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CLASSIFICATION OF MULTI-TEMPORAL SAR IMAGES FOR RICE CROPS USING COMBINED ENTROPY DECOMPOSITION AND SUPPORT VECTOR MACHINE TECHNIQUE

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Abstract—This paper presents a combined Entropy Decomposition and Support Vector Machine (EDSVM) technique for Synthetic Aperture Radar (SAR) image classification with the application on rice monitoring. The objective of this paper is to assess the use of multi-temporal data for the supervised classification of rice planting area based on different schedules. Since adequate priori information is needed for this supervised classification, ground truth measurements of rice fields were conducted at Sungai Burung, Selangor, Malaysia for an entire season from the early vegetative stage of the plants to the ripening stage. The theoretical results of Radiative Transfer Theory based on the ground truth parameters are used to define training sets of the different rice planting schedules in the feature space of Entropy Decomposition. The Support Vector Machine is then applied to the feature space to perform the image classification. The effectiveness of this algorithm is demonstrated using multi-temporal RADARSAT-1 data. The results are also used for comparison with the results based on information of training sets from the image using Maximum Likelihood technique, Entropy Decomposition technique and Support Vector Machine technique. The proposed method of EDSVM has shown to be useful in retrieving polarimetric information for each class and it gives a good separation between classes. It not only gives significant results on the classification, but also extends the application of Entropy Decomposition to cover multi-temporal data. Furthermore, the proposed method offers the ability to analyze single-polarized, multi-temporal data with the advantage of the unique features from the combined method of Entropy Decomposition and

Support Vector Machine which previously only applicable to multi-polarized data. Classification based on theoretical modeling is also one of the key components in this proposed method where the results from the theoretical models can be applied as the input of the proposed method in order to define the training sets.

1. INTRODUCTION

In many parts of Asia where rice is the staple food of the people, the monitoring of the growth of rice plants has important significance to the national economy development. Hence, there needs to be an effective means by which rice fields can be monitored in order to control and maintain a close balance between the rice production and demand. However, rice crops are mainly cultivated in warm tropical climates where rainfall is high and cloud cover is dense throughout the year. Hence, under such climate condition, Synthetic Aperture Radar (SAR) remote sensing provides unique and great capabilities, since microwaves can penetrate through clouds and has all-weather capabilities. For this reason, space-borne SAR remote sensing images are considered as suitable source for rice monitoring. Since the operation of satellites, much work has been performed to interpret the temporal variation of SAR measurements over rice fields, with a view to retrieve useful information from the satellite SAR data [1–5].

The characterization and classification of land cover using SAR data has been extensively investigated and reported in recent few decades. Cloude et al. [6–8] introduced a classification scheme called Entropy Decomposition based on the use of the two-dimensional $H-\overline{\alpha}$ feature space, where it represents major scattering mechanisms. Using this technique, parameters H and $\overline{\alpha}$ represent the entropy and the type of the scattering within the resolution cell, respectively [9]. Based on this idea, a great progress was made in the target type discrimination by the eigenvalues and their associated eigenvectors of the coherency matrix [10]. However, this technique is normally performed using polarimetric data which require more information on the polarization [11]. So far, multi-temporal data have never been considered for this classification technique. Moreover, the technique requires arbitrary selection of decision boundaries in the $H-\overline{\alpha}$ feature space [12]. As such, we extend the popularly used Entropy Decomposition technique to combine with Support Vector Machine, hence, provide a new method for better analysis for multi-temporal SAR data. Simulated result from the theoretical modeling is used as training sets and an advance machine learning, Support Vector Machine is proposed to be combined with Entropy Decomposition technique to determine the decision boundaries in the $H - \overline{\alpha}$ feature space for the multi-temporal images. The popularly used Support Vector Machine has been applied alone with good performance in hyperspectral and SAR data classification in terms of accuracy and robustness [13–16]. The properties of this technique make them well-suited to solve the problem of image classification since they can work with a relatively low number of training samples and deal with noisy samples in a robust way [17–19]. In this paper, we examine the experimental results obtained from the ground truth measurement and interpret the observations using the theoretical modeling. Then, we propose the usage of the combined technique of Entropy Decomposition and Support Vector Machine (EDSVM) to classify the rice planting schedule on multi-temporal images. This classification technique is performed on Sungai Burung, Selangor, Malaysia RADARSAT images.

The paper is outlined as follows. Section 2 describes the proposed techniques of EDSVM in the classification of the rice planting schedules and the application of the proposed technique is presented in Section 3. This includes the description of the study area and ground truth measurement. Performance comparisons between Maximum Likelihood, Entropy Decomposition, Support Vector Machine and EDSVM are provided in Section 4. In Section 5, we conclude this paper with recommendations for future work.

2. PROPOSED TECHNIQUE

In this section, the proposed technique of image classification based on the simulated results from theoretical modeling using hybrid Entropy Decomposition and Support Vector Machine (EDSVM) is presented. The flow of the proposed technique is as shown in Figure 1.

