A SURVIVAL STUDY ON CLASSIFICATION AND TARGET DETECTION FOR DATA HIDING IN HYPER SPECTRAL IMAGE

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Abstract: Hyper Spectral Image (HSI) is a spatially sampled image collected from hundreds of neighboring narrow spectral bands by hyper spectral sensors. Hyper spectral classification classifies the pixels into different categories. HSI classification is used to manage the higher dimensionality training samples. Hyper spectral target detection is used to detect the targets by developing the spectral signatures of materials. Pictographic scene hiding is used for hiding all other area except the targeted area to improve the privacy level. But, the classification accuracy and target detection rate is not improved in existing techniques. The classification and target detection performance is to be improved in hyper spectral image by addressing the existing issues. Our key objective is to improve the classification accuracy and reduce the target detection time by using new classification techniques in hyper spectral image.

Keywords: **Hyper Spectral Image, target detection, pictographic scene hiding, classification, dimensionality, spectral bands**

I. INTRODUCTION

Hyper Spectral Image (HSI) comprises the high dimensional large quantity of data because of hundreds of continuous narrow spectral bands cross the visible to infrared spectrum. Pixels in HSI are denoted by the vectors whose entries symbolize the spectral bands. The bands are used to identify the exact and robust description, detection and classification of land cover. The hyper spectral image data is collected by hyper spectral instruments like NASA Airborne Visible Infra-Red Imaging Spectrometer and Reflective Optics System Imaging Spectrometer. In recent times, hyper spectral imaging has attracted many researchers attention. Target detection in hyper spectral images is essential in many applications like search and rescue operations, defense systems, mineral exploration and border security. Many existing target detection algorithms are proposed over the years, but it fails to detect sub-pixel targets. Some of recent related works regarding the hyper spectral classification, target detection and scene hiding are reviewed in the upcoming section.

This paper is organized as follows: Section II discusses the review on different classification and target tracking techniques for effective data hiding in hyper spectral image, Section III portrays the study and analysis of the existing classification and target tracking techniques in hyper spectral image, Section IV describes the possible comparison between them. In Section V, the discussion and limitations of the existing techniques are studied and Section VI concludes the paper. The key area of research is to improve the performance of classification accuracy and target detection time while performing the classification and target detection in hyper spectral image.

II. LITERATURE REVIEW

A new bi-layer Elastic Net (ELN2) regression model was designed in [1] for Hyper Spectral Image (HSI) classification with spectral-spatial information. The designed model addressed features of HSI namely, high dimensionality of hyper spectral pixels, less labeled samples and spatial inconsistency of spectral signatures. But, the classification accuracy is not increased by Multinomial logistic regression model. A FPGA implementation is performed for Automatic Target-Generation Process by Orthogonal Projection Operator (ATGP-OSP) algorithm in [2]. The designed algorithm comprises direct memory access module and introduced the pre fetching technique to hide the latency of input/output communications.

Mixture Gradient Structured Detector (MGSD) and Mixture Gradient Unstructured Detector (MGUD) techniques are introduced in [3]. The detectors are depending on new model with gradient distribution of the noise. However, the classification accuracy is not improved using mixture gradient structured detector techniques. A Firefly Algorithm (FA) inspired band selection and optimized Extreme Learning Machine (ELM) is introduced in [4] for hyper spectral image classification. FA has chosen subset of original bands for complexity reduction of ELM network. Though the complexity and dimensionality is reduced, the true positive rate is not enhanced using firefly algorithm.

A new constrained generalized likelihood ratio test is introduced in [5] for improving the performance results and the compound test employs large number of information. But, the target detection rate is not improved using ATGP-OSP algorithm. A hyper spectral image target detection algorithm in [6] is robust for target spectral variability. The designed algorithm used inequality limitation to guarantee the outputs of target spectra. But, the feature extraction is not carried out in efficient manner using hyper spectral image target detection algorithm.

A new spectral–spatial hyper spectral image classification method with K-Nearest Neighbor (KNN) is introduced in [7]. Support vector machine attained the initial classification probability maps that help in reflecting the probability where every hyper spectral pixel belongs to different classes. But, KNN filtering algorithm failed to detect the object for hiding.

