testing data sets. Each of the data sets had 47,552 flood pixels and 396,928 nonflood pixels. Three types of texture analyses were implemented in the study: mean, entropy, and fuzzy entropy [11]. We implemented block processing of the samples to calculate the textures using 8 × 8 pixel grid blocks and stacked them for subsequent feeding into the classifier.

B. Accuracy Assessment

In the simulation, the initial parameter values for the SVM and SVM-PF approaches generated by a grid-search approach [7] implemented with tenfold cross validation produces values of $\sigma = 3.5$, $C = 512$, and $\varepsilon = 0.3$. The system model and true measurement value building were performed using particles moving in terms of the normal distribution and by imitating the observation value, respectively. The number of PF recursions depends on the minimum error values. These values are set to be smaller than the error that occurs in the conventional SVM method because we attempt to demonstrate that the SVM-PF can improve the performance although the initial parameter values are generated via grid search based on k-fold cross validation, which can normally provide useful results in certain applications. The measurement results for ten test cases using the SVM and SVM-PF approaches are shown in Table I. The evaluation is based on accuracy ($A = (tp + tn) / (p + n)$), precision ($P = tp / (tp + fp)$), and recall ($R = tp / (tp + fn)$) [12]. Positive samples ($p$) define the sample of flooding areas, whereas negative samples ($n$) represent nonflooding areas, and $t$, $f$ represent true and false classified samples, respectively. We observed that the SVM-PF method improves the performance in every measurement aspect. In all of the test cases, the accuracy, precision, and recall of the measurements are higher than those of the SVM method. The average accuracy, precision, and recall exhibit the same trend: The SVM-PF method reflects an enhancement over the SVM method. The normalized root mean square errors (NRMSEs) of the ten test cases for these three evaluation aspects are also smaller than those of the original method.

Fig. 3(c) shows the classification map produced by the conventional SVM method, and Fig. 3(d) shows the results generated by the SVM-PF approach. The photographic images were generated from the classification model from test case 4 in Table I, in which highly different classification model performances and highly different z-score measurements for the two methods can be noted (see Fig. 4(a)–(c)). We observed that the classification result generated by the SVM approach displays discrepancies, whereas the flooding areas are clearly depicted in the image produced by classification using the SVM-PF method. Fig. 4(a)–(c) shows the standard score (i.e., the z-score) of the two methods with respect to accuracy, precision, and recall, respectively. The SVM-PF produces a z-score that is superior to that of the SVM approach in every assessment and test case. In addition, Fig. 4(d) illustrates the variation in correlation (5) of another experiment during correlation testing of the SVM-PF approach at every iteration of the PF. The correlation tends to improve with further iterations and reaches the highest value at the final time step, thus demonstrating that the PF can achieve favorable parameter values. Additionally, the error rates [12], $E = (fp + fn) / (p + n)$, for all of the test cases are included in the accuracy assessment (see Fig. 5). In every test case, the SVM method has a higher error rate compared with the SVM-PF approach. Major computational complexity of a grid-search approach based on k-fold cross validation and a PF for determining the training parameter values is the time required to calculate the SVM training function. Table II lists the number of calculations required for the training function for both methods. In the table, $k$ is the $k$ value in k-fold cross validation; $M$ is the number of the setting vectors, which consist of the three particles; $n$ is the number of particles; and $K$ is the number of iterations of the PF processes. Generally, the SVM-PF is more time consuming than the SVM because it requires a substantial number of particles and a recursive process to obtain a result.
V. CONCLUSION

We have presented an SVM-based PF method for flood classification using SAR imagery and data acquired in Ayutthaya province, Thailand. The method employed a PF to estimate three key parameters of the SVM training model to search for an appropriate value of these parameters before passing them to an SVM training model. The modified parameter values have characteristics that are more suitable to training samples than those of the original model, which reflects the strong correlation between these parameters and the data set. SVM-PF is demonstrated to be better in terms of accuracy, precision, and recall analysis compared with other methods. Although the PF requires more complex computations than does $k$-fold cross validation, the SVM-PF can be applied to several applications, such as flood monitoring and flood loss estimation, which require precise knowledge of flood areas. However, the complexity is considered to be a subject that requires additional study.

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