Ground truth measurements were conducted in the rice fields at different planting schedules to obtain the physical parameters of the rice crops. This information is necessary in the theoretical modeling simulation in order to calculate the backscattering coefficient of the rice crops for different planting schedules. The backscattering coefficient is then used to form the multi-temporal coherency matrix, which will be input to the Entropy Decomposition technique to produce the multi-temporal alpha, $\overline{\alpha}_T$ and entropy, H_T. This information is then treated as the training feature vectors. Similarly, testing feature vectors that represent the whole study area can be obtained from $\overline{\alpha}_T$ and H_T of the study area. The training and testing feature vectors are then applied to Support Vector Machine technique for EDSVM classification. For comparison purpose, the backscattering coefficient values of the multi-

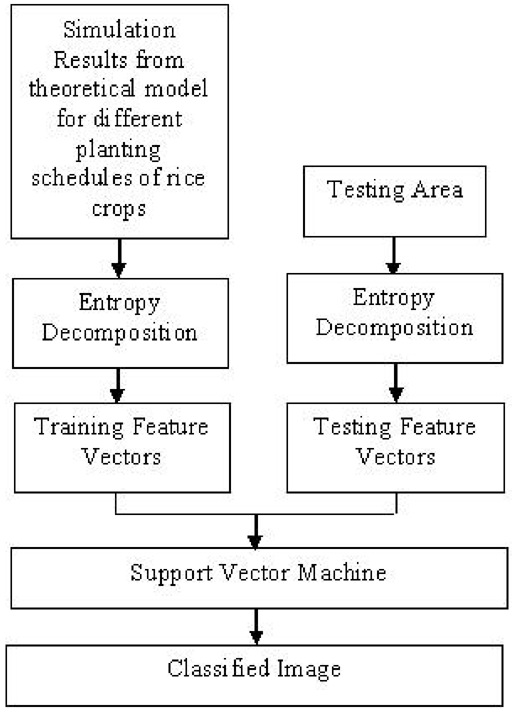


Figure 1. Flow chart of EDSVM approach.

temporal images are used to conduct Maximum Likelihood, Entropy Decomposition and Support Vector Machine classification. Maximum Likelihood classifier is chosen as a comparison classifier due to the popularity and the robustness of the algorithm. It is the most common statistical procedures used in the supervised classification. Maximum Likelihood classifier calculates the probability of the pixel belonging to a class in digital form. The pixels are then assigned to the class with the highest probability. The Maximum Likelihood classifier function in Environment for Visualizing Images software (ENVI) is used to perform this classification.

2.1. Entropy Decomposition Technique

Recently, Entropy Decomposition is popularly used to demonstrate the basic ability of polarimetry to distinguish features in an image. However, there remains a curiosity to extend this basic classification philosophy to the use of multi-temporal image. We propose a technique for the application of Entropy Decomposition in multi-temporal image by extracting and applying the backscattering coefficient values from the multi-temporal images in the Entropy Decomposition process.

In this case, each pixel in an image is expressed as the multi-temporal coherency matrix, $[T_T]$. It is obtained from the multi-temporal scattering vector,

$$k_T^{\dagger} = [S_{HH_{T1}} \quad S_{HH_{T2}} \quad S_{HH_{T3}}] \tag{1}$$

k_T where $S_{HH_{T1}}$ $S_{HH_{T2}}$ and $S_{HH_{T3}}$ are the backscattering coefficient of first, second and third multi-temporal images, respectively. The three images selected must be representative enough to represent different growth stages of the rice field and they can be arranged in any sequence but must be consistent throughout the classification process. In the case of rice field, as mentioned in Le Toan [2], the temporal backscatter variation is significant in the rice growth cycle, such as in the vegetative, reproductive and ripening stages. As the rice crops grow (vegetative stage), the backscattering coefficient will increase until it reaches its peak (reproductive stage). After that, it starts to decrease slowly (ripening stage) until the crops are harvested. Thus, the suitable three stages of growth for application in this case shall be vegetative stage, reproductive stage and ripening stage. The backscattering coefficient used can be HH, VV, VH or HV. In this paper, as RADARSAT images are used later for comparison, the HH backscattering coefficient shall be used for the application. Modification on the expressions can be done with added dimension to include more than three images. Averaging the outer product of them over the given samples yields

$$[T_T] = \left\langle k_T \quad k_T^{\dagger} \right\rangle = \begin{bmatrix} {S_{HH_{T1_1}}}^2 & S_{HH_{T1}}{S_{HH_{T2}}}^* & S_{HH_{T1}}{S_{HH_{T3}}}^* \\ S_{HH_{T2}}{S_{HH_{T1}}}^* & {S_{HH_{T2}}}^2 & S_{HH_{T2}}{S_{HH_{T3}}}^* \\ S_{HH_{T3}}{S_{HH_{T1}}}^* & S_{HH_{T3}}{S_{HH_{T2}}}^* & {S_{HH_{T3}}}^* \end{bmatrix} \tag{2}$$

where $k_T^{\dagger}$ refers to the conjugate transpose of k_T.

The multi-temporal coherency matrix $[T_T]$ can then be transformed into

$$[T_T] = [U_{T3}][\Lambda_T][U_{T3}]^{-1} \tag{3}$$

where $[U_{T3}]^{-1}$ represents the inverse matrix of $[U_{T3}]$ and

$$[\Lambda_T] = \begin{bmatrix} \lambda_{T1} & 0 & 0 \\ 0 & \lambda_{T2} & 0 \\ 0 & 0 & \lambda_{T3} \end{bmatrix}, \; [U_{T3}] = [u_{T1} \quad u_{T2} \quad u_{T3}], \tag{4}$$

$$[u_i] = [\cos\alpha_i \quad \cos\alpha_i \sin\beta_i \quad \sin\alpha_i \sin\beta_i], \; i = T1, T2, T3. \tag{5}$$

where λ_i and u_i are the eigenvalues and eigenvectors of $[T]$ with $i = T1, T2, T3$.

