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Modified Approach of Support Vector Machine for Classification of AVHRR Image Data

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Abstract: Weather forecasting applications use various pattern recognition techniques to analyze clouds information and other meteorological parameters. Different types of cloud appear in Advanced Very High Resolution Radiometer (AVHRR) image. The objective of this research is to classify the different types of clouds observed in a satellite cloud image. Image classification categorizes all pixels in a digital image into one of several classes or themes. Gray Level Co-Occurrence Matrix (GLCM) is used to extract features. All those features cannot be used precisely in classification. For precise usage, Opposition based Particle Swarm Optimization (OPSO) is used for optimization. In this study an image classification framework is developed with Support Vector Machine (SVM). Median filter is used for noise reduction. An efficient and effective image classifier system often consists of a defined set of classes. These precisely defined classes are well separated by a set of features that are typically derived from the multi-dimensional image data. Finally, SVM categorizes the image into four categories: namely clear sky, low level clouds, mid-level clouds and high level clouds.

Key words: Classification, cloud image, feature extraction, gray level co-occurrence matrix, preprocessing.

INTRODUCTION

Satellite images of clouds have become a common component in weather analysis system. There is huge image content appearing every second through multiple competing satellites systems (Onsi and Hoda, 2012). Satellite data are used in short-range forecasts, tropical cyclone monitoring, aviation forecasts etc. This leads to quick and improved forecasts. Satellite images obtained through remote sensing is a demanding procedure in terms of data manipulation and computing power (Petcu *et al*., 2007). Remote sensing emerged as essential information collection technique in environmental monitoring, resource investigation and other research (Ahmadi and Hames, 2009). Classification of objects is a complex problem for machines due to the raise of high-capacity computers, availability of high quality and low-priced video cameras (Kamavisdar *et al*., 2013; Leigh *et al*., 2014).

For extracting information classes from multi-band raster images, the satellite image has to be analyzed (Guerra *et al*., 2011). The process of grouping image pixels into categories or classes to produce a thematic representation is called image classification (Dean and Smith, 2003). Thematic Mapper (TM) can be created by the resulting raster image from image classification (Yang *et al*., 2013, 2014). The classifier is a computer program that accomplishes a specific task for image classification and the classifiers are created by learning algorithms (Wang, 2014). These techniques are distinguished in two main ways as supervised and unsupervised classifications.

Supervised classification can be classified as parallelepiped, maximum likelihood, minimum distances and Fisher classifier methods (Perumal and Bhaskaran, 2010). Two different phases of supervised classification algorithm are training phase and testing phase. In the training phase, properties of typical image features are isolated and unique description of each classification category is created (Tang *et al*., 2013). Based on the quality of training sites, the quality of a supervised classification differs. Sequence of operations to be carried out for supervised classification is defining training sites, extracting features and classifying image. The accuracy can be improved by selecting more training site (Poggi *et al*., 2005; Bachmann *et al*., 2005).

Unsupervised classification aims to discover groups of similar instances within the data. This classification has no information about the class label of data and the number of classes (Palaniswami *et al*., 2006). Some unsupervised classification techniques are hierarchical clustering, partition algorithm and k-nearest neighbor algorithm (Ari and Aksoy, 2010). Unsupervised classification techniques depend on inter-class variability,

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which is represented by the occurrence of different class types in an image. The best approach can easily distinguish the types and mask them out from the image (Domadia *et al*., 2014). Unsupervised classification is a classical problem in pattern recognition which is called clustering.

Gomez and coauthors showed the properties of co-occurrence statistics combined to six gray-scale quantization levels by which breast lesions on ultrasound images were classified. GLCM was calculated using the region which was delimited by a minimum bounding rectangle. By averaging texture descriptors of the same distance reduction of feature space dimensionality was carried out. In order to assess the discrimination power of texture features, Fisher Linear Discriminant Analysis (FLDA) was used. The quantization level could not affect the discriminating power in the single texture features.

