Polarisation Transform Analysis for Detection of Shallow Buried Non-Metallic Landmines in Microwave X-Band Region

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ABSTRACT

Alternative approaches and models continue to be investigated and evolved to correctly locate and identify a buried mine with minimum risk. Though microwave remote sensing based detection of shallow buried landmines provides such a risk free alternative, it is a highly complex and computationally intensive task involving several parameters. The present paper deals with the use of data obtained in multiple polarizations and their transforms approximating rough surface conditions in sand for landmine detection. Data in both HH and VV polarizations in microwave X-band frequency (10 GHz, 3cm) was generated using a live landmine (with explosives less fuze) for the present study under field conditions. Various transforms such as image differencing, image ratioing and polarization discriminant ratio (PDR) were studied for its effect on landmine detection. However, it was found that most of the clutter and noise gets suppressed on using a transform obtained by subtracting the difference of data in two polarizations from its sum. The surface roughness conditions have been approximated as available in western parts of India and which are suitable for application of microwave radar remote sensing for detection of minefields. With the advent of satellites providing data in various polarizations, it has now become relevant to investigate methods which can be used for landmine detection using polarization techniques. The proposed analysis is expected to be useful in future in detection of landmines using multi-polarization satellite data in microwave X-band in deserts such as those existing in the western borders of India.

Keywords : Microwave X band, landmines, detection, thresholding, polarization, image transforms, image ratioing, image differencing , polarization discriminant ratio.

1. INTRODUCTION

Landmines are often spread over large minefields which are either unmarked or poorly marked and therefore usefulness of ground/vehicle based methods in these areas is limited [1]. A review by Maathuis *et al* of satellite and airborne sensors for remote sensing based detection of minefields and landmines indicates suitability of satellite based methods for landmine detection over land based methods particularly with the advent of satellites that can provide data in different polarizations [2].

Landmine detection methods exploit the dielectric contrast between various intermediate mediums such as air, soil and mine. However, due to lack of metallic content and shallow depths, the dielectric contrast between the layered soil medium and the mine overlaps with the dielectric contrast existing at the air-ground interface and results in diminished backscatter response. This makes detection of landmines extremely difficult. In microwave remote sensing, the backscatter intensity is dependent basically on two parameters *i.e*. system parameters and target parameters. System parameters include frequency, polarisation and incidence angle while the target parameters include surface roughness, scattering, dielectric constants, orientation and shape of the target [3, 4, 5]. When incident microwave radiation strikes the interface between two media, the incident energy is effectively absorbed or scattered. Two types of scattering can occur which are dependent on surface roughness and surface dielectric properties. These are known as surface scattering and volume scattering. Electromagnetic scattering caused due to surface roughness is a field of active research and extremely relevant in landmine detection. Ulaby *et al* [3] have carried out detailed investigations of various aspects of electromagnetic scattering and provided models for scattering under different surface roughness conditions. A theoretical model incorporating layered media analysis using microwave remote sensing in P-band (441 MHz, 68 cm) for estimation of backscattered electric field from a buried reflector has also been reported and the theoretical results well supported with experimental results conducted in Negev Desert [5]. Electromagnetic scattering however is an exceedingly complex phenomenon and despite extensive research however, no single model can account for all the parameters and the complexity of their interrelationship [3, 6, 7].

A number of studies have demonstrated the use of data in multiple polarizations to detect manmade objects in natural clutter background [8, 9, 10] including detectability of ships in the ocean [11, 12, 13]. The data obtained in two different polarizations provides an additional discriminant, as a result, a scene imaged in orthogonal polarizations (i.e., HH- and VV polarization) show variations in the intensity of detected backscatter that depends on the relative smoothness of the objects in the scene. Further, it has been found that smooth surfaces tend to have a higher value for the ratio of difference of data in two polarizations (*i.e*., HH- and VV- polarization) to its sum [14]. This ratio is known as polarization discrimination ratio (PDR) and has also been used for retrieval of soil moisture in microwave X-band [15], where this ratio minimizes the effect of roughness. Data in multiple polarizations also provide sufficient information to characterize scattering mechanisms from various sources [12]. The data in different in polarization however does not appear to have been explored for improving detectability of buried targets (landmines) by minimization of surface effects.