Based on the idea of Entropy Decomposition [6], multi-temporal alpha, α_T and entropy, H_T are proposed as follows:

$$\overline{\alpha}_T = P_{T1}\alpha_{T1} + P_{T2}\alpha_{T2} + O_{T3}\alpha_{T3} \tag{6}$$

and

$$H_T = -\sum_{i=1}^{3} P_i \log_3(P_i) \tag{7}$$

where P_i are the probability obtained from the eigen values of $[T_T]$ as expressed in

$$P_i = \frac{\lambda_i}{\sum\limits_{k=1}^{3} \lambda_k}, \quad i = T1, T2, T3. \tag{8}$$

However, the main disadvantage of the Entropy Decomposition is that the location of the decision boundary is arbitrary [12]. Studies have been done on the RADARSAT image using Entropy Decomposition for selected rice fields with different planting schedules and the distribution of the feature space are as shown in Figure 2. It is depicted that H_T and $\overline{\alpha}_T$ for rice field for different planting schedules are found to be overlapping to each other and thus, the separation between classes are difficult to be done.

In this study, theoretical model simulation is used to define the training sets of each planting schedules. This model is based on Radiative Transfer Theory where the formulation is solved iteratively to obtain up to second order solutions [20]. A more detailed description of the theoretical modeling is included in Appendix. The input physical parameters for the theoretical model are collected from the ground truth measurement. The information obtained from the theoretical model simulation are then used to produce H_T and $\overline{\alpha}_T$ from Entropy Decomposition technique. These values are drawn on the $H_T - \overline{\alpha}_T$ feature space based on different planting schedules as shown in Figure 3.

It is found that the separation between the second and third planting schedules is better now. However, the clusters for the first planting schedule and non rice are still overlapping to each other. To surmount this problem, Support Vector Machine is used to find the decision boundaries of the rice planting schedules in a higher dimensional feature space. Hence, an image classification technique based on the calculated results from theoretical models is proposed using combined Entropy Decomposition and Support Vector Machine (EDSVM).

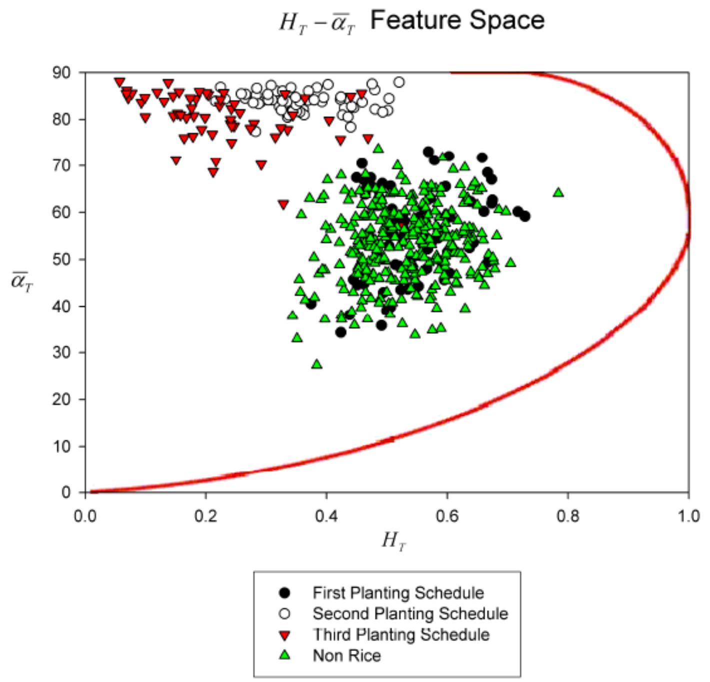


Figure 2. $H_T - \overline{\alpha}_T$ feature space for different rice planting schedules obtained from images.

2.2. Support Vector Machine

Support Vector Machine is proposed to combine with Entropy Decomposition to create a better separation between classes. The Support Vector Machine algorithm is a machine learning technique based on statistical theory [21] that can be used for classification purposes. In this study, Support Vector Machine classifier is used to train the different rice planting schedules based on the simulated results of theoretical modeling. This is possible by utilizing the special property of Support Vector classifier, which finds an ideal separating hyperplane in a higher dimensional feature space.

For a given training sample belonging to two different classes, Support Vector Machine 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

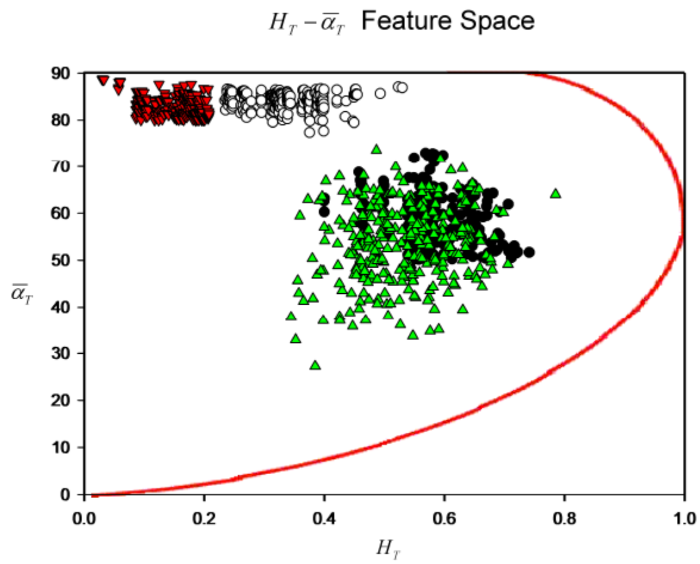


Figure 3. $H_T - \overline{\alpha}_T$ feature space for different rice planting schedules obtained from theoretical modeling.

the case where the data cannot be separated linearly by means of a hyperplane [22].