MATERIALS AND METHODS

This research present higher efficient classification algorithm using modified SVM to develop a better classified output with better detection rate. The proposed method has three phases: pre-processing, feature extraction, parameter optimization and classification. Pre-processing is carried out in two steps such as image conversion and noise reduction. RGB color images are converted to equivalent gray scale image in image conversion stage because RGB modelled images are very complex to classify. Noise reduction using median filter is used to maintain clarity. In feature extraction the images are transformed into a reduced representation. GLCM features such as auto correlation, contrast, cross correlation, cluster prominence, cluster shade, dissimilarity, energy, sum of square variance, area, homogeneity, perimeter, circularity, entropy and maximum probability are extracted. These extracted features are optimized using opposition PSO. The resultant image of feature extraction is used to separate the individual object in feature space by using modified SVM classifier. This classifier works on a sufficient number of cloud images training samples to create a function from a set of labelled training data for a successful classification. The architecture of proposed method is explained in Fig. 1

Preprocessing: Preprocessing is used to enhance certain features and suppress unwanted distortion in an image. A database $D = \{l_1, l_2, ...l_n\}$ can be divided into testing database and training database. The training database is given as $T_r = \{l_j\}$ where $l_j \subset D$ and the testing database is given as $T_e = \{l_i\}$ where $l_i \subset D$ Let $l_x = \{x_1, x_i, x_{i+2} ... x_{i+n}\}$ be the image from the database. This image undergoes pre-processing in two stages; namely color map conversion and noise removal.

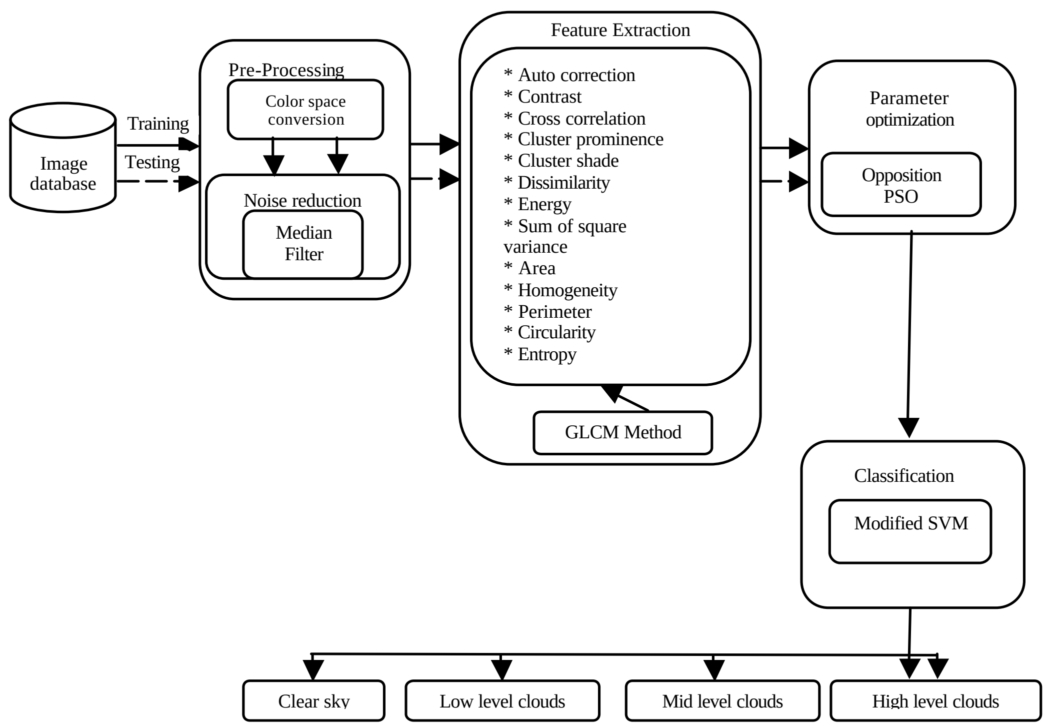

Fig. 1: Architecture of proposed method

Color map conversion: The input image is a color image which is complex to process. To reduce this complexity color map conversion is performed. RGB image is converted into gray scale image using the Matlab function rgb2gray (). Gray scale image is an image in which the value of each pixel is a single sample that carries only intensity information.

