Polynomial Discriminant Radial Basis Function for Steganalysis

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Summary
Steganalysis plays an important role in identifying unacceptable information transmitted through internet communication system. In the process of steganalysis many untoward incidents can be avoided. Many techniques have been proposed and new techniques are tried with different combinations to maximize the efficiency of retrieving hidden information. We have proposed a combination of polynomial vector with Fisher's discriminant function using the information of bitplane and radial basis neural network (PVDRBF). Each set of pixel is preprocessed to obtain interpolated pixels using PDV. This is further trained by Fisher's discriminant method that transforms once again into 2-dimensional vector. A processing of training the RBF is adopted to obtain set of final weights. During implementation, the final weights are used to classify the presence of hidden information.

Key words:
Polynomial vector, Interpolation, bitplane, Steganalysis, Carrier image, Covert image.

1. Introduction

Steganalysis is the process of identifying the presence of hidden information in a text, image, audio, or video [1,2,3]. Most of the present literature on steganalysis follows either a parametric model [10, 11, 12] or a blind model [4, 5, 6, 7, 8, 9]. A generic steganalysis method that can attack steganography blindly, detect hidden data without knowing embedding methods, will be more useful in practical applications. A framework for steganalysis based on supervised learning has been designed in [13]. The framework was further developed and tested. A mere significant work has been carried out on supervised steganalysis, using neural networks as a classifier [14, 15]. Fishers' linear discriminant function (FLD) as a classifier has shown impressive results for steganalysis work [37]. We extend the present neural network based steganalytic work by combining a polynomial interpolated fisher's discriminant method with the radial basis function neural network function.

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2. Methodology

Machine learning theory based steganalysis assume no statistical information about the stego image, host image and the secret message. This work falls under the category of supervised learning employing two phase strategies: a) training phase and b) testing phase. In training phase, original carriers are separated by bitplane method and are interpolated by preprocessing into polynomial vectors. This is further trained by Fisher's discriminant method to obtain φ1 and φ2 discriminant vectors. The n-dimensional patterns are inner-producted to obtain 2-dimensional vector which is trained by neural classifier to learn the nature of the images. RBF takes the role of neural classifier in this work. By training the classifier for a specific embedding algorithm a reasonably accurate detection can be achieved. RBF neural classifier in this work learns a model by averaging over the multiple examples which include both stego and non-stego images. In testing phase, unknown images are supplied to the trained classifier to decide whether secret information is present or not. The flowcharts of both the phases are given below in figure 1:

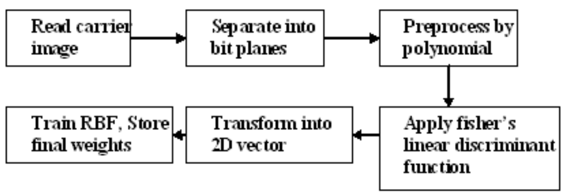

Fig. 1a. Training Phase

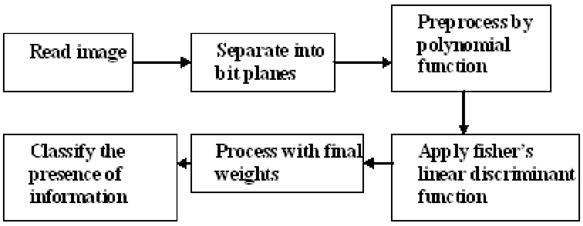

Fig. 1b. Testing Phase

2.1 Bitplane processing

In this research work 256-color or 8-bit images are considered. Each image is split into 8 planes, each plane contains one bit of all the pixels.