III. CLASSIFICATION AND TARGET DETECTION TECHNIQUES IN HYPER SPECTRAL IMAGE

A hyper spectral image has fine spectral resolution of many narrow frequency bands. The bands provide the wealth of spectral information of scene. The hyper spectral images are spectrally over determined in single image cell where the spectra of bands are attained. With the development of optical sensing technology, hyper Spectral Image (HSI) collects the spectral and spatial information of monitored scene. The large amount of spatial and spectral information in HSI assures the higher identifiability for classification. In HIS, many bands are correlated and provide the redundant information for classification related issues. In order to improve the classification accuracy and target detection rate, this work introduces new techniques for addressing the existing issues after reviewing the literatures.

3.1. Bi-layer Elastic Net Regression Model for Supervised Spectral-Spatial Hyper spectral Image Classification

A new framework leading to exact spectral-spatial classification called bi-layer Elastic Net (ELN^2) penalty approach is designed. The designed approach uses the spectral information using the ELN_RegMLR that failed to remove the correlated feature. In first layer, spectral-only ELN-based MLR (ELN_RegMLR) classifier is employed to calculate the quality of selected bands using cyclical path-wise coordinate descent algorithm. ELN_RegMLR is a pixel-wise classification method without consideration of correlation between the spatially adjacent pixels. In second layer, spatial MRF-based gradient priors are integrated into ELN penalty over hidden marginal probability of posterior distribution to improve the spatial smoothness and classification accuracy. The designed approach is ELN regularized ELN_RegMLR spectral-spatial classifier represented as ELN^2_RegMLR as described in figure 3.1. The designed approach comprises two essential steps. The first one is learning where posterior probability distributions are modeled by MLR with sparsity promoting ELN regularization term. The second one is classification that infers an image of class labels as implicit marginal probability from posterior distribution constructed on the learned classifier and an MRF-based gradient ELN prior on hidden field.