Noise removal by median filter: The satellite images have certain distortions in the form of noises due to atmospheric gases and other forms. These noises have to be removed by using median filter. The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighbouring entries. Where, M_l = Med (l_x) = median ($\{x_1, x_i, x_{i+2}\ldots_{xi+n}\}$) where, $x_1, x_i, x_{i+2}\ldots_{xi+n}$ represents the pixel of an image.

Feature extraction using glcm method: GLCM method is used to extract second order statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of gray level in an image. The co-occurrence matrix is given by the equation:

$$Gl = \sum_{p-1}^{m}\sum_{q}^{n}\begin{cases}1\ , & M_I(p,q) = I\text{and}\,M_I(p+\Delta v, q+\Delta o) = J\\ 0\ , & \text{Otherwise}\end{cases}$$

Where:
P, q = Spatial positions
L, J = Intensity values
V, o = Offset values

A GLCM is a histogram of co-occurring gray-scale values at a given offset over an image. Using this GLCM matrix features of an image are calculated as follows; Auto Correlation:

$$f_1 = AC = \sum_{pq}(pq)\,Gl(p,q)$$

Contrast:

$$f_2 = C = \sum_{pq}(p-q)^2\,Gl(p,q)$$

Cross correlation:

$$f_3 = CR = \sum p \sum q\,(pq)\,Gl(p,q) - \mu_p\mu_q / s_p s_q$$

Where:

$$\mu_p = \sum_{p,q=0}^{N-1} p \times Gl(p,q)$$

$$s_p = \sqrt{\sum_p\sum_q (p-\mu_p)^2 Gl(p,q)}$$

$$s_q = \sqrt{\sum_p\sum_q (q-\mu_q)^2 Gl(p,q)}$$

Cluster prominence:

$$f_4 = CP = \sum_{p,q}\left(p+q-M_r\,M_c\right)^4 Gl(p,q)$$

Cluster shade:

$$f_5 = CS = \sum_{p,q}\left(p+q-M_r\,M_c\right)^3 Gl\,(p,q)$$

Dissimilarity:

$$f_6 = DS = \sum_{p,q}(p+q(\,Gl\,(p,q)$$

Energy:

$$f_7 = E = \sum_{p,q}\left(Gl\,(p,q)^2\right)$$

Variance (sum of squares):

$$f_8 = SS = \sum_{p,q}(p-\mu)^2\,Gl(p,q)$$

Area:

$$f_9 = A = \sum_{pq}[\,Gl(p,q)]^2$$

Homogeneity:

$$f_{10} = HO = \sum_{p,q} 1Gl\,(p,q)/1-(p,q)^2$$

Perimeter:

$$f_{11} = P = 4A$$

Circularity:

$$f_{12} = C = \frac{P^2}{4pA}$$

Entropy:

$$f_{13} = Ey = \sum_{p,q} Gl\,(p,q)\log Gl\,(p,q)$$

Max probability:

$$f_{14} = MP = MAX\,Gl(p,q)$$

Opposition based PSO: Let, $P_1, P_2,\ldots P_n$ be the particle. Each particle P_i has position f_i and velocity v_{ij}. Where: $f_i = f_1\, f_2, f_3, \ldots f_{14}$

The initial solution for OPSO can be given as:

$$op_i = a_j^p + b_j^p - x_{ij}$$

Calculate the fitness for the solution set using:

$$fit_i = \{\min(op_{ij})^2\}$$

Table 1: Cloud types

Generation	Day and night downlinks
Resolution	Can be set via setup. Optimum is 1km as algorithm is based on IR channels.
Channels used	VIS (CH1), CH4, CH5, CH3B
Physical values	0 (no cloud i.e., Clear sky) 1 (low-level), 2 (mid-level), 3 (high-level)

