A Hybrid Entropy Decomposition and Support Vector Machine Method for Agricultural Crop Type Classification

Chue-Poh Tan\textsuperscript{1}, Hong-Tat Ewe\textsuperscript{2}, and Hean-Teik Chuah\textsuperscript{1}

\textsuperscript{1}Faculty of Engineering, Multimedia University
Persiaran Multimedia, 63100 Cyberjaya, Selangor, Malaysia
\textsuperscript{2}Faculty of Information Technology, Multimedia University
Persiaran Multimedia, 63100 Cyberjaya, Selangor, Malaysia

Abstract—This paper presents the development of Synthetic Aperture Radar (SAR) image classifier based on the hybrid method of “Entropy Decomposition and Support Vector Machine” (EDSVM) for agricultural crop type classification. The Support Vector Machine (SVM) is successfully applied to the key parameters extracted from Entropy Decomposition to obtain good image classifications. In this paper, this novel classifier has been applied on a multi-crop region of Flevoland, Netherlands with multi-polarization data for crop type classification. Validation of the classifiers has been carried out by comparing the classified image obtained from EDSVM classifier and SVM. The EDSVM classifier demonstrates the advantages of the valuable decomposed parameters and statistical machine learning theory in performing better results compared with the SVM classifier. The final outcome of this research clearly indicates that EDSVM has the ability in improving the classification accuracy for agricultural crop type classification.

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1. INTRODUCTION

Over the past few years, research in image processing for images acquired by polarimetric synthetic aperture radar (SAR) systems has raised much interest in the remote sensing community. Compared to conventional SAR systems, more detailed information on the target is expected from fully polarimetric SAR system. Using such a system, the characterization and classification of crop type may be significantly improved.

The potential of SAR in discriminating among different agricultural crop type has been demonstrated in several studies [1–3]. Previously, Van Zyl [4] proposed an unsupervised classification to classify terrain types by identifying the scattering process as odd bounce, even bounce or diffuse scattering. The ocean surface and flat ground basically have the characteristics of Bragg scattering (odd bounce) while the city blocks, buildings, and hard targets have the characteristics of double bounce scattering (even bounce) and forest and heavy vegetation have the characteristics of volume scattering (diffuse scattering). It is interesting to find that this classification algorithm provides information for terrain type identification. For a refined classification into more classes, Cloude and Pottier [5] proposed an unsupervised classification algorithm based on their target decomposition theory that utilized two parameters: the entropy, $H$, and alpha, $\alpha$. The entropy, $H$ measures the randomness of scattering mechanisms, and the angle $\alpha$ characterizes the scattering mechanism. However, the main disadvantage of this algorithm is the arbitrary location of decision boundaries in the $H - \alpha$ feature space [6]. To surmount this insufficiency, we propose a combined method of Entropy Decomposition and an advance machine learning method based on Support Vector Machine (EDSVM) to perform the agricultural crop type classification. This method offers an efficient classification with unique properties of SVM in providing the optimal discrimination between the agricultural crop type.

The paper is divided into five sections. Section II presents the background on the proposed technique for the agricultural crop type classification. In this section, the basic concept of the Entropy Decomposition and Support Vector Machine are discussed. Section III briefly describes the site used for the classification. The results and accuracy assessment with the comparisons between SVM and EDSVM are discussed in Section IV. In Section V, we conclude this paper with the discussion on future work.
2. PROPOSED TECHNIQUE

EDSVM is a method that combines Entropy Decomposition (ED) and Support Vector Machine (SVM). In ED, the most important parameter obtained from the output of radar systems is the $3 \times 3$ coherency matrix $[T]$. The coherency matrix $[T]$ is obtained from an ensemble of scattering matrix samples $[S_i]$ by forming the Pauli scattering vectors [7].

$$[S_i] = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \rightarrow k = \frac{1}{\sqrt{2}}[S_{HH} + S_{VV} \quad S_{HH} - S_{VV} \quad 2S_{HV}].$$

(1)

Averaging the outer product of them over the given samples yields

$$[T] = \langle k k^+ \rangle = \begin{bmatrix} \langle|S_{HH} + S_{VV}|^2 \rangle & \langle(S_{HH} + S_{VV})(S_{HH} - S_{VV})^*\rangle & 2\langle(S_{HH} + S_{VV})S_{HV}^*\rangle \\ \langle(S_{HH} - S_{VV})(S_{HH} + S_{VV})^*\rangle & \langle|S_{HH} - S_{VV}|^2 \rangle & 2\langle(S_{HH} - S_{VV})S_{HV}^*\rangle \\ 2\langle(S_{HH} + S_{VV})^*S_{HV}\rangle & 2\langle(S_{HH} - S_{VV})^*S_{HV}\rangle & 4\langle|S_{HV}|^2 \rangle \end{bmatrix}$$

(2)

where $k^+$ refers to the conjugate transpose of $k$ and $(S_i)^*$ is the conjugate element of $(S_i)$. The coherency matrix $[T]$ is Hermitian positive semi-definite, therefore it can always be digitalized by a unitary similarity transformation of the form

$$[T] = [U][A][U]^{-1}$$

(3)

where $[U]^{-1}$ represents the inverse matrix of $[U]$ and

$$[A] = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix},$$

(4)

$$[U] = [u_1 \quad u_2 \quad u_3],$$

(5)

$$[u_i] = [\cos \alpha_i \quad \cos \alpha_i \sin \beta_i e^{j\delta_i} \quad \sin \alpha_i \sin \beta_i e^{j\gamma_i}].$$