Another issue in this regard pertains to assessment of the surface roughness that has been minimized. Since an uncertainty in an image is referred as an error, fuzziness or ambiguity present in the image, therefore, surface roughness effects may also be assessed using uncertainty measures such as Shannon entropy or various manipulations of entropy measures [16].

The aim of this paper is to investigate the usefulness of algebraic transforms including a new proposed transform of data in two polarizations (HH and VV) for improving landmine detection through minimization of surface roughness effects and to assess surface roughness minimization achieved using Shannon entropy as a measure of uncertainty.

2. EXPERIMENTAL SETUP

2.1 Scatterometer system

An indigenously developed monostatic scatterometer has been used for the experiments in this study. A schematic layout of the scatterometer system is given in Figure-1 (a). The system consists of one pyramidal horn antenna connected through a circulator to microwave transmitter on one side and power meter on the other side. An isolator producing an isolation of 35 dB has been used to generate experimental data in both HH and VV polarizations. A wooden box measuring 120 cm by 120 cm in size has been constructed and filled with dry sand for mines to be buried. The height of the base of X-band antennae from the surface is 100 cm. Measurements have been taken in far field region. The system has provision to move the antennae in both X and Y directions. The horizontal bars on the two sides (called X-Y direction) have been marked serially in steps of 5 cm from 1 to 24 to make a grid. The circulator and the antenna are moved laterally (Y-direction) from 1 to 24 at each of the horizontal (X-direction) positions from 1 to 24 for collection of data, thus making a total of 24 x 24 positions. This gives a pixel size of 5 cm x 5 cm. It is considered that a minimum resolution of 5 cm x 5 cm would be necessary for detection of a buried landmine.

(a) Experimental Setup

(b) Live Antitank Mine

Length=25 cm,
Width= 25 cm,
Height=7 cm,
Weight = 7 kgs

(c) Dimensions (cm)

(d) Indigenous Wooden Profiler

(e) Rough surface - 2 cm

(f) Rough surface – 3cm

Fig 1- Experimental setup for surface roughness experiments.

The experiments have been conducted in open field under natural illumination. A live antitank mine without fuses but containing high explosives (TNT) buried at the centre of the experimental setup has been considered in these experiments. The experiments have been conducted under rough surface conditions. An indigenous wooden profiler as shown in Figure-1 (d) has been developed for maintaining periodic variations of different surface roughness conditions. It consists of adjustable props at the base whose heights can be varied. Surface roughness is described using rms (root mean square) height which is the average variations in surface roughness heights. The surface roughness height in the experiments has been varied from 1 cm to 5 cm at intervals of 1 cm using the adjustable profiler. Figure-1 (e) and (f) show the surface roughness height at 2 cm and 3 cm respectively. The set of experiments conducted have been summarized in Table-1.

Table -1 : Summary of Design of Experiments

Microwave Frequency Band	X-Band only
Medium and Moisture Condition	Dry Sand
Surface roughness conditions	Rough surface
Surface Roughness Depth (cm)	1, 2 ,3, 4, 5
Polarisation	HH and VV
Location of Mine	Buried at the Center
Mines used in the Experiments	Live Antitank Mine without Fuze
Number of experiments to collect data	5

3. THEORETICAL APPROACH

Landmines are designed to be buried at shallow depths. Microwave frequencies in X-band (10 GHz frequency and 3 cm wavelength) are expected to provide both adequate penetration and resolution for detection of mines at shallow depths at which these are usually buried [2, 17]. Therefore all the experiments in this research have been conducted in microwave X – band only.

