CROP FIELD CLASSIFICATION USING RADAR IMAGES

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Abstract- The rising food demand requires regular agriculture land-cover updates to support food security initiatives. Agricultural areas undergo dynamic changes throughout the year, which manifest varying radar backscatter due to crop phenology. In certain crops similar backscatter is shown if their phenology intersects, but varies later when their phenology differs. Hence, classification techniques based on single-date remote sensing images may not offer optimal results for crops with similar phenology. Moreover, methods that stack images within a cropping season as composite bands for classification limit discrimination to one feature space vector, which can suffer from overlapping classes.

Index Terms – High Dynamic Conditional Random Fields (HDCRF), RADARSAT, TerraSAR-X, Conditional Random Fields (CRFs), Maximum Likelihood Classifiers (MLC).

I. INTRODUCTION

Imaging radar is used to monitor and map evolving phenomena on the earth surface. TerraSAR-X microwave images is used to capture crops in different phenology states. Phenology refers to the evolutions that crops go through right from seeding to the moment they are harvested. The distinct development phases cause backscatter variation, which is an important discrimination component in radar crop land-cover mapping applications. For instance, different crops may be in the same phonological state at an instant in time, hence exhibit similar backscatter. The Dynamic Conditional Random Fields (DCRF) models have a duplicated structure of temporally connected CRFs, which encode image-based phenology and expert-based phenology knowledge during classification. Ensemble method generates an optimal map based on class posterior probabilities estimated by DCRFs. These techniques improved crop delineation at each epoch, with higher order DCRFs (HDCRFs) giving the best accuracy.

II. PROPOSED SYSTEM

In existing system, a method for the multi temporal and contextual classification of geo-referenced optical remote sensing images acquired at different epochs and having different geometrical resolutions is presented. This method is based on Conditional Random Fields (CRFs) for contextual classification.

The CRF model is expanded by temporal interaction terms that link neighboring epochs via transition probabilities between different classes. In order to be able to deal with data of different resolution, the class structure at different epochs may vary with the resolution. The goal of the multi temporal classification is an improved classification performance at all individual epochs, but also the detection of land-cover changes, possibly using lower resolution data. In existing system, it is noted that incorrect determination of transition matrix could lead to erroneous transfer of information to other epochs consequently reducing classification accuracy.
As shown in the Fig 1, the architecture of a proposed system is as follows, the correlation coefficient (CC) can recognize the pixels with strong relationships. Therefore, a classification method by combining CC and JSR (CCJSR) classification is proposed. This can be accomplished by three main steps. In the first step, a test sample can be linear represented by the atoms in an over complete dictionary and sparse vectors. In this step, JSR is used to produce the residual for every class. In the second step, CC is used to calculate the degree of similarity between the training and test samples. In the last step, a decision function is used for classification based on the residual of JSR and the degree of correlation. The proposed method combines two major factors, spectral similarity and local spatial consistency, for crop type classification.

III. EXPERIMENT AND RESULT

The methodology for the system is to design and develop HDCRF by image acquisition. Spectral Simultaneous Orthogonal Matching Pursuit (SOMP) is used for signal acquisition and recovering band information. Pre-process or de-noising of images are done for the better quality of image. Signal segmentation is done and HDCRF is applied to calculate random fields of terrain. The next step is to design a framework which maps optimal seasonal crop. This can be achieved by train the model based on the parameters such as seasons, temperature and humidity. Binarization is performed to convert the pixel information into binary information. After designing framework, the crop classification can be implemented.

Fig 2 shows the steps for accurate results classification. In crop mapping classification methodology, the Joint Spectral Classification (JSRC) is used for classification of hyper spectral images. Regression tasks are operated by constructing multitude of decision trees at training time. Co-relation co-efficient is calculated for irregular shapes to find the loss of data. After that, normalization is performed if co-efficient value is more and is normalized. The study of external properties is done using morphology and morphological dilation is done to find lossy information. Land masking is done for feature extraction and feature selection. Similarities between the train and test data are found using correlation and are classified based on the results.
To design efficient morphological and feature extraction for extracting invariant feature from different sensor types using morphology and morphological dilation is done to find lossy information. Land masking is done for feature extraction and feature selection. Similarities between the train and test data are found using co-relation and are classified based on the results. The level 0 Data flow diagram in Fig 3 shows all the possible steps for making noise free image from the RADAR images.

As shown the Figure 4 & 5 the preprocessing steps are considered and watershed and Fisher algorithm is used for the segmented radar images. Maximum Likelihood Classifiers and Support vector machine classifiers are used to classifying crops.
Fig 5: Level 1 Data flow Diagram

Fig 6: Snapshot displaying image acquisition and pre-processing

Fig 6 shows the details of acquisition and preprocessing data. The results of the proposed system are read in the following steps. The first step is Load Dataset. Here, The Indian Pines dataset is collected from public dataset. It has testing dataset and ground truth dataset. Finally both the dataset is loaded to crop type classification. Next step is Data Splitting. In dataset splitting, randomly select training samples and testing samples respectively.

Finally classification, After splitting of training and testing, crop type classification is implemented based on correlation co-efficient and joint sparse representation. In that, the CC is introduced into the JSR classifier, so as to combine the local spatial information and nonlocal spectral information in an effective way. A classifier that combines JSR and CC is proposed. The proposed CCJSR is composed of two components (CC and JSR). The major steps of the classification as follow as, calculate the CCs among the training and test samples and the representation residuals are calculated using the JSR. Finally, the class label of each pixel is determined based on the defined decision function.

IV. CONCLUSION

A crop type classification method based on Joint Sparse Representation (JSR) and Co-relation Co-efficient (CC) is developed. Considering that JSRC may include between class interference, CC is introduced to model the spectral similarity among pixels in the CCJSR method. Compared with the original JSRC, the CCJSR method can make full use of the spatial contextual information and spectral similarity information at the same time. Furthermore, a decision function is introduced to achieve the balance between JSR and CC. Experiments
performed on the Indian Pines data set demonstrate that CCJSR can improve the performance of the JSRC effectively. The proposed system will not only classify the crops but also predicts the crops to be cultivated based on the natural disasters and seasons, therefore, loss of yield can be minimized.

REFERENCES


