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Sparse Representation based Classification on Automatic Target Recognition

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Abstract- This paper introduces a sparse representation based classification on automatic target recognition in Synthetic Aperture Radar (SAR) image. Here, it exploits an analytic signals of real valued function generalize to capture the characteristics of SAR image. The multiple components of the monogenic signal are applied into recently developed framework, sparse representation-based classification (SRC). The nonliteral operating conditions such as structural modifications, random noise corruption, and variations in depression angle, are performed with various baseline algorithms. It also includes the working function of linear support vector machine, SRC and sparse representation of monogenic signal. The Moving and Stationary Target Acquiration and Recognition database will demonstrate under standard operating condition and robust towards noise corruption and depression variations.

Index terms- The monogenic signal, monogenic scale space, spare representation based classification.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) has been used in many fields with high resolution optimal imaging sensors. SAR provides a capability of monitoring the environmental, earth resource mapping and military surveillance system that requires broad area imaging at high resolution. This imaging technique will also acquires during inclement weather conditions. The main function of automatic target recognition (ATR) is to detect and recognize the object in image by synthetic aperture radar. The signal processing uses automatic target recognition techniques to find out the unknown targets. So, one-foot resolution of the radar will easily discriminate small and large vehicles from the surrounding. SAR ATR will define a distance metric condition between the query and templates generated by various aspect view image of the object. The decision is made to find out the target to which the template belongs. SAR has three separate stages detection, discrimination and classification. The detection focuses on finding the local Regions of Interest (ROI) which include targets and numerous false alarms. The discrimination is used to filter the natural clutter out, for the identities of targets. The SAR images contain coherent speckle noise, which lowers the image quality significantly, so it is very difficult to interpret them from multiple distributed targets.

Here sparse representation is used to search for the most compact representation of signal in terms of linear combination, using multi scale and multi orientation. The sparse representation is generated by evaluating the class of samples, which could recover the query as accurate as possible. The training set generates a methodology which usually defines distance between the test sample and the templates. The correlation pattern recognition has been presented to improve the performance of training set. The nonlinear classifier is used for the SAR ATR for the better performance in conventional template based approaches. A set of classifier is to be trained by the training samples in order to reduce their complexity, over a given range of aspect angles. Thus the performance of an algorithm is limited by the accuracy of the aspect angle estimate.

Sparse Representation based Classification (SRC) are recommended to the framework which is extensively utilized in many classification. The framework is re-explained from the perspective of class manifolds in the classification on MSTAR targets. The SRC focuses on extracting effective features to improve the classification performance. In a 2D monogenic wavelet transform the analytic signal yields local amplitude and local phase an

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appropriate local signal that preserve the split of identity. The main advantages of monogenic wavelet transform offer a geometric representation for gray scale image. The monogenic binary coding is presented for biometric recognition in which the components of the monogenic signals are encoded by various binary pattern schemes. This paper introduces the score level fusion at various scales used to generate three different feature descriptions, from which three sparse representation based classification can be built. The fusion method can improve the target classes which is not effective and not linearly separable. MSTAR images have high dimensionality and speckle noise thus makes the classification more complicated and influencing the pattern recognition worse. So it recommends suppressing the speckle noise and reducing the dimensionality. MSTAR data set include target recognition under standard operating condition, extended operating condition towards noise corruption as well as configuration and depression variation.

2. RELATED WORK

The SAR image is usually affected by multiplicative noise known as speckle. This noise provides a poor quality of SAR image and consequently, the interpretation of image and shape detection become difficult. Increasing the image quality and reducing speckle effect becomes a crucial process in the recognition system. There are different filter to reduce speckle, so median filter is used because speckle noise is not strong in the reconstructed images. The SAR images of the same target taken at different aspect angles show great differences, which precludes the existence of a rotation invariant transform. This results from the fact that a SAR image reflects the fine target structure at a certain pose. The database used for training is same set of images and their performance is evaluated under identical testing condition in terms of confusion matrices. MSTAR dataset result the performance for a number of class samples of automatic target recognition which represent both standard and extended operating conditions. Automatic classification of targets in SAR imagery is performed using topographic features. Three strategies of learning and representation builds support vector machine, quadratic mutual information cost function for neural networks, and a principal component analysis extended with multi-resolution.