(6)

The angle $\bar{\alpha}$ characterizes the scattering mechanisms as it indicates surface scattering when $\bar{\alpha} = 0^\circ$, volume scattering when $\bar{\alpha} = 45^\circ$ and multiple scattering when $\bar{\alpha} = 90^\circ$, respectively [8]. In order to obtain the averaged scattering mechanisms from surface scattering to multiple scattering, the average alpha is defined as

$$\bar{\alpha} = P_1\alpha_1 + P_2\alpha_2 + P_3\alpha_3,$$

(7)

$$P_i = \frac{\lambda_i}{\sum_{k=1}^{3} \lambda_k}$$

(8)

where $P_i$ are the probabilities obtained from the eigen values of $[T]$. The angle $\beta$ is twice the polarization orientation angle. The angle $\delta$ is the phase difference between decomposed $(S_{HH} + S_{VV})$ and $(S_{HH} - S_{VV})$ terms and the angle $\gamma$ is the phase difference between the decomposed $(S_{HH} + S_{VV})$ and $S_{HV}$ terms [9]. To introduce the degree of statistical disorder of each target, the entropy $H$ is defined in the Von Neumann sense from the logarithmic sum of eigen values of $[T]$ as

$$H = -\sum_{i=1}^{3} P_i \log_3(P_i).$$

(9)

However, the main disadvantage of the entropy decomposition is that the location of the decision boundary is arbitrary [6]. Thus, to overcome this problem, we propose a combined method of Entropy Decomposition and an advance machine learning method based on Support Vector Machine (EDSVM).

The SVM algorithm is a machine learning technique based on statistical theory [10] that can be used for classification purposes. The aim of Support Vector Machine classifier is to find an ideal separating hyperplane in a higher dimensional feature space. For a given training sample belonging to two different classes, SVM derives a hyperplane, which is at a maximum distance from the closest points belonging to both the classes. To find the optimal separating hyperplane, assume
that the two classes to be distinguished are linearly separable, and denote the input space $X$ with input vectors, $\vec{x}$ and the training set $T_r = \{(x_1, y_1), \ldots, (x_N, y_N)\}$, where $x_i \in X$ and $y_i \in Y$, $Y = \{1, -1\}$. In practice, it will often be the case where the data cannot be separated linearly by means of a hyperplane. One of the basic ideas behind SVM is to have a mapping $\Phi$ from the original input space $X$ into a high-dimensional feature space $F$.

The SVM method solves for

$$\min ||w||^2$$  \hspace{1cm} (10)

with

$$y_i(\langle \Phi(\vec{x}_i), w \rangle + b) \geq 1 \quad \text{for} \quad i = 1, \ldots, N$$  \hspace{1cm} (11)

where $\vec{w}$ is a vector perpendicular to the hyperplane while $b$ determines the displacement of the hyperplane along the normal vector $\vec{w}$ [11]. To solve the constrained minimization problem, the Lagrangian dual problem method is introduced as

$$\max l = \sum_{i=1}^{N} l_i - \frac{1}{2} \sum_{i,j=1}^{N} l_i l_j y_i y_j \langle \Phi(\vec{x}_i), \Phi(\vec{x}_j) \rangle$$  \hspace{1cm} (12)

subject to

$$l_i \geq 0, \quad i = 1, \ldots, N, \quad \text{and} \quad \sum_{i=1}^{m} l_i y_i = 0$$  \hspace{1cm} (13)

with Lagrange multipliers $l_i \geq 0$. After solving this dual problem, the decision function implemented by the classifier for any test vectors $x$ is expressed by

$$f(x) = \text{sgn} \left( \sum_{i=1}^{N} l_i y_i \langle \Phi(\vec{x}), \Phi(\vec{x}_i) \rangle + b \right).$$  \hspace{1cm} (14)

### 3. SITE DESCRIPTION

The JPL L band polarimetric SAR image of Flevoland (Netherlands) is used for the crop classification purpose. The sample image was downloaded from ESA’s Earth Observation and it was originally processed with 4-look average in Stokes matrix with pixel size of 12 m. The L-band multipolarized image for the study area was taken on 30 May 1990 with 1024 samples and 750 lines. Figure 1 blue. The topography is almost perfectly flat, and the general altitude is three meters below sea level. This site is composed of various crop plantations, bare soil, forest and waterbody. Eight crop classes are identified, comprising stem bean, potato, lucerne, wheat, beet, rape seed, peas and grass.

![Figure 1: Flevoland study area HH assigned in red, HV assigned in green and VV assigned in blue.](image-url)
4. RESULTS AND DISCUSSION

Using multi-polarization polarimetric AIRSAR data of Flevoland, the overall accuracy of the aforementioned classification techniques for selected testing areas as presented in [12] with different window size are shown in Figure 2. The optimum window size is 9 and the accuracy of 76.28% for SVM classifier and 98.39% for the proposed EDSVM classifier, respectively.

From these results, the classified images with the optimum window size for SVM and EDSVM are shown in Figure 3(a) and Figure 3(b), respectively.

5. CONCLUSION

The project is aimed to investigate the hybrid method of EDSVM in the classification of agricultural crop type using the multi-polarized AIRSAR image. The potential of the proposed classifier has been demonstrated and it has shown a desirable result compared to SVM classifier. Our future work shall extend this to multi-frequency and multi-temporal data.
REFERENCES