3.1 Surface roughness effects to be minimized

Surface roughness of a feature controls how the microwave energy interacts with the target surface and refers to the average height variations on the surface defined in terms of the wavelength of the EM wave measured in centimeters. A surface is considered "rough", if the height variations are much greater than the wavelength and "smooth", otherwise. Mathematically according to Charlton *et al*.[18], smooth and rough surfaces are defines as under :-

$$h < \frac{\lambda}{25 * Sin\alpha}, \quad \text{(smooth surface)} \quad \text{and} \quad h > \frac{\lambda}{4.4 * Sin\alpha}, \text{(rough surface)} \qquad (1)$$

where h is surface roughness, λ is wavelength, α is grazing angle *i.e* angle with respect to plane of incident surface.

Further, a landmine is buried below the surface of the earth and an EM wave traveling towards the landmine and the resulting backscatter passes through different layers characterized by different dielectric constants [19, 20, 21]. A landmine is buried below the surface of the earth and an EM wave traveling towards it subjected to multiple interactions between different mediums with different dielectric constants as shown in Figure-2. Daniels *et al*.[5] have proposed a model for estimation of backscattered electric field from an object buried under smooth surface as given in Equation 2 which models subsurface propagation of electrical field that contributes to the surface roughness effects that need to be minimized.

$$E_R = \sqrt{1 - 4k^2 \sigma^2 \cos\theta_1 \exp\left(-\tfrac{1}{2}\sin\theta_1\right)} \times \frac{R_{1-2} + R_{2-3}\exp\left(-2\gamma_2 H\right)}{1 + R_{1-2} + R_{2-3}\exp\left(-2\gamma_2 H\right)} \tag{2}$$

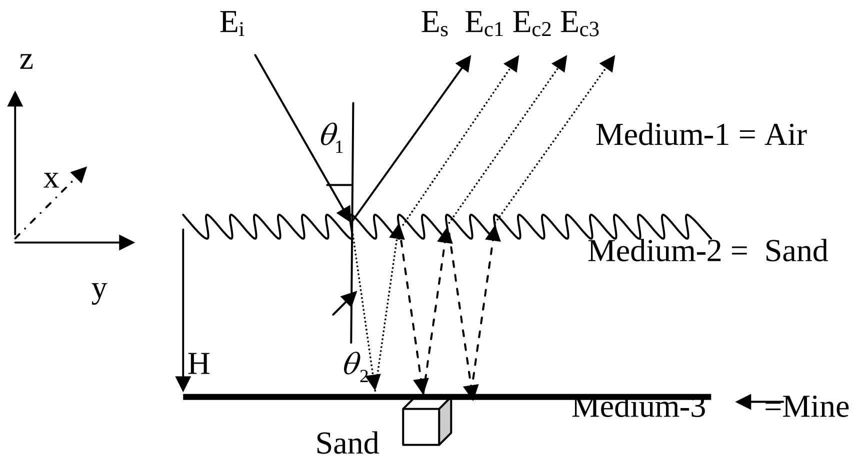

Fig 2 : Microwave propagation in an air-soil-mine interface

3.2 Assessment of surface roughness minimisation

Entropy is a kind of measurement of a system's disorder, instability, randomness, fuzziness, imbalance, uncertainty *etc* [16]. Entropy is a concept from information theory where it denotes the average uncertainty in any information source. Information entropy for a discreet sample space can be defined as follows. Let A be a probabilistic experiment where,

X = discreet sample space, P = probability distribution

p_i = probability of outcomes $x \in X_i$ satisfying $p_i \geq 0$ and $\sum_{i=1}^{r} p_i = 1$

Then the Shannon information entropy is defined as -

$$H_r(X) = E[-\log p_i] = -\sum_{i=1}^{n} p_i \log p_i \tag{3}$$

The Shannon entropy as defined above is symmetric *i.e* ordering of the probabilities do not influence its value $H_r(X)$, it is non-negative and additive. Shannon entropy has therefore been used as a measure for surface roughness minimization.

4. IMPLEMENTATION

A series of image processing steps have been formulated for implementation of various experiments in the present study for subsurface landmine detection using data in different polarizations. The implementation steps are briefly discussed below -

4.1 Data preprocessing

Following implementation steps have been formulated for this study :-

(a) Calibration of raw data with respect to a perfect reflector such as an aluminum sheet having a conductivity of 3.5×10^7 Seimens/meter and reflectivity coefficient ≈ 1.