2.1 Sparse Representation based Classification

Sparse representation based classification (SRC) has been proved to be an effective classifier. However, it is well known that the overcomplete basis for computing the test samples sparse representation is constructed by all training data. When the size of the training data is large, the computational complexity restricts SRC to be applied in many real-time recognition problems. To address this problem, an efficient and effective approach is proposed. The SRC method is based on the assumption that any test sample lies in the subspace spanned by the training samples belonging to the same class. So the construction of the over-complete dictionary of the proposed method is based on the following the fact that the samples used for the sparse representation of the test sample should be only sample in the classes which the test sample may belong to rather than all training samples. So a more compact over complete dictionary is built for computing the sparse representation of the test samples, which greatly reduces the computational complexity. Specifically, for each test samples which are computed using k-nearest neighbour, then the set of classes is defined as neighbour class of the test sample and used to determine the most samples. All the test samples of neighbour classes are used to construct the overcomplete set for the computation of the sparse representation. The experimental result of the MSTAR database not only reduces the computational complexity, but also increases the performance of recognition as the influence from the noise classes which is eliminated.

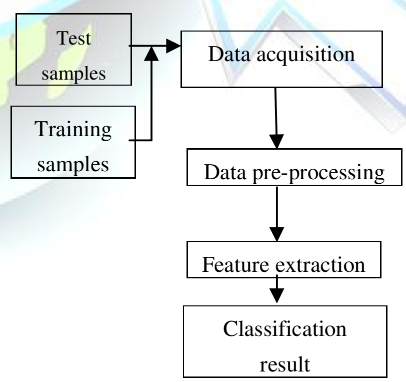

Fig 1: Flow process diagram of SRC

2.1.1. Representation based on classification

The proposed method achieves the performance similar to the baseline algorithms under minor and medium EOC difference on depression (or standard operating condition). However, when the major EOC difference on depression is considered, which demonstrates better advantage than the

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reference methods. On the other hand, the results also prove that the tolerance towards variation in depression could be improved with the monogenic signal representation. From the experimental results, we are able to perform the following methods that the classification via score-level fusion outperforms the baseline methods, especially under the nonliteral experimental setup, *e.g.*, different configurations and depressions. Beside that classification via kernel combination always achieves the best performance. The results prove that the tolerance towards variation in configuration and depression could be improved by monogenic signal representation.

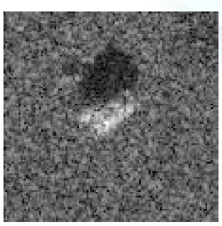
2.2 Support Vector Machine

Support Vector Machine (SVM) are a new statistical learning technique that can be used for training classifier based on polynomial function, radial basis function, neural network. It uses a hyper linear separating plane to create a classifier. This vector machine provides a possibility to find a solution by making a nonlinear transformation of the original input space into a high dimensional feature space, where an optimal separating hyper plane can be found.

3. PERFORMANCE DESCRIPTION

3.1 Data Acquisition

Synthetic aperture radar is a form of radar in which multiple radar images are processed to yield higher resolution images that would be possible by conventional methods. SAR system employs a linear antenna mounted on a moving platform which is used to illuminate the target area. The SAR ATR is performed using the MSTAR database to classify the targets.



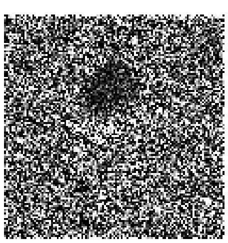


Figure 2: Binarization of the image

Here the SAR image which is generated upload the maximum number of images to database represented as monogenic signal. The input of a query image is taken from image database captured by the various view of the object.

3.2 Data pre-processing

In order to standardize the information each images is classified by the depression of target. SAR images taken at different aspect views shows great difference of scattering phenomenology.The pre-processing steps improve the result to get better threshold value, accuracy over multiple components simultaneously. It also unifies the sizes of the images, reduces the complexity and improves the performance of the classifiers.

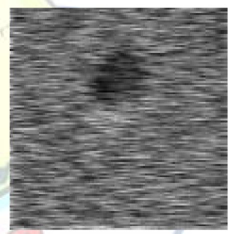


Figure 3: Image before filtering

3.3 Filtering

Median filtering is to replace each pixel value in an image but the median of its neighbourhood. The median filter is normally used to reduce noise in an image usually like the mean filter. It performs much better than standard averaging FIR filter which tend to significant portion of signal high frequency content along with noise. Here the speckle noise in SAR is generally serious, causing difficulties for image interpretation.

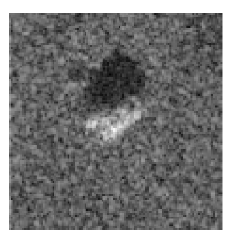


Figure 4: Image after filtering

So median filter is used to remove the noise which is severely corrupted by the defectives i.e. the locations are randomly decided. The median filter considers each pixel in the image to decide whether it is representative of its surrounding. The median filter is performed by sorting all the pixel value from the surrounding neighbourhood into numerical order and replaces the pixel with middle pixel value. The median filter has the tendency of removing noise from corrupted images. It also decompose the query image in Savitzky-galay filter that can applied to a set of digital data point for the purpose of smoothing data, that is to increase the signal to noise ratio without greatly distorting the signal. So the filtering method reduces the noise in corrupted images.