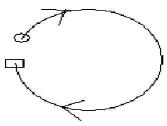

Fig. 2a. Carrier

Fig. 2b. Message

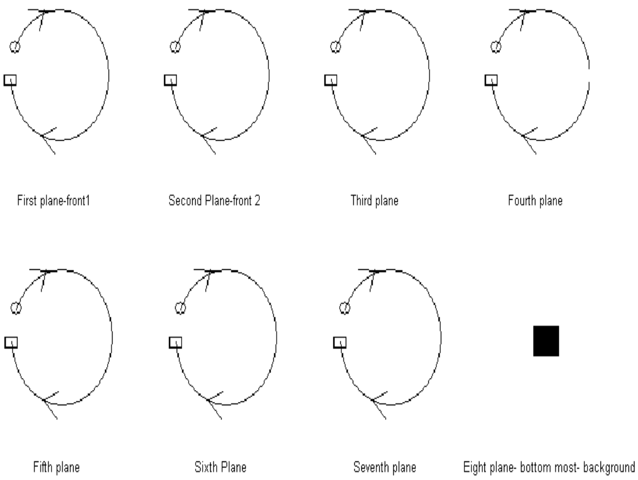

Fig. 2c. The mixed image through bitplane method

2.2 Polynomial Interpretation

Polynomial interpolation is the interpolation of a given pattern set by a polynomial set obtained by outer producting the given pattern. It can also be described as, given some points, the aim is to find a polynomial which goes exactly through these points [16, 17]. Polynomial Interpolation forms the basis for computing information between two points.

Let X present the normalized input vector, where
$X = \{X_i\}$; i=1,…nf,

X_i is the feature of the input vector, and

nf is the number of features

An outer product matrix X_{OP} of the original input vector is formed, and it is given by:

$$Xop.. = .. \begin{bmatrix} X1X1 & X1X2 & X1X3 \\ X2X1 & X2X2 & X2X3 \\ X3X1 & X3X2 & X3X3 \end{bmatrix}$$

Using the X_{OP} matrix, the following polynomials are generated:

i) Product of inputs (NL1)
it is denoted by:

$\Sigma w_{ij} x_i$ (i≠j) = Off-diagonal elements of the outer product matrix. (1)

The pre-processed input vector is a 3-dimensional vector.

ii) Quadratic terms (NL2)
It is denoted by:

$\Sigma w_{ij} x_i^2$ = Diagonal elements of the outer product matrix. (2)

The pre-processed input vector is a 3-dimensional vector.

iii) A combination of product of inputs and quadratic terms (NL3)
It is denoted by:

$\Sigma w_{ij} x^i$(i≠j) + $\Sigma w_{ij} x_i^2$ = Diagonal elements and Off-diagonal elements of the outer product matrix. (3)

The pre-processed input vector is a 6 dimensional vector.

iv) Linear plus NL1 (NL4)
The pre-processed input vector is a 6-dimensional vector. (4)

v) Linear plus NL2 (NL5)
The pre-processed input vector is a 6-dimensional vector. (5)

vi) Linear plus NL3 (NL6) (6)
The pre-processed input vector is a 9-dimensional vector.

In Eq. (1) through Eq. (6), the term 'linear' represents the normalized input pattern without pre-processing. While training the FLD, anyone of the 6 polynomial vectors can be used as input depending upon the requirements. The abbreviation 'NL' represents the non-linearity. The number next to 'NL' is used to identify the type of polynomial generated. The combination of different polynomials with FLD and RBF is given. in table 1.

NL1 +FLD +RBF	NL4 +FLD +RBF
NL2 +FLD +RBF	NL5 +FLD +RBF
NL3 +FLD +RBF	NL6 +FLD +RBF

Table 1: Combination of PVDRBF

2.3 Fisher's Linear Discriminant Function

The process of changing the dimensions of a vector is called transformation. The transformation of a set of n-dimensional real vectors onto a plane is called a mapping operation. The result of this operation is a planar display. The main advantage of the planar display is that the distribution of the original patterns of higher dimensions (more than two dimensions) can be seen on a two dimensional graph. The mapping operation can be linear or non-linear. R.A. Fisher developed a linear classification algorithm [18] and a method for constructing a classifier on the optimal discriminant plane, with minimum distance criterion for multi-class classification with small number of patterns [19]. The method of considering the number of patterns and feature size [21], and the relations between discriminant analysis and multilayer perceptrons [20] has been addressed earlier. A linear mapping is used to map an n-dimensional vector space $\Re^n$ onto a two dimensional space. Some of the linear mapping algorithms are principal component mapping [22], generalized declustering mapping [23, 24, 25, 26], least squared error mapping [27] and projection pursuit mapping [28]. In this work, the generalized declustering optimal discriminant plane is used. The mapping of the original pattern 'X' onto a new vector 'Y' on a plane is done by a matrix transformation, which is given by