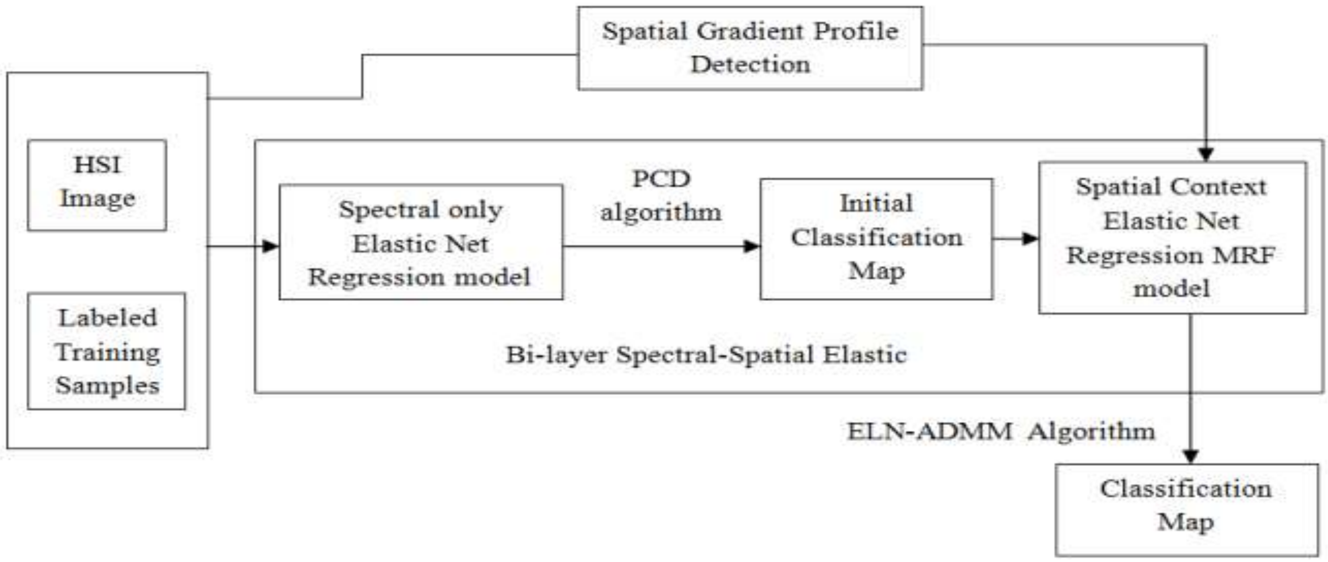

Fig 3.1 Framework of the proposed ELN^2 _Reg MLR method

An ELN^2 is designed for initial regularized probability classifier to collect the spatial and contextual information. Spatial prior and contextual information is collected as the ELN regularizer that is determined by gradient-profile-based MRF on implicit marginal probability than class labels. ELN regularizer supports the pixels in same neighborhood within the same class. A new two-stage ELN^2_RegMLR algorithm is introduced to address the ELN^2 regression model using path-wise coordinate descent algorithm and alternating direction technique of multipliers.

3.2. FPGA Implementation of Algorithm for Automatically Detecting Targets in Remotely Sensed Hyper spectral Images

Hyper spectral imaging is called as an imaging spectroscopy. The hardware architecture is used to execute the Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm with I/O communications. For data input, DDR3 SDRAM is employes and Direct Memory Access (DMA) is controlled by MicroBlaze with help of prefetching approach. The reconfigurable unit implemented the version of ATGP-OSP algorithm. RS232 controller is employed to send the estimated number of end members through an RS232 port. In the development stage, RS232 port is used for debugging. A general architecture is used to make the hardware/software code sign with fixed part and a reconfigurable part. MicroBlaze is said to be a lesser performance and lesser consumption soft-core embedded processor. MicroBlaze uses the reconfiguration process and adaptation of system for many I/O.

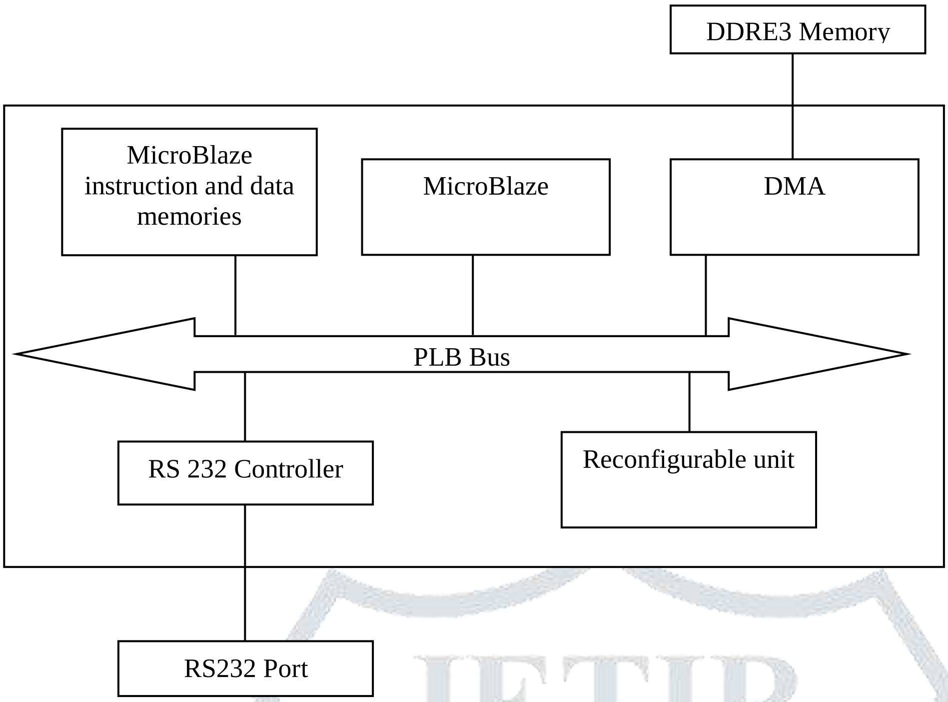

Fig 3.2 Hardware architecture used to implement the complete system

Figure 3.2 describes the hardware architecture to implement the entire system. The modules are employed to perform ATGPOSP algorithm with I/O communications to the PLB bus. Every module are described and presented the step-by-step description that performs the target detection from hyper spectral image. The first decision taken for ATGP-OSP algorithm is to compute the inverse of UTU matrix multiplication. A method is designed with the hardware features like parallelization. Gauss–Jordan elimination method is employed in ATGP-OSP algorithm as it has desirable features in terms of ulterior hardware implementation.