Find p_{best} such that it's fitness in minimum:

$$p_{best} = \{op_{ij}\}$$

Such that fitness of op_{ij} is minimum:

- Choose the particle with the best fitness value of all the particles as the g_{best}
- Calculate particle velocity according to the below equation
- Update particle position according to the below equation

This OPSO is used for parameter optimization of SVM algorithm; The fitness function is given by:

$$Opt = \min(F)$$

Where:

$$F = \frac{1}{N_s}(OS - OT)^2$$

Where:

N_s = No. of sampling variance
OS = Obtained output of SVM
OT = Target output

$$I = \{If\}; \quad If \in Nf$$

Where, If is the best solution from f_i

Classification using SVM: SVMs are a useful technique for image classification. SVMs are related to the simplified linear classifier's family. SVMs are also viewed as a unique case of Tikhonov regularization. A strange property is that they minimize the practical classification error and boost the geometric margin at the same time. Therefore, they are named as maximum margin classifiers. The equation given below is the SVMs' objective function which may recognize the support vector for the classification:

$$objective_{func}(of) = \sum wi\ k(SV_i, PR) + bi$$

Where:

ω_i = Weight
K = Kernel function
Sv_i = Support vectors
PR = Vector for classification
b_i = Bias

The equation is the objective function for an optimization method which finds the support vectors, weights and bias for classifying the vector PR. In case of a linear kernel, K is a dot product. PR Vector is used for training process to classify the cloud images.

Dataset description: AVHRR is the primary meteorological imaging instrument flying on the NOAA satellites: a six-channel radiometer that samples energy in visible and IR parts of the electromagnetic spectrum. Cloud parameters based on data of the AVHRR/3 sensor aboard the National Oceanic and Atmospheric Administration-19 (NOAA-19) platform are derived at WDC-RSAT operationally up to six times per day. The Cloud Classification was designed to operate on imagery from the AVHRR data. AVHRR is the primary meteorological imaging instrument incorporated on the orbiting. NOAA satellites: a six-channel radiometer that samples energy in visible and IR parts of the electromagnetic spectrum. This product categorizes clouds into low-level, mid-level, high-level, and convective (i.e., clear sky). Table 1 shows the cloud type based on the physical values and the channels are also mentioned.

Extended Clouds from AVHRR (CLAVR-x) is a processing system used for cloud classification based on the cloud properties cloud emissivity, cloud optical depth, cloud fraction cloud-top height, cloud-top temperature, cloud-top pressure and cloud amount at the pixel level daily. CLAVR- x's main mission was cloud detection and CLAVR-x did not generate a full suite of cloud products and its operation was limited to the afternoon orbiting AVHRR sensors prior to the launch NOAA-L (NOAA-16). Fig. 2 and Fig. 3 shows the AVHRR NOAA-19 satellite image retrieved by CLAVR-x based on cloud top height at two different timing on the same day.

In this study, the sample databases of clouds based on AVHRR/3 channel data of fifty samples were used. Theory analysis and experiment show that 3 channel data can be used to distinguish clouds, along with the band combination with each other. AVHRR image samples contain spectrum features, gray features, channel difference features and the gray scale statistical features. Based on theory analyses and experiments, 14 features were extracted from the satellite cloud image for identifying cloud type.