One of the basic ideas behind Support Vector Machine is to have a mapping Φ from the original input space X into a high-dimensional feature space F [23]. The decision boundary which is linear in F corresponds to a non-linear decision boundary in X as shown in Figure 4 [13].

The Support Vector Machine technique solves

$$\min \|\vec{w}\|^2 \tag{9}$$

constrained to

$$y_i \left(\langle \Phi(\vec{x}_i), \vec{w} \rangle + b \right) \text{ for } i = 1, \ldots, N. \tag{10}$$

where $\vec{w}$ is a vector perpendicular to the hyperplane while b determines the displacement of the hyperplane along the normal vector $\vec{w}$ [24]. To solve the constrained minimization problem, the Lagrangian dual problem technique is introduced as

$$\text{maximize } L(l) = \sum_{i=1}^{N} l_i - \frac{1}{2} \sum_{j=1}^{N} l_i l_j y_i y_j \left\langle \Phi(\vec{x}_i), \Phi(\vec{x}_j) \right\rangle \tag{11}$$

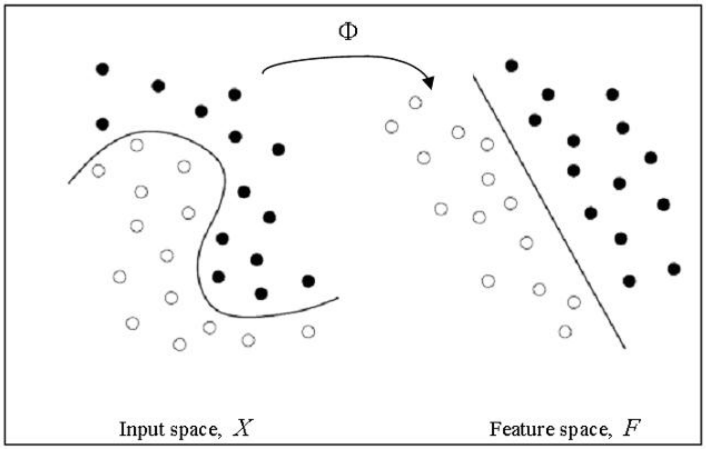


Figure 4. Linear separation in the feature space, F.

$$\text{subject to } l_i \geq 0,\ i = 1, \ldots, N \text{ and } \sum_{i=1}^{m} l_i y_i = 0. \tag{12}$$

with Lagrange multipliers $l_i \geq 0$ [25]. After solving this dual problem, the decision function implemented by the classifier for any test vectors x is expressed by

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{N} l_i y_i \left\langle \Phi(\vec{x}_i), \Phi(\vec{x}_j) \right\rangle + b\right). \tag{13}$$

Multi class Support Vector Machine is usually implemented by combining several two-class Support Vector Machine. We use the 'one-against-one' approach [26] in which $k(k-1)/2$ are constructed where k is the number of classes and each trains data from two different classes. This strategy was first used on Support Vector Machine by Friedman [27] and Kreßel [28]. In the classification, voting scheme was used where each binary classification is considered to be a vote and the pixel will be assigned to the class with the maximum votes. Studies show that 'one-against-one' obtains better accuracy and shorter training time [29] compared to other multi class SVMs, namely one-against-all and Directed Acyclic Graph Support Vector Machine (DAGSVM). Therefore, with the unique feature of multi class Support Vector Machine, it is possible to further improve the classification of crop fields.

3. APPLICATION OF PROPOSED TECHNIQUE

In radar imagery, rice fields appear very dark during the flooded vegetative phase, and turn brighter during the reproductive and ripening phase [3]. As such, the multi-temporal images are useful to identify the variation of backscattering coefficient for rice monitoring. In order to achieve accurate classification, preprocessing of the images is an essential step.

3.1. Image Preprocessing

First, the multi-temporal images are geocoded using PCI software. The purpose of geocoding is to match the RADARSAT-1 image to the actual position on the ground based on the GCP points. The location of the rice fields can be identified easily from each image of the multi-temporal images.

The geocoded images of September 15, October 9, and November 2, 2006 are as shown in Figures 5(a), (b) and (c), respectively. Since the phase information from the backscattering coefficient of these pixels is not correlated among multi-temporal images, the intensity values of the backscattering coefficient for these pixels are actually used for the image classification.

After that, an area of 1024×1024 pixels is selected from the geocoded image for purpose of the classification of rice planting schedules. This study area is chosen to cover the wide area of rice fields. Lee filter is also applied on the study area to reduce speckle. Figure 6 shows the selected study area for the multi-temporal images. Besides, ground truth measurement has also been conducted on the selected plots of the study area.