3.3 Target Detection Method for Hyper spectral Image depending on Mixture Noise Mode

Hyper spectral target detection is the method of finding the ground material in hyper spectral image when the spectral signature of material is identified earlier. Hyper spectral target detection is employed for military and civilian purposes. Hyper spectral target detection examines the water quality, forest fire danger, land-utilized condition and enemy military dispositions. In hyper spectral imaging system, the spectrum is partitioned into many narrow and contiguous bands with different wavelengths. With high wavelength resolution, a hyper spectral image are considered as collection of images. Each image covers the narrow wavelength range. The hyper spectral image is divided into the three-dimensional data cube with two spatial dimensions and spectral dimension.

Sub pixel hyper spectral detection is a type of method to identify the targets in image when spectrum of the targets is known. In sub pixel detection, the key factors that vary the target observations are estimation of noise statistics. A stronger model of noise is introduced to consider the distribution of noise and their gradient. Depending on the new model, two new hybrid detectors, namely Mixture Gradient

Structured Detector (MGSD) and Mixture Gradient Unstructured Detector (MGUD) are introduced with gradient distribution of the noise.

IV. COMPARISON OF CLASSIFICATION AND TARGET DETECTION TECHNIQUES IN HYPER SPECTRAL IMAGE & SUGGESTIONS

In order to compare the classification and target detection techniques in hyper spectral image, number of features is taken to perform the experiment. Various parameters are used for improving the performance of classification and target detection techniques for effective data hiding in hyper spectral image.

4.1 Classification Accuracy

Classification accuracy is defined as the ratio of number of correctly classified features to the total number of features. It is measured in terms of percentage (%). The classification accuracy is mathematically formulated as,

$$Classification\ Accuracy = \frac{Number\ of\ correctly\ identfied\ features}{Total\ number\ of\ features}$$

When the classification accuracy is higher, the method is said to be more efficient.

Table 4.1 explains the classification accuracy with respect to number of features ranging from 10 to 100. Classification accuracy comparison takes place on existing ELN^2 regression model, ATGP-OSP algorithm and MGSD & MGUD. From the table value, it is clear that the classification accuracy using ELN^2 regression model is higher when compared to Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm and Mixture Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD).

Table 4.1 Tabulation for Classification Accuracy

Number of Features (Number)	Classification Accuracy (%)		
	ELN^2 Regression model	ATGP-OSP Algorithm	MGSD &MGUD
10	71	64	55
20	73	66	57
30	76	69	59
40	79	72	62
50	81	75	65
60	83	78	68
70	85	80	71
80	87	83	73

90	89	86	76
100	92	89	80

The graphical representation of classification accuracy is shown in figure 4.1. From figure 4.1, classification accuracy based on the different number of features is described. From the figure 4.1, bi-layer elastic net (ELN^2) regression model has higher classification accuracy than Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm and Mixture Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD).