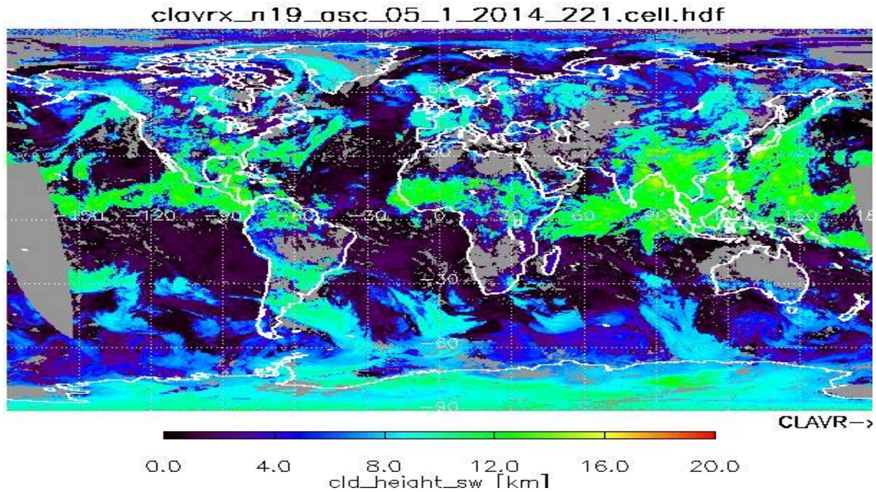

Fig. 2: Input image

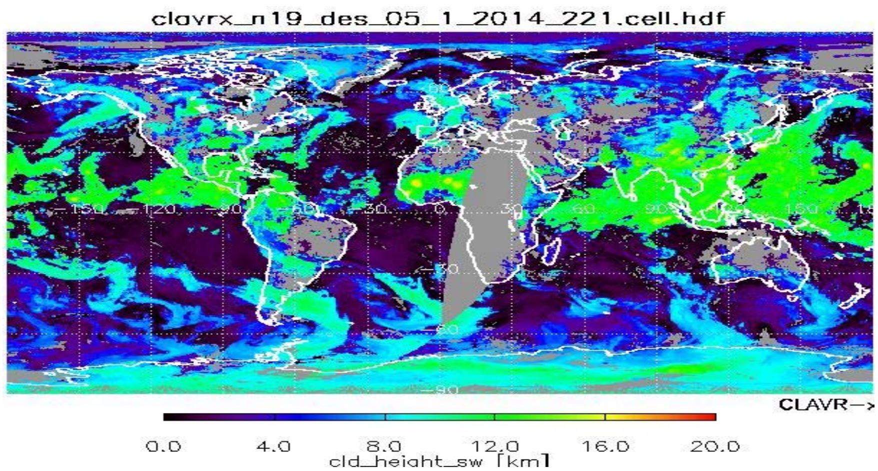

Fig. 2: Input image

RESULTS

A classifier to classify the satellite cloud images using OPSO and SVM is implemented in MATLAB. The existing system which uses PSO for parameter optimization is compared over OPSO. The input cloud images are classified under any of the four categories: clear sky, low level clouds, mid level clouds and high level clouds. The input image is the satellite cloud image which is shown in Fig. 2 and Fig. 3. The four types of classified images are shown in Fig. 4-7. The clear sky images are shown in Fig. 4. Lower level clouds are those clouds which appears in the lower layers of atmosphere as shown in Fig. 5. Middle level clouds appear in the middle layers of the atmosphere which is shown in Fig. 6. Clouds in the highest levels of the troposphere are higher level clouds as illustrated in Fig. 7.

The performance of the proposed work is evaluated and compared with existing work using 9 measures namely: Sensitivity, Specificity, Precision, Negative Predictive Value (NPV), False Positive Rate(FPR), False Discovery Rate (FDR), accuracy, F1score, Mathews Correlation Coefficient(MCC). Table 2 provides the values of 9 measures for 4 classes by PSO and OPSO. It shows that the sensitivity for all the classes using OPSO is higher than PSO. Specificity and precision are higher for class1 using OPSO. Both PSO and OPSO maintain unity value for specificity and precision for class 2-4. The NPV for all the classes using OPSO is higher than PSO. The FPR and FDR tends to be zero in all classes of OPSO. In PSO these values are zero for class2, class3 and class4. The accuracy values for all classes are comparatively higher for OPSO than PSO.