(b) Normalization of the calibrated readings using the following equation

$$E_{normalised} = \frac{E_{observed} - E_{\min}}{E_{\max} - E_{\min}} \quad (4)$$

where $E_{\max}$ and $E_{\min}$ are the maximum and minimum values of backscatter in the observed data, and $E_{observed}$ is the observed backscattered intensity at particular point.

(c) Deconvolution using an appropriate convolution filter depending upon the antenna swath.

Due to limited dielectric variations between the landmine and the medium in which it is buried, clutter may result due to dielectric contrast at various medium interfaces, surface roughness and the small size of the landmine. The backscatter from the landmine is likely to be restricted to a few pixels only and may often get submerged in the backscatter from the surroundings. Therefore, two different approaches, namely, full image data preprocessing and local window data preprocessing has been considered. In this case of **full image data preprocessing**, the full raw image generated in the experiments is subjected through the series of data preprocessing steps enumerated above. The advantage of this method is that it results in analysis of actual raw backscatter image. However, in the case of subsurface landmine, where the backscatter from the landmine may not show any significant variation in comparision to that from the surroundings, full image data preprocessing may lead to loss of mine features. In the case of subsurface landmines, the backscatter response in a scatterometer measurement is usually restricted to limited number of pixels only and therefore in order to identify pixels containing mine like features, l**ocal window based data preprocessing** may be more useful. In this case, first, a new image is generated by multiplying an identity matrix of the same size as the raw image with the mean backscatter value of the raw image, then the new image is further scaled down by multiplying it by a fraction in the range of 0.5 to 0.8, the exact value of may be separate for each case and is determined after analysis of each experiment. The raw image is then divided into several blocks of smaller windows and at a time, one of these windows is transferred to its corresponding position in the new image and the new image processed through various data preprocessing steps outlined earlier. An optimal size of window depends upon the size of the mine, resolution, likely presence of other objects in the surroundings and the clutter. In the present case, a size of 8x8 pixels window has been found to be sufficient due to the size of the landmine used in the experiments, however greater window sizes should may be preferred as this may speed up the processing.

4.2 Segmentation of suspected region containing the landmine

Data preprocessing culminates into an output image from which extraction of desired attributes during the post processing stage becomes easier [22, 23]. Landmine detection requires that pixels constituting the mine be extracted. For automated segmentation of a suspected region containing the minefield, thresholding can be used which however requires selection of a threshold value, say, '*t*' [24, 25]. Since, the mine feature in an image constitute a limited number of pixels and there may be an overlap in backscatter intensities of the mine and its surroundings, selection of an threshold value '*t*' remains a challenge. A survey of image thresholding techniques by Sezgin *et al* (2004) [26] indicates that clustering based techniques give results with greater accuracy. Therefore, in the present study, one clustering based thresholding technique (Otsu's thresholding technique [27]) has been considered which aims at minimizing the 'within class variance' and maximizing the 'between class variance' [25] to achieve segmentation.

4.3 Algebraic transform analysis of multi-polarisation data

The data in HH and VV polarizations contain significantly different information of the ground objects such as shape, orientation *etc*. This is the result of the dielectric constant of the objects and its interaction with the polarized wave. Mine like features under rough surface cannot be identified or highlighted even after data-preprocessing using data in single polarization because of undesired surface roughness effects. In such cases, it may be useful to use an appropriate algebraic transform of the data in two polarizations. Basic image transformations apply simple arithmetic operations to the image data *e.g* image subtraction (subtraction of corresponding pixel values in two images) and image ratioing *etc*. These transformations can also be used for analysis of data in HH and VV polarizations. The significance of image subtraction and ratioing lies in the fact these two operations have the capability of suppressing certain information and highlighting the other. Besides, polarization discrimination ratio (PDR) is known to be capable of enhancing certain hidden information which otherwise may not get enhanced using simple subtraction or ratioing [15]. It however remains to be explored whether these operations can lead to enhancement of mine like features. Thus, three basic polarisation transforms have been considered in the present study which are defined as under :-