3.2. Ground Truth Measurement

The understanding of rice growing conditions and cultural practices are crucial in order to retrieve rice crop parameters and develop an algorithm for rice monitoring. Thus, ground truth measurements for an entire rice crop season have been conducted at 12-day intervals from September 15, 2005 to December 5, 2005 at Sungai Burung, Selangor, Malaysia. The dates are chosen so as to coincide with RADARSAT-1 image acquisitions.

Ten different test fields in the region are selected and shown in Figure 7. Test fields 3, 5 and 8 are later excluded from the study because of incomplete data collection due to heavy rains and partial destruction of the rice fields. Parameters that were measured include plant geometry such as plant height, leaf length, leaf width, leaf thickness, plant density, plant water content and plant biomass. The measurement was done by a group of researchers from Multimedia University and Malaysian Centre for Remote Sensing (MACRES) as collective effort for various research purposes.

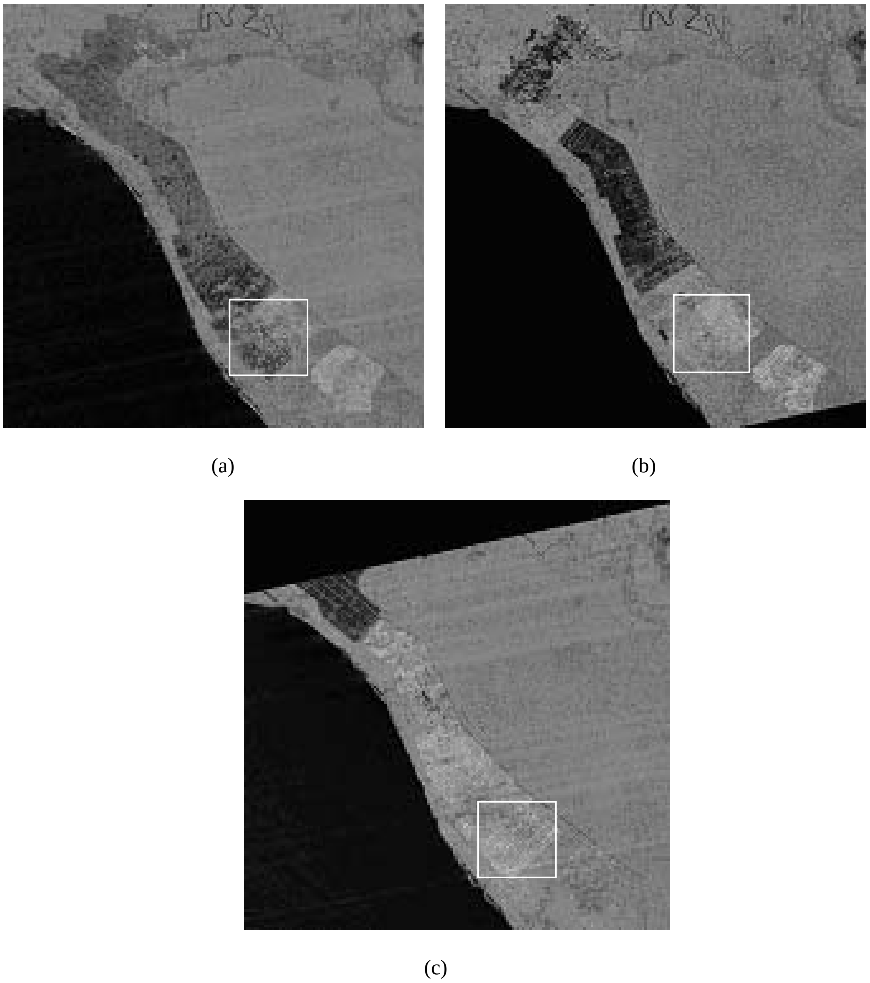
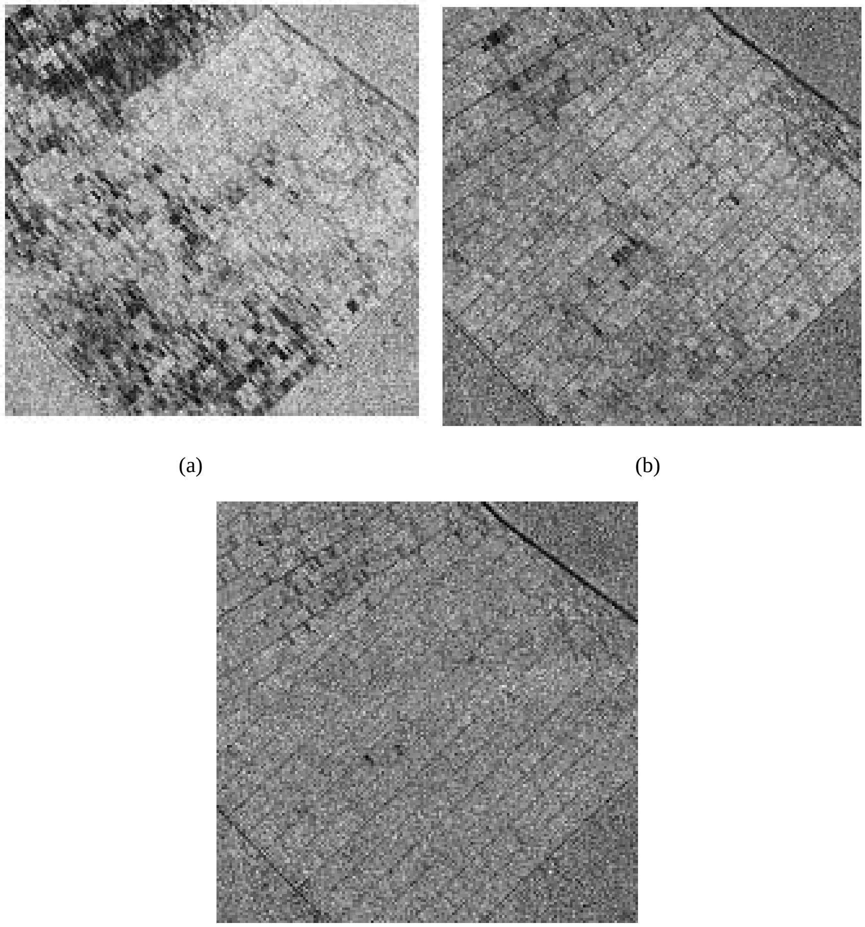