3.4. Neural Network Pattern Recognition Tool

In pattern recognition the neural network is used to classify input into a set of target categories. The neural network pattern recognition tool will help to select data which creates and train a network and evaluate its performance using mean square error and confusion matrices. A two layer feed forward network with sigmoid hidden and output neurons can classify vector arbitrary well, given enough neurons in its hidden layer. The network will be trained with the scaled conjugate gradient back propagation, in which an example data set is loaded for defining the target data, by importing in the simple classes. To define the pattern recognition neural network numbers of hidden neurons are applied to perform training. The train network uses scaled conjugate gradient back propagation. Training automatically stops when generalization stops improving as indicated by an increase in mean square error of the validation samples. Training multiple times will generate different result due to different initial condition and sampling.

4. EXPERIMENTS AND DISCUSSION

The MSTAR database has SAR target which are collected at two different depression angles (15^o and 17^o). The classifier using this database is to be trained using target at the 17 depression angles and tested on target at the 15 depression angles. The overall recognition rate is obtained using various methods. The truth target with multi variant standardise the training set while the remaining are used for testing, from which the EOC different on depression and configuration are simultaneously evaluated. This result that tolerant towards variation in configuration and depression could be improved by monogenic signal representation. The one foot resolution of the image allows the radar to discriminate from the surrounding areas.

4.1 Verification of Target

The SAR image are cropped around 128x128 pixel to 80x80 pixel size utilized to principal component analysis. The three different target TG1, TG2, TG3 are utilized, from which one is taken at 17^o depression while the remaining are collected at 15^o depression are used for testing i.e. the variant used for testing are not contained in the training set.

4.1.1 Comparison with the Conventional Method

The proposed method has baseline algorithm which is used to assess the accuracy of individual class as well as confusion matrices. The recognition rates are obtained by different conventional method SRC, MSRC, KSVM, SUM, MAP which improves the overall accuracy as well as individual recognition rate in baseline methods. This is because both configuration and depression are significantly different between the image used for training and those used for testing the target. The classification in the Hilbert space always outperforms the ones in spatial domain to get better accuracy. The classifications via score level fusion and kernel achieve significant improvement in overall accuracy. The monogenic signal representation is capable to capture the broad spectral information and simultaneous spatial localization with compact support, also contributes better performance. It provides the samples into the Hilbert space with a nonlinear mapping. Thus the similarities between a pair of samples can be measured in a sufficiently feature space.

4.1.2. Retrieve Output Target Recognition.

To retrieve output target recognition the corrupted pixels are randomly chosen from the image levels the noise corruption. The robust version of SRC, which solves the extended norm minimization deals with the occlusion the performance are degraded with the range of corruption increased. The proposed methods are much more robust towards the EOC difference on depression than the other base line methods. Images taken at 17^o depressions are used to train the algorithm, while the other captured at 15, 30, and 45 are used for testing. The overall recognition rate is obtained by confusion matrices using various methods. It adheres to standard set FORT to trained the algorithm at an operating condition at 17^o depression and test them at an operating condition of 15^o depression i.e. a change of 2^o from 17^o to 15^o exceeds between the image used for training and those for testing. These two targets with multi- variant are standard to get better accuracy level. To observe the performance of individual target the recognition rate with respect to each target class are performed with corresponding confusion matrices. Most of the target could be corruptly recognized with the depression and configuration of the baseline method. The output target recognition could improve the accuracy, threshold value especially under extended operating condition. Thus it improves the performance by combining multiple components simultaneously.

5. CONCLUSION

The proposed method introduces a unifying framework for target recognition, based on the classification derived from multiple components of the monogenic signal at different scales. It will evaluate the class of samples that could recover the query as accurately as possible. It is robust towards EOC difference on depression and configuration, as well as noise corruption. MSTAR data set include target recognition under extended operating condition towards noise corruption as well as configuration and depression variation. The proposed method could improve the recognition accuracy and threshold. So the geometric analysis is done without considering the color information and it would be much more attractive to have a complete representation of the monogenic signal into magnitude and phase with color/geometric interpretation. The MSTAR database unify the sizes of the image reduces the complexity and improve the performances of classifiers. Thus it will focus on improving the robustness of SRC. Thus provides excellent performance for improving target recognition.

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