$$Y=AX \quad (7)$$

Where

$$A = \begin{bmatrix} \varphi_1 \\ \varphi_2 \end{bmatrix} \quad (8)$$

and φ1 and φ2 are the discriminant vectors (also called projection vectors).

An overview of different mapping techniques [29, 30] is addressed earlier. The vectors φ1 and φ2 are obtained by optimizing a given criterion. The plane formed by the discriminant vectors is the optimal vectors which are the optimal discriminant planes. This plane gives the highest possible classification for the new patterns.

The steps involved in the linear mappings are:

Step 1: Computation of the discriminant vectors φ1 and φ2: this is specific for a particular linear mapping algorithm.

Step 2: Computation of the planar images of the original data points: this is for all linear mapping algorithms.

2.3.1) Computation of discriminant vectors φ_1 and φ_2

The criterion to evaluate the classification performance is given by:

$$J(\varphi) = \frac{\varphi^T S_b \varphi}{\varphi^T S_w \varphi} \quad (9)$$

Where

S_b the between class matrix, and

S_w the within class matrix which is non-singular.

$$S_b = \sum p(\omega_i)(m_i - m_o)(m_i - m_o)^T \quad (10)$$

$$S_w = \sum p(\omega_i) E\left[X_i - m_o)(X_i - m_i)^T \omega_i\right] \quad (11)$$

where

$P(\omega_i)$ a priori the probability of the i^{th} pattern, generally, $p(\omega_i) = 1/m$

m_i the mean of each feature of the i^{th} class patterns, (i=1.2…,m),

m_o the global mean of a feature of all the patterns in all the classes,

X {xi, I=1, 2,…L} the n-dimensional patterns of each class,

L the total number of patterns.

Eq.(9) states that the distance between the class centers should be maximum. The discriminant vector φ_1 that maximizes 'J' in Eq. (9) is found as a solution of the eigenvalue problem given by:

$$S_b \varphi_1 = \lambda_{ml} S_w \varphi_1 \quad (12)$$

where

λ_{ml} the greatest non-zero eigenvalue of $(S_b S_w^{-1})$

φ_1 eigenvalue corresponding to λ_{ml}

The reason for choosing the eigenvector with maximum eigenvalue is that the Euclidean distance of this vector will be the maximum, when compared with that of the other eigenvectors of Eq.(12). Another discriminant vector φ_2 is obtained, by using the same criterion of Eq.(9). The discriminant vector φ_2 should also satisfy the condition given by:

$$\varphi^T_2 \varphi_1=0 \quad (13)$$

Eq.(13) indicates that the solution obtained is geometrically independent and the vectors φ_1 and φ_2 are perpendicular to each other. Whenever the patterns are perpendicular to each other, it means, that there is absolutely no redundancy, or repetition of a pattern. The discriminant vector φ_2 is found as a solution of the eigenvalue problem, which is given by:

$$Q_p S_b \varphi_2 = \lambda_{m2} S_w \varphi_2 \quad (14)$$

where

λ_{m2} the greatest non-zero eigen value of $Q_p S_b S_w^{-1}$, and

Q_p the projection matrix which is given by

$$Q_p = I - \frac{\varphi_1 \varphi_1^T S_W^{-1}}{\varphi_1^T S_W^{-1} \varphi_1} \quad (15)$$