Figure 5. Geocoded RADARSAT-1 images acquired on (a) 15 September 2005 (b) 09 October 2005 (c) 02 November 2005.



(a) (b) (c)

Figure 6. Selected study area of Sungai Burung acquired on (a) 15 September 2005 (b) 09 October 2005 (c) 02 November 2005.

4. RESULTS AND DISCUSSION

In this study, the pattern of the rice planting schedule has been observed from the $H - \overline{\alpha}$ feature space and it is useful for the rice monitoring purpose. An improved classifier has been developed by combining the Entropy Decomposition and Support Vector Machine classifiers to extend the application to multi-temporal data and produce an efficient classification.

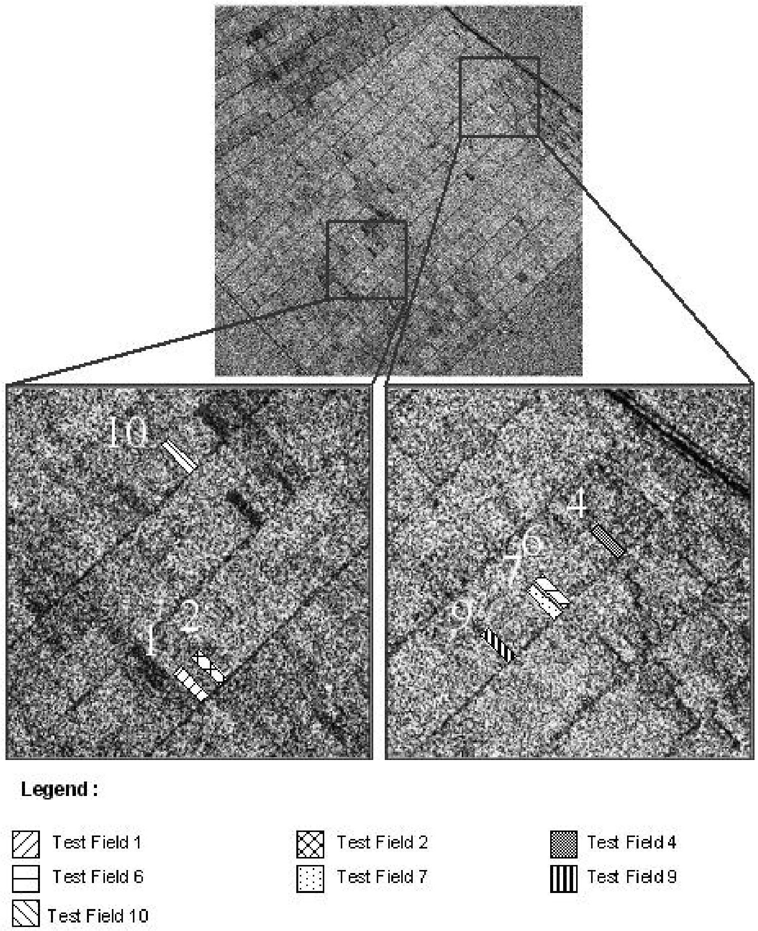


Figure 7. A superimposed image of the multi-temporal RADARSAT-1 images dated 15 of September, 2005, 09 of October, 2005 and 02 of November, 2005 (in grayscale) showing 7 test fields at Sungai Burung, Selangor, Malaysia.

The classification is done on the images with different window sizes. An accuracy assessment has been done to obtain the optimal window size and the results are shown in Figure 8. From the accuracy assessment results, it is shown that the results from EDSVM outperform those of Maximum Likelihood, Entropy Decomposition and Support Vector Machine. The optimal window size for the classification of rice growth is 7. The overall accuracy obtained from Maximum