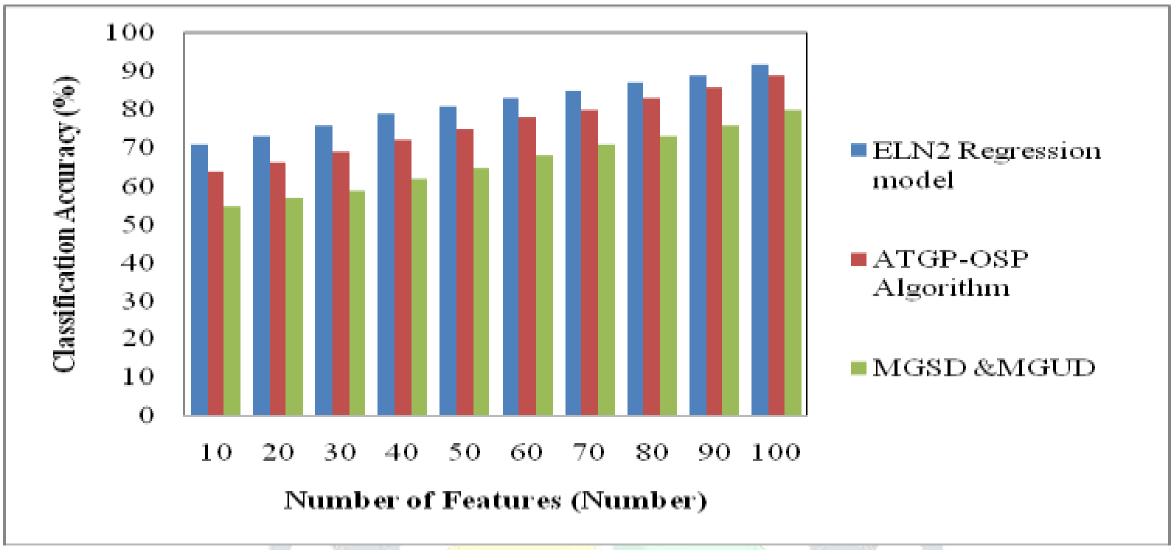

Figure 4.1 Measure of Classification Accuracy

Research in bilayer elastic net (ELN^2) regression model has 7% higher classification accuracy than Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm and has 23% higher classification accuracy than Mixture Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD).

4.2. Target Detection Time (TDT)

Target detection time is defined as the amount of time taken to detect the target. It is the difference of ending time and starting time of target detection. It is measured in terms of milliseconds (ms).The mathematical formula of target detection time is given by,

$$TDT = Ending\ time - Starting\ time\ of\ target\ detection$$

When the target detection time is lesser, the method is said to be more efficient.

Table 4.2 Tabulation for Target Detection Time

Number of Features	**Target Detection Time (ms)**		
	ELN^2 Regression	**ATGP-OSP**	**MGSD & MGUD**

(Number)	model	Algorithm	
10	59	25	37
20	63	28	40
30	65	29	43
40	68	32	45
50	69	35	48
60	72	39	52
70	75	43	56
80	78	46	59
90	81	49	63
100	84	52	65

Table 4.2 explains the target detection time with respect to number of features ranging from 10 to 100. Target Detection time comparison takes place on existing ELN^2 regression model, ATGP-OSP algorithm and MGSD & MGUD. From the table value, it is clear that the target detection time using ATGP-OSP algorithm is lesser when compared to bi-layer elastic net (ELN^2) regression model and MGSD & MGUD. The graphical representation of target detection time is illustrated in figure 4.2