where

I an identity matrix

The eigenvector corresponding to the maximum eigenvalue of Eq. (14) is the discriminant vector φ_2. In Eq.(12) and Eq. (14), S_W should be non-singular. The S_W matrix should be non-singular, even for a more general discriminating analysis and multi-orthonormal vectors [31, 32, 33]. If the determinant of S_W is zero, then singular value decomposition (SVD) on S_W has to be done. On using SVD [34, 35], S_W is decomposed into three matrices U, W and V. The matrices U and W are unitary matrices, and V is a diagonal matrix with non-negative diagonal elements arranged in the decreasing order. A small value of 10^{-5} to 10^{-8} is to be added to the diagonal elements of V matrix, whose value is zero. This process is called perturbation. After perturbing the V matrix, the matrix S_w^1 is calculated by:

$$S_w^{\ 1} = U * W * V^T \quad (16)$$

where

S_W^1 the non-singular matrix which has to be considered in the place of S_w.

Minimum perturbed value should be considered, which is just sufficient to make S_w^1 non-singular. As per Eq.(13), when the values of φ_1 and φ_2 are innerproducted, the resultant value should be zero. In reality, the innerproducted value will not be zero. This is due to floating point operations.

2.3.2) Computation of two-dimensional vector from the original n-dimensional input patterns

The two-dimensional vector set y_i is obtained by:

$$y_i = (u_i , v_i) = (X_i^T \varphi_1 , X_i^T \varphi_2) \quad (17)$$

The vector set y_i is obtained by projecting the original pattern 'X' onto the space, spanned by φ_1 and φ_2 by using Eq.(17). The values of u_i and v_i can be plotted in a two-dimensional graph, to know the distribution of the original patterns.

2.4 Radial Basis Function

A radial basis function (RBF) whose value depends only on the distance from the origin. If a function 'h' satisfies the property $h(\boldsymbol{x})=h(||\boldsymbol{x}||)$, then it is a radial function. Their characteristic feature is that their response decreases (or increases) monotonically with distance from a central point. The centre, the distance scale, and the precise shape of the radial function are parameters of the model, all fixed if it is linear [36]. A typical radial function is the Gaussian which, in the case of a scalar input, is

$$h(x)=\exp((-(x-c)^2)/(r^2)) \quad (18)$$

Its parameters are its centre *c* and its radius *r*.

RBF networks have traditionally been associated with radial functions in a multi-layer network. The input layer carries the outputs of FLD function. The distance between these values and centre values are found and summed to form linear combination before the neurons of the hidden layer. These neurons are said to contain the radial basis function with exponential form. The outputs of the RBF activation function is further processed according to specific requirements.

3. Implementation

3.1 Training

1. Decide number of cover images.
2. Read each Image and separate into bitplanes. Choose bitplanes corresponding to background of the image (5,6,7,8) bits.
3. Preprocess the data to any NL

4. Calculate the principal component vector by

$$Z = Z * Z^{T}$$

where

Z denotes the intensities of image

5. Find eigenvector of the Z matrix by applying eigen process.

6. Calculate the φ_1 and φ_2 vectors.

φ_1 = eigenvector ($S_b * S_w^{-1}$)

$S_b = \sum (PCV_i - M_0) (PCV_i - M_0)^T / N$

where:

PCV_i (i = 1,2,3)

PCV_1, Principal component vector1

PCV_2, Principal component vector2

PCV_3, Principal component vector3

M_0 = Average of $(PCV_1 + PCV_2 + PCV_3)$

$S_w = (\sum (PCV_i - M_i) (PCV_i - M_i)^T) / N$

where:

M_{i} (i = 1, 2, 3)

M_1, average of PCV_1

M_2, average of PCV_2

M_3, average of PCV_3

7. Calculate φ_2 vector.

φ_2 = eigenvector ($Q\, S_b\, S_w^{-1}$)

$Q = I - ((\varphi_1 * \varphi_1^{-1} * S_w^{-1})/(\varphi_1^{t} * S_w^{-1} * Phi\_\varphi_1))$

8. Transfer for N dimensional vector into 2 dimensional vector.

$U = \varphi_1 * PCV_{i\,(1,2,3)}$

$V = \varphi_2 * PCV_{i\,(1,2,3)}$

9. Apply RBF.

No. of Input = 2

No. of Centre = 2

Calculate RBF as

RBF = exp (-X)