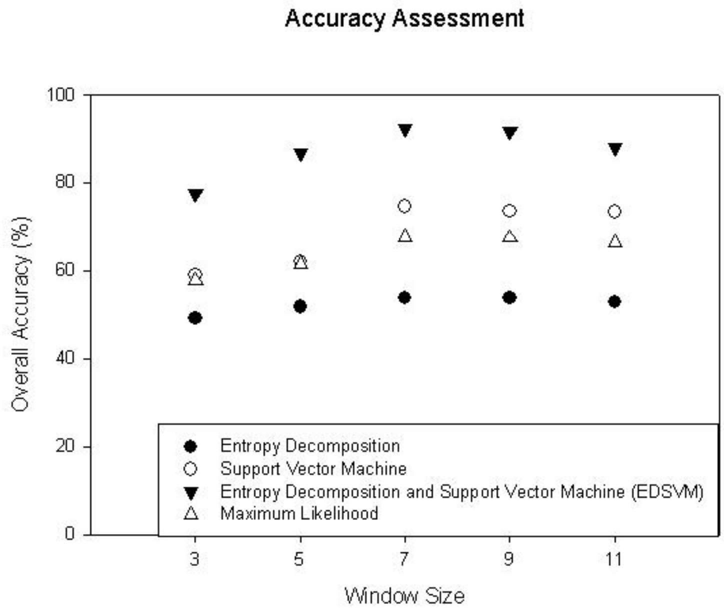


Figure 8. Accuracy assessment with different window sizes.

Likelihood technique is 67.66%, Entropy Decomposition technique is 53.77%, Support Vector Machine is 74.63% and EDSVM is 92.33%. Figure 9 shows the classified results using Maximum Likelihood, Entropy Decomposition, Support Vector Machine and EDSVM for the window size 7×7.

From the classified image using Entropy Decomposition (ED) technique, it can be seen that there are misclassifications for most of the classes. First planting schedule and non rice classes are not classified correctly due to poor separation between the classes when using Maximum Likelihood technique (Figure 9 (a)). Misclassification also occurs on the first planting schedule and non rice classes when using only Entropy Decomposition technique (Figure 9(b)). On the other hand, some of the first and third planting schedules rice fields are wrongly classified as non rice areas in the Support Vector Machine classification (Figure 9(c)). However, EDSVM has managed to separate them well (Figure 9(d)). It is clearly indicated that EDSVM has yielded good separation for the rice planting schedules.

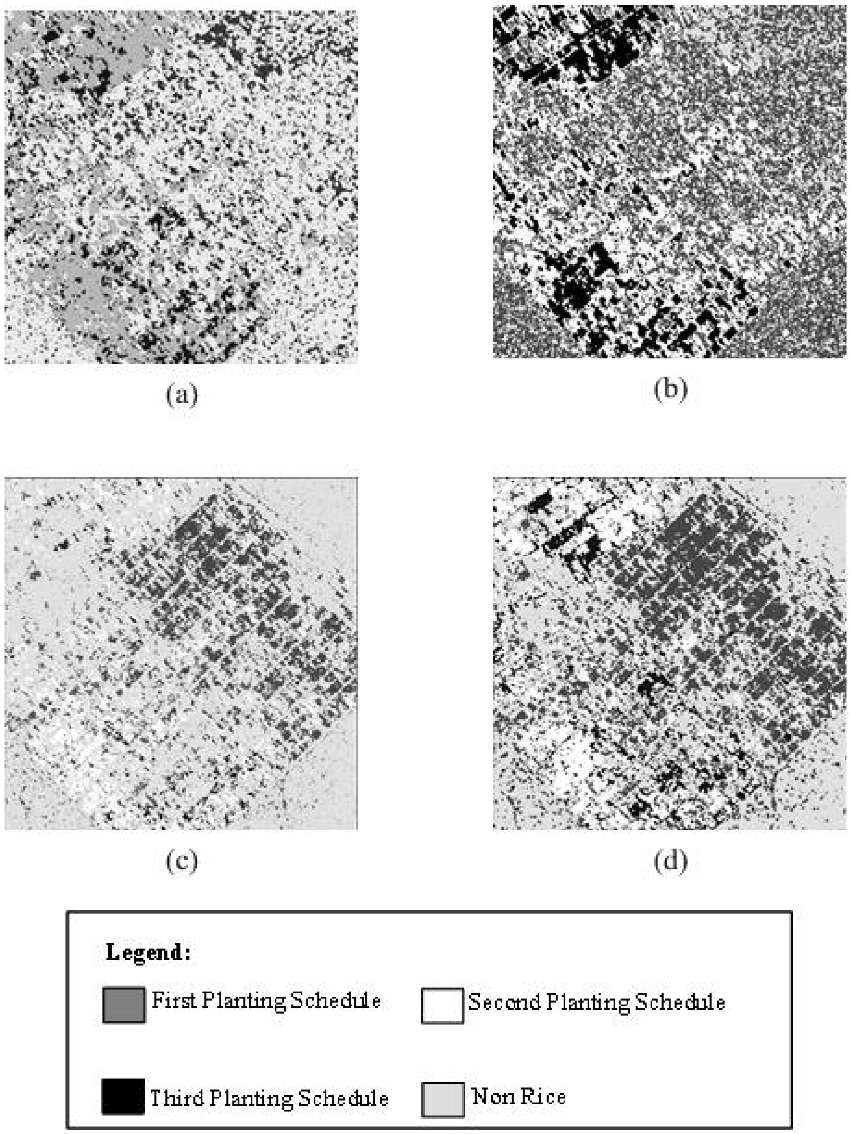


Figure 9. Classified images with window size 7×7 for (a) Maximum Likelihood, (b) Entropy Decomposition, (c) Support Vector Machine and (d) EDSVM.