The F1 score and Mathews Correlation Coefficient (MCC) shows great hike for all classes using OPSO than

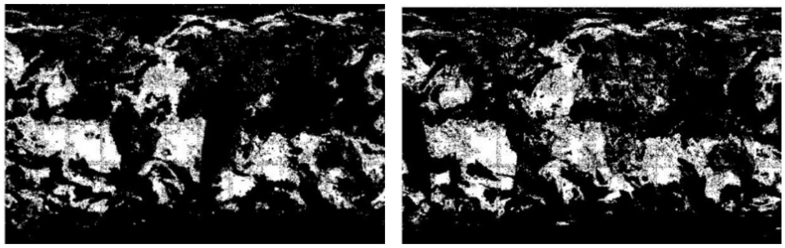

Fig. 4: Clear sky

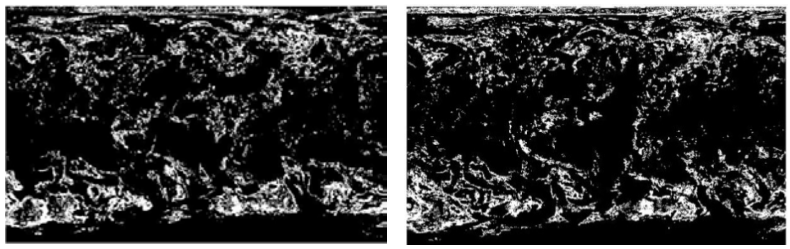

Fig. 5: Low level cloud

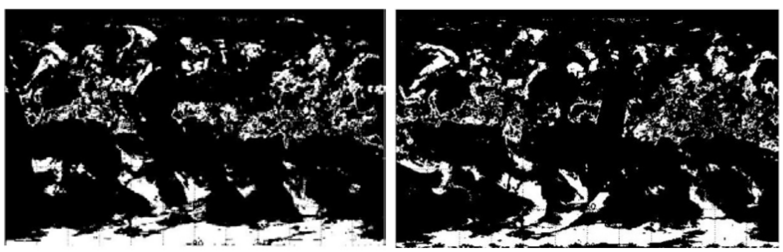

Fig. 6: Mid level clouds

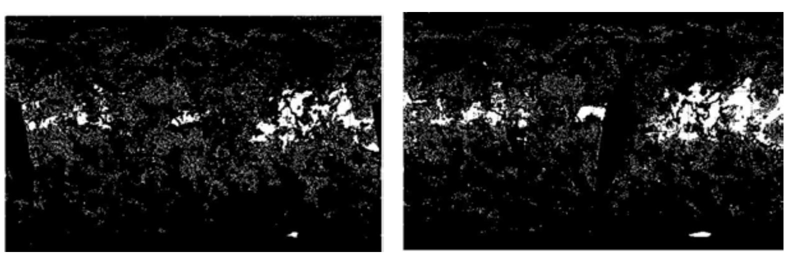

Fig. 7: High level clouds

Table 2. Comparison of performance measures for four classes by PSO and OPSO

	Class 1		Class 2		Class 3		Class 4	
	PSO	OPSO	PSO	OPSO	PSO	OPSO	PSO	OPSO
Sensitivity	0.3	0.433	0.2	0.4	0.222	0.407	0.3	0.4
Specificity	0.978	1	1	1	1	1	1	1
Precision	0.819	1	1	1	1	1	1	1
NPV	0.808	0.841	0.789	0.833	0.796	0.837	0.810	0.833
FPR	0.022	0	0	0	0	0	0	0
FDR	0.182	0	0	0	0	0	0	0
Accuracy	0.808	0.858	0.8	0.85	0.807	0.853	0.825	0.85
F1 score	0.439	0.605	0.333	0.572	0.364	0.579	0.462	0.571
MCC	0.417	0.604	0.397	0.577	0.421	0.584	0.493	0.577

PSO. Figure 8-12 show the performance of the proposed work. It can be further analyzed and interpreted by calculating the mean, median, standard deviation, best and worst values.