Calculate Matrix as

G = RBF

$A = G^T * G$

Calculate

$B = A^{-1}$

Calculate

$E = B * G^T$

10. Calculate the final weight.

F = E * D

11. Store the final weights in a File.

3.2 Testing

1. Read steganographed image and separate into bitplanes. Choose plane 5,6,7,8 one by one
2. Preprocess the data to an NL
3. Innerproduct with $\varphi_1 * \varphi_2$ obtained during training
4. Find eigenvector of the Z matrix by applying eigen process.

Calculate RBF centre as $RBF_{(1 X 3)}$ = exp (-X) is the gaussian function

Output of the network (1 X 1) = $RBF_{(1 X 3)}$ X Final $weight_{(3 X 1)}$

5. Classify the pixel as containing information or not.

4. Results and Discussion

The simulation of steganalysis has been implemented using MATLAB 7®. Sample sets of images considered are gray colored. The different sets of cover images considered in the simulation are presented in figure 3. The information image is shown in figure 2 (b). Encryption technique has not been considered during the simulation. The different ways the secret information scattered in the cover images are given in figure 4.

Fig.3 Three cover images under consideration

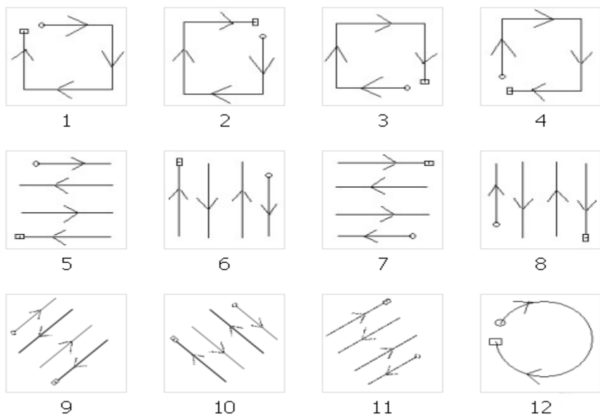

Fig.4 Distribution of information image in cover image

In this simulation, the information is embedded using least significant bit (LSB). This method will not be indicated to the steganalysis method proposed. Only the bits corresponding to background are considered during steganalysis as the foreground does not help in hiding information. The simulation environment is given in table-

2. The outputs of the FLD using NL1 through NL6 is shown in figure 5, and table 3 gives the length of polynomial vector developed. Figure 6 gives outputs of Polynomial with FLD and RBF during training, identifying the hidden information. All the methods are able to identify the hidden information.

Size of the image	256 * 256
Number of bits in each pixel of the cover image considered	4 bits (background)
Number of bits preferred in each message image	4bits (foreground)
Method of embedding	replacing all the background four bits of cover image by four information bits (foreground) of message image or replacing any one bit or any two bits or any three bits of cover image with equal number of bits of message image