5. CONCLUSION

The paper is intended to assess the use of the multi-temporal RADARSAT-1 images for the classification of rice planting schedule. For this purpose, the combined technique of EDSVM based on theoretical modeling are applied to perform a good separation between the different rice planting schedules. This novel technique not only gives significant results on the classification, but most importantly, it extends the application of Entropy Decomposition to cover the multi-temporal data. Our future work will be done to evaluate on other useful parameters extracted from SAR data to further improve the classification accuracy.

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APPENDIX A. THEORETICAL MODEL

A theoretical model is developed to enable the study of the scattering mechanisms involved in the backscattering of rice canopies throughout the entire season. The parameters of the training areas from the ground truth measurements are used as the input to the theoretical model to simulate the multi-temporal coherency matrices of the rice fields, the results of which will be applied to determine the training sets of the proposed technique.

In the development of the theoretical model, the rice canopy is modeled as a single layer or double layer medium, depending on its growth stage, over a smooth water surface. The phase matrices of needles and cylinders are used to represent the rice leaves and stems respectively. For the rice grains, tiny cylinders are used. During the early stages of growth, the stems are still submerged underwater. Therefore, only a single layer of needles is used to model the canopy [Figure A1(a)]. When the plants mature, two layers are used. Needles are used in both layers while cylinders are used in the lower layer to represent the stems [Figure A1(b)]. Tiny cylinders are added to the top layer when the plants enter the reproductive stage [Figure A1(c)].

In sparse media, far field and non-coherent approximations are used in the calculation of the phase matrix. In this model, however,

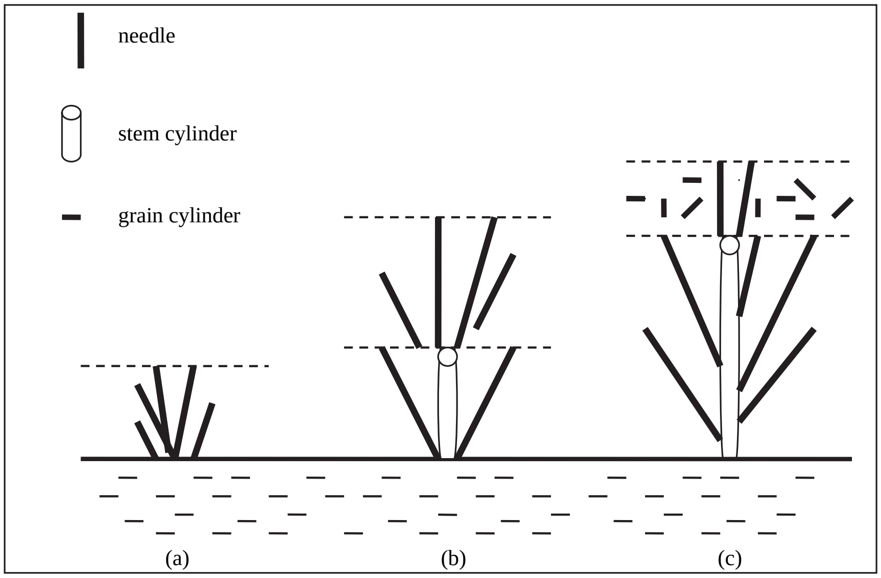

Figure A1. Variations in the model used for the computation of backscattering coefficients of paddy fields in the (a) early vegetative stage, (b) late vegetative stage and (c) reproductive stage.

the rice fields are modeled as electrically dense media, where the average distance between the scatterers are small in comparison to the wavelength of the incident wave. The Dense Medium Phase and Amplitude Correction Theory (DM-PACT) [30, 31] is used to account for the coherent effects between scatterers, while the Fresnel Corrections [32] are used to consider the near field effects. The phase matrices are then applied to the radiative transfer equation [33], given as:

$$\cos\theta \frac{d\overline{I}}{dz} = -\overline{\overline{\kappa}}_e \overline{I} + \int \overline{\overline{P}}\,\overline{I} d\Omega \tag{A1}$$

where $\overline{I}$ is the Stokes vector that describes the intensity of the wave, while $\overline{\overline{\kappa}}_e$ and $\overline{\overline{P}}$ are the extinction matrix and phase matrix of the medium, respectively. The equation is solved up to the second order to obtain the intensity of the backscattered wave. The backscattering coefficient can then be obtained using the equation:

$$\sigma_{pq} = \frac{4\pi \cos\theta_s I_{sp}}{I_{iq}} \tag{A2}$$

where p and q represent the backscattered and incident polarizations respectively and can be ν or h. θ_s is the angle of the scattered field with respect to the normal of the medium. I_{sp} is the intensity of the backscattered waves, while I_{iq} is the intensity of the incident wave. The first order solutions contain terms that include single volume scattering and surface-volume scattering. On the other hand, the second order solutions give the double volume scattering terms.

In this study, the theoretical model is used to calculate the multi-temporal coherency matrix of rice crop canopies over a range of values at various stages of growth. For each particular stage of growth, a range of possible values of plant geometry and canopy heights based on measured ground truth data are used as input parameters for the theoretical model [34]. The plant dielectric constants are calculated using the equation in [35]. A statistical distribution is used for the leaf angles, based on the equation given in [36]. These are then used to generate a range of possible values for the coherency matrices at each stage of growth to assist in determining the decision boundaries needed for classification.

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