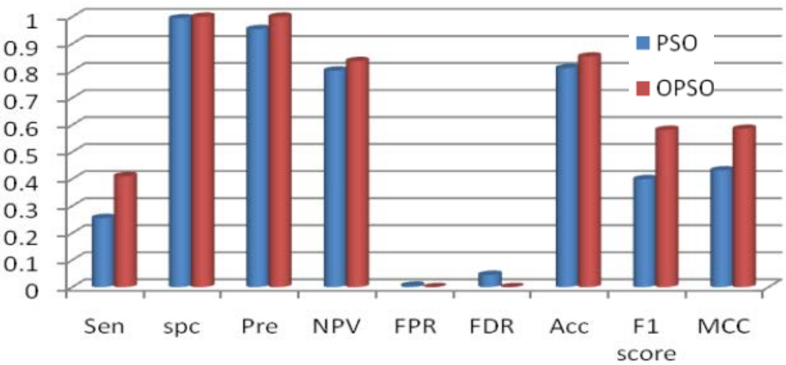

Fig. 8: Comparison of performance measures for mean by PSO and OPSO

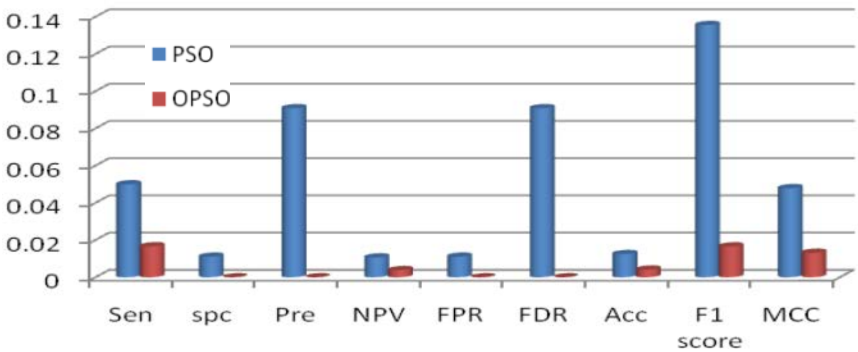

Fig. 9: Comparison of performance measures for median by PSO and OPSO

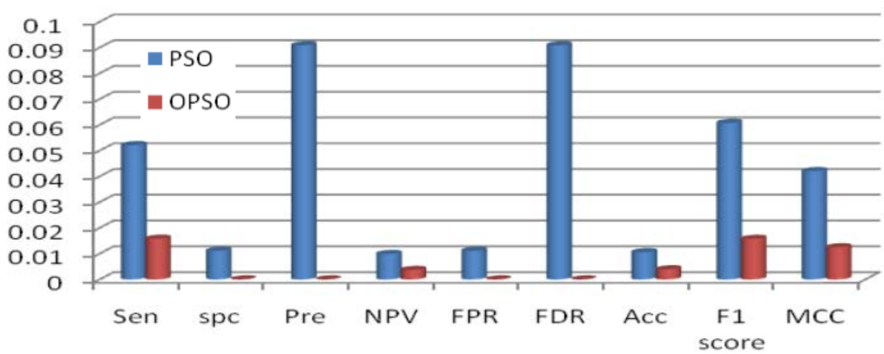

Fig. 10: Comparison of performance measures for standard deviation by PSO and OPSO