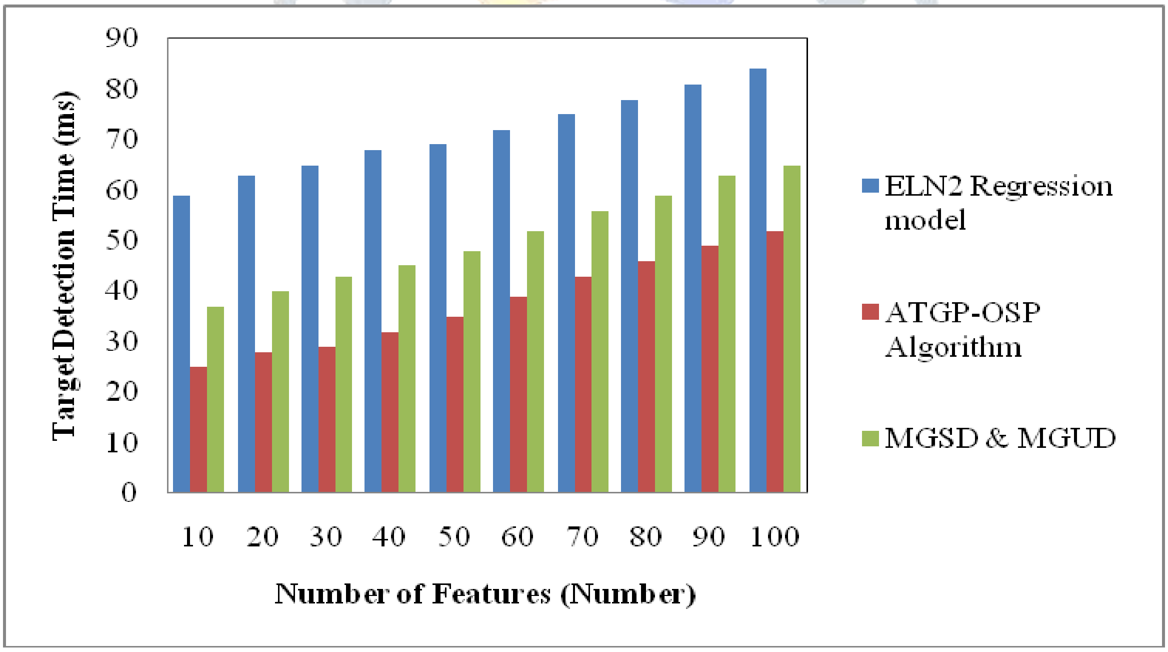

Figure 4.2 Measure of Target Detection Time

From figure 4.2, target detection time based on the different number of features is explained. From the figure 4.2, Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm consumes lesser target detection time than bi-layer elastic net (ELN^2) regression model and Mixture

Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD). Research in Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm consumes 48% lesser target detection time than bi-layer elastic net (ELN^2) regression model and has 26% lesser target detection time than Mixture Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD**).**

4.3. Privacy Level

Privacy level is calculated based on the secured transmission of the data after the pictographic scene hiding inside the hyper spectral image. The privacy level is defined as the ratio of number of features transmitted in private manner to the total number of features. It is measured in terms of percentage (%). The privacy level is mathematically formulated as,

$$Privacy\ level = \frac{Number\ of\ features\ transmitted\ in\ private\ manner}{total\ number\ of\ features}$$

When the privacy level is higher, the method is said to be more efficient.

Table 4.3 explains the privacy level with respect to number of features ranging from 10 to 100. Privacy level comparison takes place on existing bi layer elastic net (ELN^2) regression model, Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm and Mixture Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD)

Table 4.3 Tabulation for Privacy Level

Number of Features (Number)	**Privacy Level (%)**		
	ELN^2 Regression model	**ATGP-OSP Algorithm**	**MGSD & MGUD**
10	59	66	72
20	62	68	74
30	64	71	77
40	67	73	80
50	69	76	82
60	72	79	85
70	75	81	88
80	78	84	91
90	81	87	93
100	84	89	96

From the table value, it is clear that the privacy level using Mixture Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD) is higher when compared to bi layer elastic net (ELN^2) regression model and Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm. The graphical representation privacy level is illustrated in figure 4.3.