(i) Image ratio - VV / HH (5)

(ii) Image differencing – $VV - HH$ (6)

(iii) Polarimetric discrimination ratio – $\frac{(VV - HH)}{VV + HH}$ (7)

In addition, a new transform obtained as the sum of images in two polarizations minus the difference of images *i.e*., (HH+VV) - (HH- VV) has been proposed and considered. In each case, first, the data in HH and VV polarization has been preprocessed and analyzed for identification of a suspected region followed by the transform under study.

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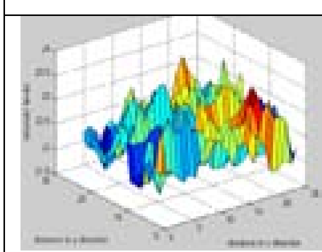
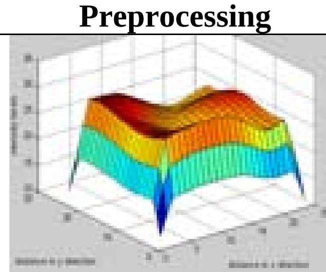
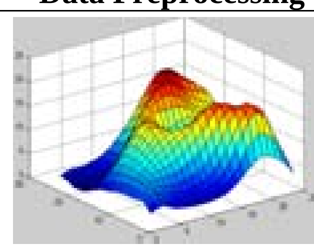
5. RESULTS AND DISCUSSIONS

In this study, experiments have been conducted to study surface roughness effects and data generated in different polarizations has been subjected to various algebraic transforms to study minimization of surface roughness effects. Based on the analysis of algebraic transforms, a transform has been proposed that results in minimization of surface roughness thereby enhancing the detection of surface landmine. An assessment of minimization of surface roughness has also been made using Shannon entropy. The results are discussed in this section.

5.1 Effect of local window based data preprocessing

Data preprocessing has been carried out using two different methods namely, full image data preprocessing and local window based data preprocessing. The aim of data preprocessing is to process the image to an extent at which extraction of desired attributes from the image become feasible. It is noticed that the plot for the raw data (Figure 3(a)) is highly random due to clutter from various sources including that from the corner of boxes. Data preprocessing after calibration and convolution is shown in Figure 3(b) which though comparatively smooth does not significantly aid detection. The dielectric variations due to mine in the presence of clutter are likely to be discernible in only a few pixels and hence local window based data preprocessing as explained in section 4.1 appears more suitable for data preprocessing. In this case, barring a small window, rest of the image is suppressed below the mean backscatter value of the image. It produces a zooming effect for the window selected and results in a preprocessed image in which mine like and non mine like features are easy to segment. The results of local window based data after preprocessing at the end of convolution stage is shown in Figure 3(c). This result can be compared with the convoluted plots obtained with full image data preprocessing shown in Figure 3(b). A dip at the centre in the convoluted plot with full image data preprocessing is noticed, however the variation is not pronounced enough to highlight presence of any object. On the other hand, the results obtained with local window based data preprocessing significantly improve the results and the convoluted plot in this case shows a clear dip at the location of the landmine which can be clearly distinguished from its surroundings. This makes the local window based data preprocessing very attractive as it makes segmentation of a suspected region containing mine during the post processing stage much easier.

3-D Plot After Data Preprocessing For Anti Tank Mine		
Raw data	**Full Image Data Preprocessing**	**Local window Image Data Preprocessing**
		
(a)	(b)	(c)
Fig 3 : Effect of local window based data preprocessing		

5.2 Effect of surface roughness on mine feature extraction

The data in *HH* and *VV* polarization has been preprocessed through various preprocessing steps and then individually subjected to Otsu's thresholding for mine feature extraction. The results at surface roughness depth of 1.0 cm for each of the two polarizations are shown in Figure–4. A comparison of the number of pixels segmented indicate that the backscatter from the mine is severely cluttered and the segmentation achieved in each case indicates much higher number of pixels than the actual number of pixels likely to constitute the landmine.