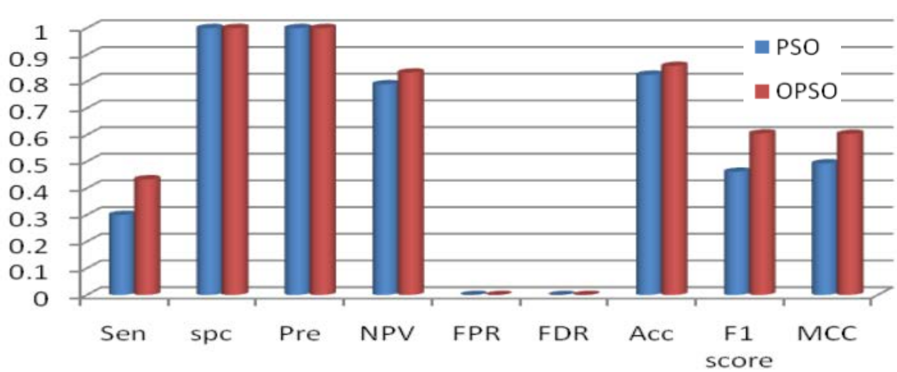

Fig. 11: Comparison of performance measures for best value by PSO and OPSO

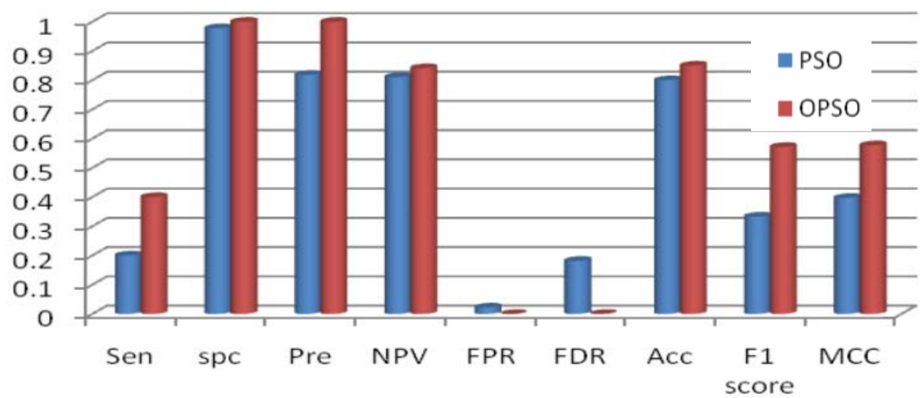

Fig. 12: Comparison of performance measures for worst value by PSO and OPSO

The mean value of proposed work is higher than existing work (Ari and Aksoy, 2010). The median value of OPSO is lower than PSO. In certain case, the value tends towards zero affirming that the proposed research is better than existing works. The standard deviation of proposed work is lower than existing work to show that OPSO has less deviation in all measures. The best value for PSO and OPSO almost matches in all the cases. But OPSO overtakes the value in sensitivity, NPV, accuracy, F1 score and MCC. The worst value of OPSO is higher for all measures except in FPR and FDR. By this analysis, it is clear that OPSO outperforms PSO in performance.

DISCUSSION

In this study, cloud image classification using modified SVM was proposed. The feature extraction algorithm extracts certain features based on which classification is carried out. This classifier works on a sufficient number of cloud-training samples to create a function from a set of labeled training data for a successful classification. Our proposed method is implemented with MATLAB and the results are analyzed. The extracted features are optimized for proper classification.

Accurate cloud classification is useful for many surface and atmospheric applications. The kernel type and parameter affects the decision boundaries and this would reduce the performance of SVM. The OPSO overcomes the problem of SVM by its generalization ability. The combination of OPSO with SVM classifier method improves the performance and accuracy rate. The outcome of this research will be the accomplishment of incredible ability with higher efficiency in classification algorithm and developing a better classified output with better detection rate. Thus by using modified SVM and GLCM features, we can create a function from a set of labeled training data for a successful classification. Under various circumstances, practical scenarios, the consistent performance is expected from the estimation methodology.

CONCLUSION

The result of the cloud classification is implemented on the basis of cloud top height of the Clavr-x image. The research can be further improved by calculating the listed parameters, such as cloud emissivity, cloud optical depth, cloud fraction, cloud-top temperature, cloud-top pressure and cloud amount for weather analysis. Better accuracy is achieved in this method. Cloud classification means accurate categorization of clouds according to high, mid and low levels. These high, mid and low-level clouds are further classified into particular sub classes.

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