Table 2: Simulation environment

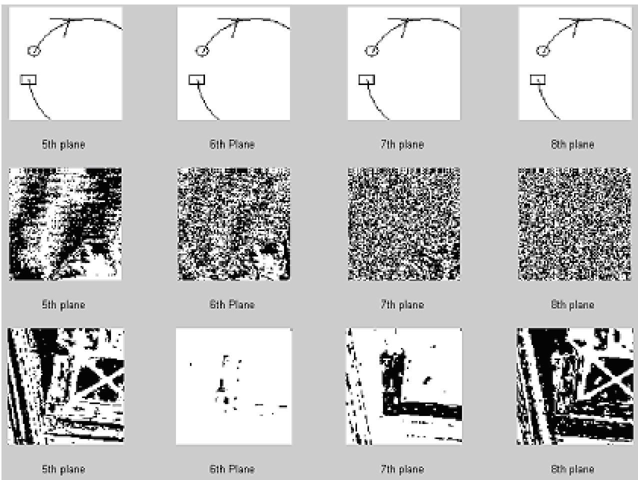

Fig 5. Each row corresponds to one image – background bits are shown

Method	**Polynomial vector length**
NL1	36
NL2	9
NL3	45
NL4	45
NL5	18
NL6	54

Table 2: Polynomial vector

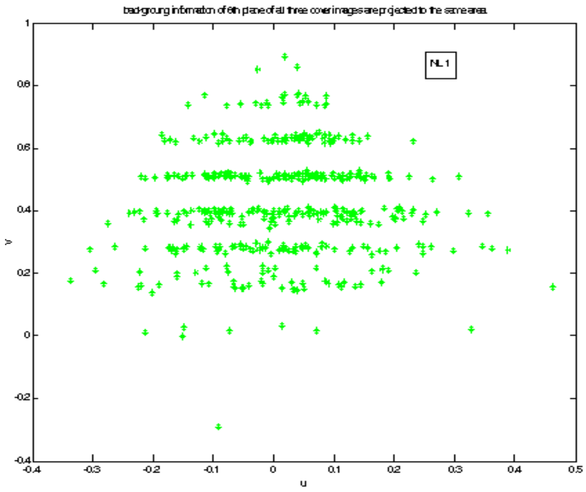

Fig 5a. FLD output of cover image using NL1

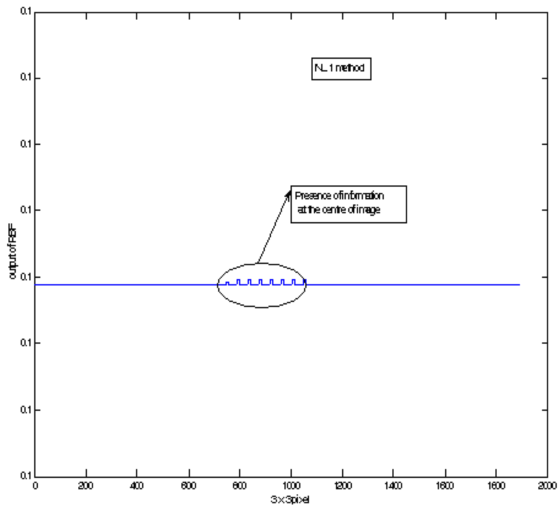

Fig 6a. Hidden information identified using FLD+RBF with polynomial using NL1

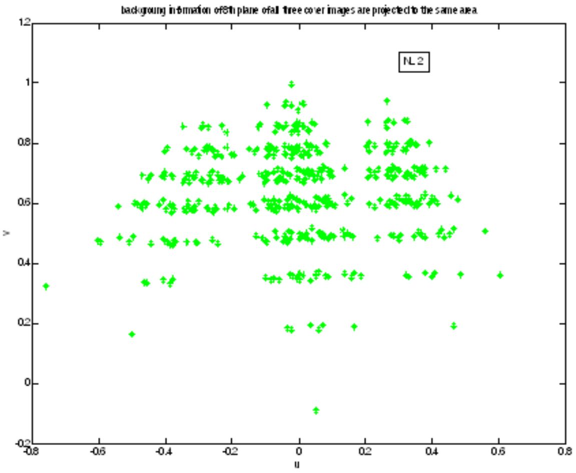

Fig 5b. FLD output of cover image using NL2

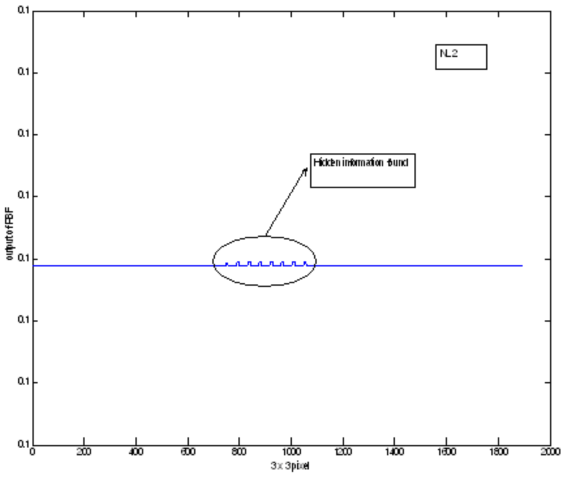

Fig 6b. Hidden information identified using FLD+RBF with polynomial using NL2

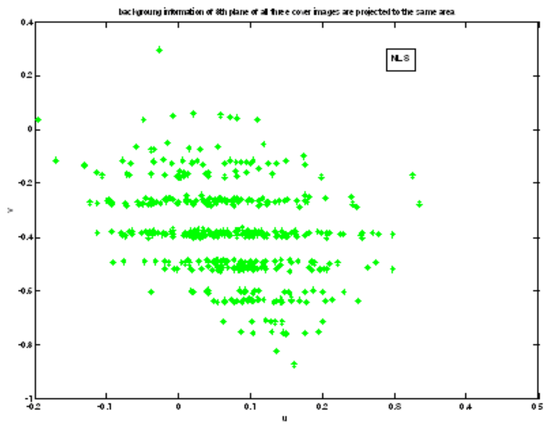