Mine Feature Extraction using Otsu Thresholding

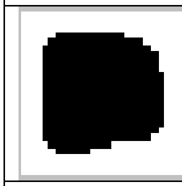
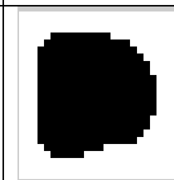
HH	VV
	
(a)	(b)

Fig 4 – Effect of surface roughness on mine feature extraction

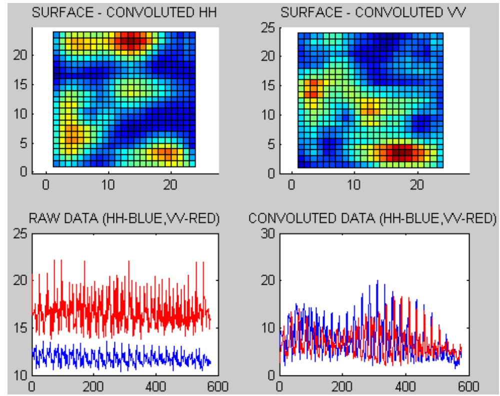
5.3 Analysis of algebraic transforms (Local window based data preprocessing)

Local window based data preprocessing has been considered in the analysis of the transforms and therefore the data extracted in a block of 8x8 pixel window is preprocessed with rest of the image backscatter suppressed below the mean image backscatter value. The results at a surface roughness depth of 2.0 cm for various transforms (including the proposed transform) using this method are shown in Figure-5. The layout within each plot has been described in a table shown on the left of each plot. These results however have been shown only for that 8x8 pixel window which gives most accurate segmentation. Since in all the cases the mine has been kept at the centre of the box, hence the correct results are obtained when the 8x8 pixel window is extracted from the centre. In all other cases where a window has been selected at places where there is no mine, the segmentation achieved is erratic. Surface plots in each polarization shown in Figure-5(a) are found to be severely cluttered at all depths. Signal plots for the raw data show that the data in each of the polarization lie in different ranges and convoluted plot shows an overlap. It is noticed that there is an overlap at the centre where the mine is located and the undesired backscatter values often found to lie outside the overlap. Figure-5(b) shows the histograms for all the algebraic transforms including the proposed transform. It can be noticed that the proposed transform retains both the higher discriminating features and also has the backscatter in the same range as the original data. Figure-5 (c) shows the segmentation achieved with the local window based data preprocessing for all the algebraic transforms. It can be noticed that the segmentation achieved using thresholding for the proposed transform (bottom left corner of the plot) segments the mine features most accurately.

5.4 Assessment of surface roughness minimization

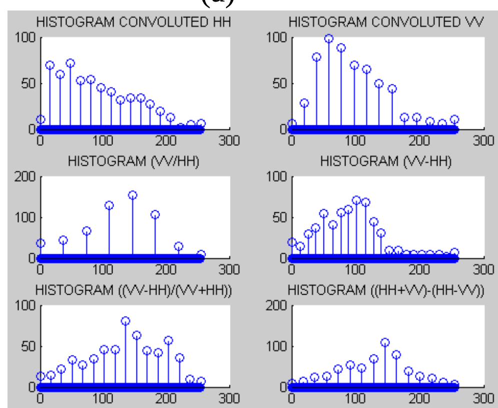
An assessment of surface roughness minimization using Shannon entropy has been carried out. Figure-6 shows a bar plot of Shannon entropy for data in individual polarization and the data obtained after subjecting them to all the algebraic transforms across all depths. In the figure, entropy has been plotted along y axis and the surface roughness depth along x - axis. Each bar shown in colour refers to either the data in individual polarisation or an algebraic transform. In the

Surface Plot – HH Polarisation	Surface Plot – VV Polarisation
Signal Plot – Raw HH and VV Polarisation	Signal Plot – Convoluted HH and VV Polarisation
Layout of Plots in this Figure	