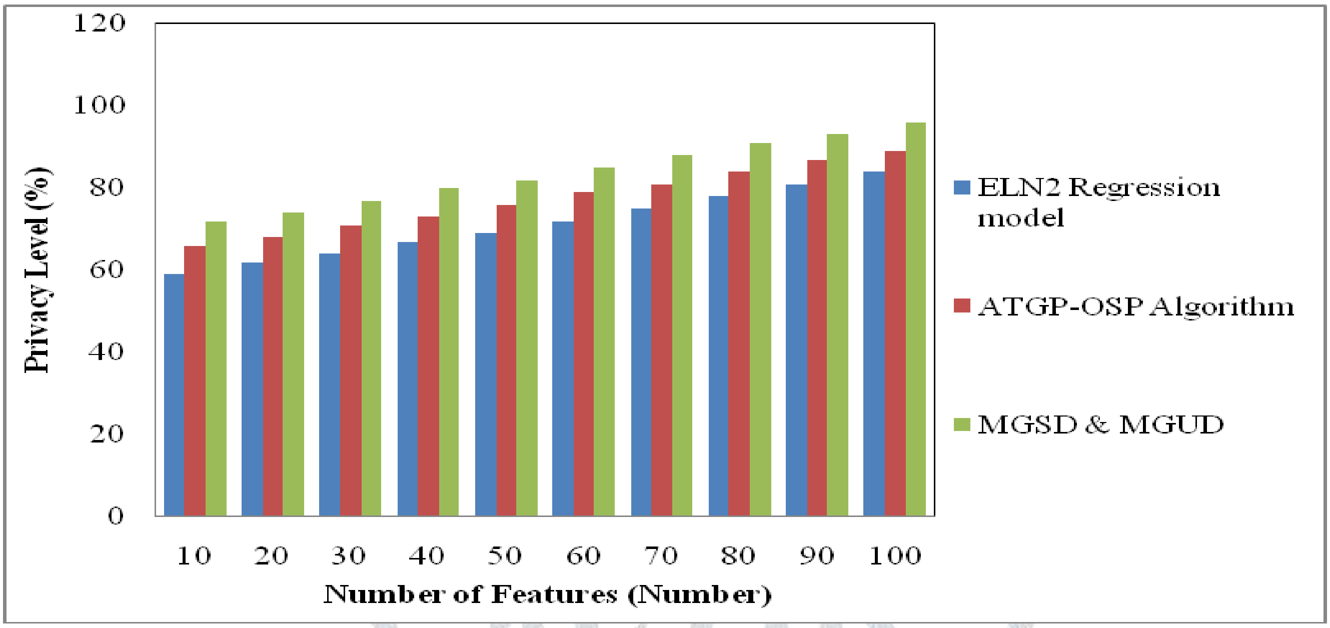

Figure 4.3 Measure of Privacy Level

As shown in figure 4.3, privacy level based on the different number of features is explained. From the figure 4.3, Mixture Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD) has higher privacy level than bi-layer elastic net (ELN^2) regression model and Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm. Research in Mixture Gradient Structured Detector (MGSD) & Mixture Gradient Unstructured Detector (MGUD) has 14% higher privacy level than bi-layer elastic net (ELN^2) regression model and has 8% higher privacy level than Automatic Target-Generation Process by Orthogonal Subspace Projector (ATGP-OSP) algorithm.

V. DISCUSSION ON LIMITATION OF CLASSIFICATION AND TARGET DETECTION TECHNIQUES IN HYPERSPECTRAL IMAGE

An FPGA implementation is carried out by automatic target-generation process by orthogonal projection operator (ATGP-OSP) algorithm. ATGP-OSP algorithm comprised the direct memory access module and executed pre fetching technique to hide the latency of input/output communications. FPGA-based hardware version of ATGP-OSP using pseudo inverse operation identifies many targets in hyper spectral image. FPGA implementation increased the target detection accuracy from hyper spectral image. But, target detection rate is not improved using ATGP-OSP algorithm. FPGA implementation failes to attain better utilization of hardware resources.

ELN^2 regression model is designed for HSI classification with spectral-spatial information. The regression model addresses the special problematic features of HSI namely, high dimensionality of hyper spectral pixels, lesser labeled samples and spatial inconsistency of spectral signatures. But, classification accuracy is not increased using Multinomial logistic regression model. Noise distribution in hyper spectral images is introduced and it is processed with better noise characterization to improve the detection performances. MGSD and MGUD depend on new model with gradient distribution of the noise. The hyper spectral image target detection results are improved. However, the classification accuracy is not performed using MGSD and MGUD techniques.

5.1. Related Works

A feature learning algorithm is efficient for hyper spectral image classification. The learning-based feature extraction algorithm [5] classifies the information better than pre-defined feature extraction algorithm. However, the feature extraction is not carried out in effective way by feature extraction algorithm. A new technique [9] classified the hyper spectral images on ridgelet transformed domain. Support Vector Machines (SVM) with radial basis function kernel is used for categorizing the classes that are nonlinearly distributed in hyper spectral scene. But, the classification time was not minimized using support vector machine.

Hyper spectral imaging with Mixtec codex [10] reveales many hidden pictographic scenes under layer of gypsum and chalk gesso. Due to the organic nature of paints, technique failes to reveal in a non-invasive manner. Pixel-based and object-oriented classifications are studied [11] for land-cover mapping. However, the scene hiding is not carried out in efficient manner.

5.2. Future Direction

The future direction of classification and target detection techniques for efficient data hiding in hyper spectral images are carried out with help of new classification and pictographic scene hiding techniques for improving the privacy level and classification as well as target detection performance.

VI. CONCLUSION

A comparison of different existing classification and target detection techniques for data hiding is studied in hyper spectral image. From the study, it is observed that the existing techniques increases the target detection time and reduces the classification accuracy. The survival review shows that the existing classification and pictographic scene hiding techniques are not used for increasing the performance in hyper spectral image. In addition, the privacy level remains unaddressed. The wide range of experiments on existing techniques computes the relative performance of the many classification and target detection techniques with its limitations. Finally, from the result, the research work is carried out using new classification and pictographic scene hiding techniques for enhancing privacy level in hyper spectral image.

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