Fig 5c. FLD output of cover image using NL3

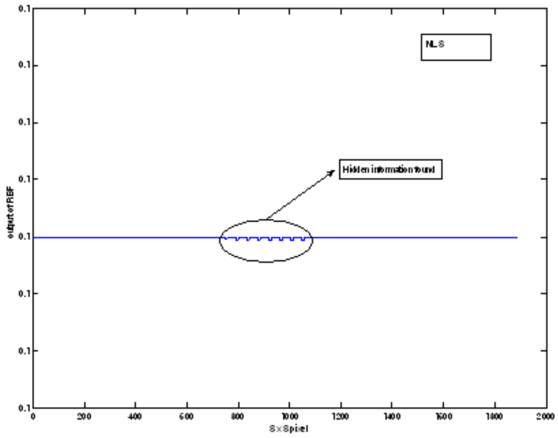

Fig 6c. Hidden information identified using FLD+RBF with polynomial using NL3

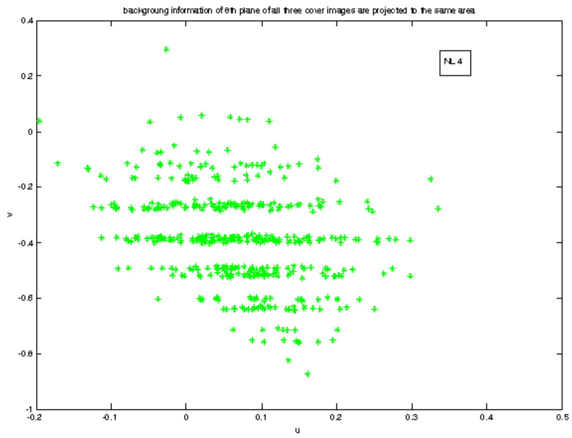

Fig 5d. FLD output of cover image using NL4

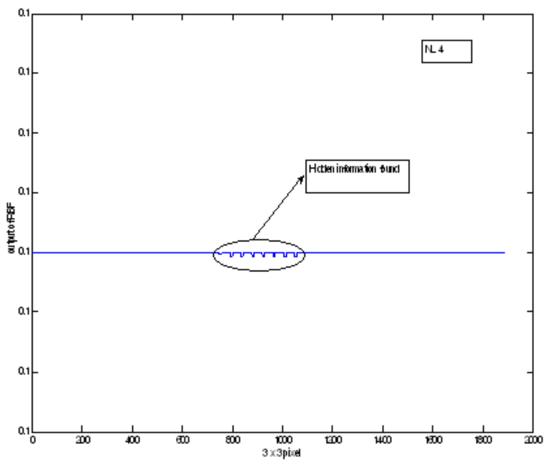

Fig 6d. Hidden information identified using FLD+RBF with polynomial using NL4

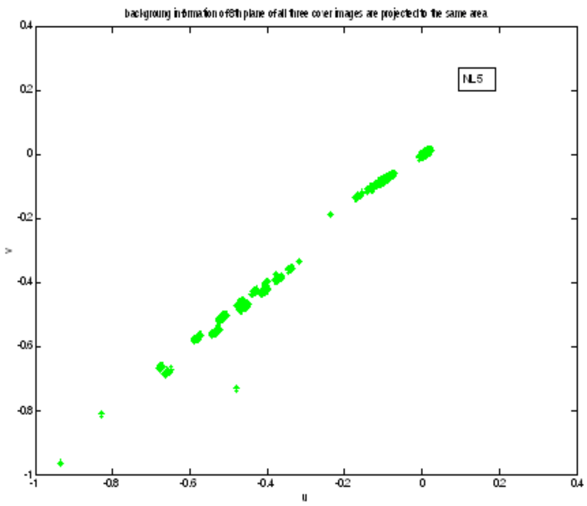

Fig 5e. FLD output of cover image using NL5

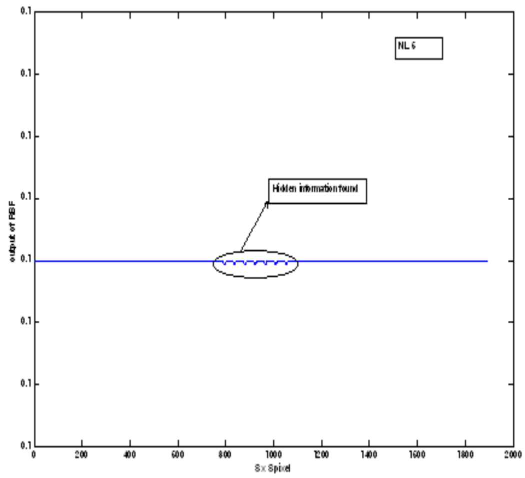

Fig 6f. Hidden information identified using FLD+RBF with polynomial using NL6

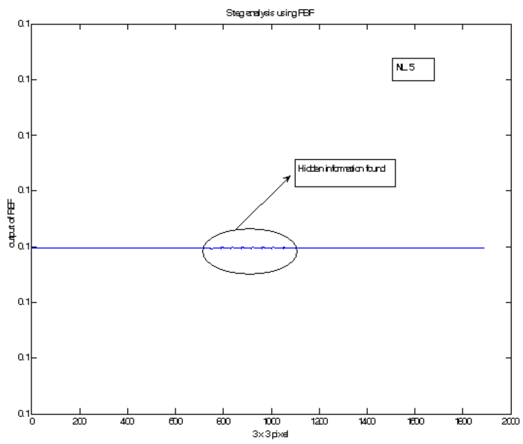

Fig 6e. Hidden information identified using FLD+RBF with polynomial using NL5

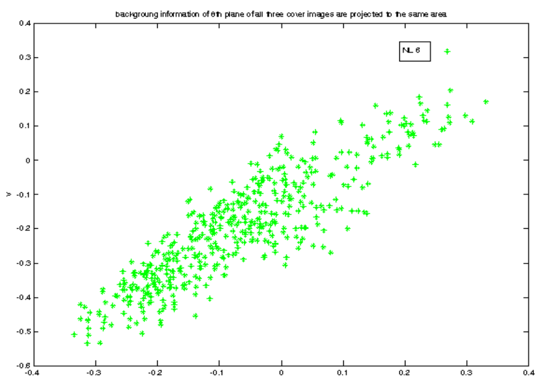

Fig 5f. FLD output of cover image using NL6

5. Conclusion

Steganalysis has been implemented using preprocessed vector with FLD, RBF. The outputs of the algorithms for one steganographed image have been presented. Secret information is getting retrieved by the proposed algorithms with various degrees of accuracies. It can be noticed that the combined method FLDRBF with polynomial is giving a newer direction to detecting the presence of hidden information. The cover images chosen for the simulation are standard images. The percentage of identifying the hidden information is more than 98%, The proposed method has to be tried with different types of hidden information.

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