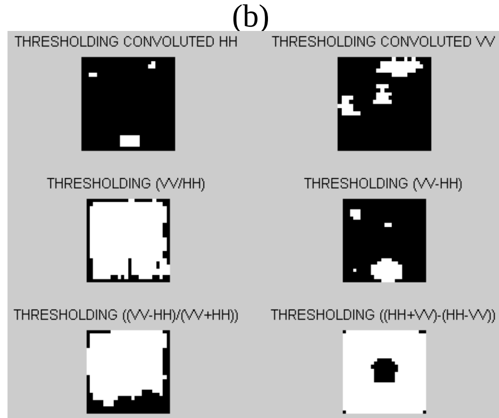
(a)

HH Polarisation	VV Polarisation
Ratio (VV/HH)	Difference $(VV-HH)$
PDR $\frac{VV-HH}{VV+HH}$	Proposed Transform $(HH+VV)$ - $(HH-VV)$
Layout of histogram plots	



(b)

HH Polarisation	VV Polarisation
Ratio (VV/HH)	Difference $(VV-HH)$
PDR $\frac{VV-HH}{VV+HH}$	Proposed Transform $(HH+VV)$ - $(HH-VV)$
Layout of Segmentation plots	



(c)

Fig 5 – Analysis of algebraic transforms (Local window based data preprocessing)

experiments, the Shannon entropy for data in HH and VV polarization has never been found the same at any of the surface roughness depths. Various transforms have been obtained by combining the data in two polarizations and the entropy for the transformed data has always been found to be lower than the total entropy (obtained by adding) of data in *HH* and *VV* polarization. This apparently indicates that each of the transforms achieve some degree of surface roughness minimization. Further, between the two polarizations, the entropy for the *VV* polarization is found to be lower than that of *HH* polarization. When only the entropy of *VV* polarization is considered (*i.e* the lower entropy of the two polarizations), it is found that only the proposed transform has a lower entropy than that of *VV* polarization. It therefore implies that for a transform to result in both effective surface roughness minimization and to yield correct segmentation, the transform must result in an entropy value that is lower than the lowest entropy in both the polarizations.

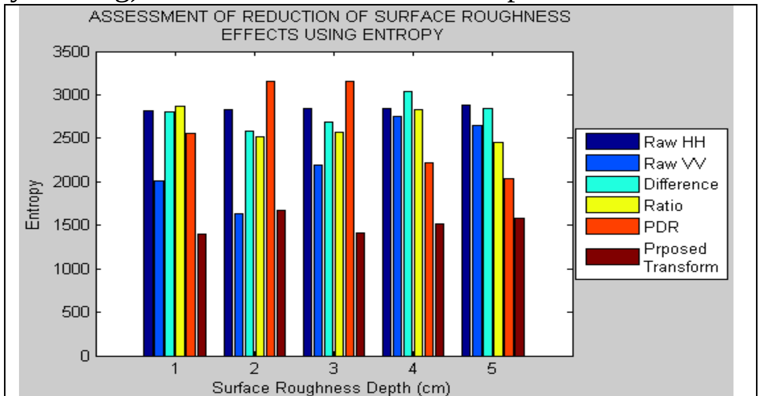


Fig.6. Assessment of surface roughness minimization

6. CONCLUSION

In the present study, an analysis of various effects that result in diminished backscatter from a subsurface landmine termed as surface roughness effects, has been carried out. Various algebraic transforms of data obtained in *HH* and *VV* polarization has been explored for surface roughness minimization. It has been found that a transform evolved as difference of the sum images and difference images $((HH+VV)-(HH-VV))$ retains most of the discriminating features present in the data in two polarization and reduces most of the undesired effects. When data preprocessing is done using local window based method and then subjected to the proposed transform, it produces most accurate detection results at all the depths. An assessment of surface roughness minimization indicates that all the algebraic transforms yield some degree of surface roughness minimization but for surface roughness minimization to be adequate to give correct segmentation, the transform must result in an entropy value which is lower than the lowest entropy for the data in either of the polarizations.

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