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Adaptive Steganography technique using DIDC Model

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Abstract-Digital media emergence has taken the world by storm, further with the growth of digital media also causes the high risk of security and it needs to be addressed. Data security is protecting the data, normally data protecting is parted into two category i.e. cryptography and stenography. Steganography provides the high-level security by hiding one data under the other; the data can be image, text or any other formats, image steganography is one of the highly research area and several researcher have proposed different technique. The main challenge in image steganography is to innocuous image without any suspicion, furthermore the existing steganography focuses only on minimizing the distortion function. In this paper, we aim to develop an adaptive steganography technique named DIDC, which is basically based on the DPEs that approaching the rate transformation bound under the Steganography algorithm. Furthermore, the DIDC is evaluated by considering the two feature set SRM and max SRMd2 and error detection rate as the parameter, the comparison analysis shows that DIDC model outperforms not only state-of-art but also existing NFM model. Further, we also plot the AUC and the observation suggest the remarkable result.

Keywords: - Data hiding, Digital Steganography, rate transformation bound, DIDC, DPEs.

I. INTRODUCTION

Encryption is referred as one of the important techniques for securing the data. This can be done as convert the data into other format utilizing few encryption algorithms that can't be understood easily by the normal-users [1]. This encryption techniques is done via keys that may be symmetric or to utilize the encryption algorithm. There are two types of encryption methods such as the methods of symmetric key encryption that utilizes the shared-key can be utilized for both of the decryption and encryption methods and the methods of public-key encryption in which there are two various keys like public and private key are utilized. Either that can be utilized for the encryption or other can be utilized for the decryption method. One of the methods are utilized the methods of symmetric key, which is known as AES algorithm. The AES algorithm is the standard of advanced encryption that can have 128, 156 and 192 bits of keys. In this algorithm the number of rounds are totally depends on the key size. The process of encryption can be performed in the AES algorithm by the help of permutation and substitution operations. Data hiding [2] is a process to hide the data (representing few information) into the cover image.

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The process of data hiding links two types of the data one is the embedded data and another one is the cover image-data. The correlation among these two data categorizes various application. In secret communication, the secreted data may be not relevant to cover image. In these two applications, the hiddenness of the hidden data is very eminent constraint. In data hiding cases, the cover image experiences few transformation because of data hiding and that can't be reversed back to the cover image. Few permanent transformation has followed to cover image after the extraction of hidden data. In few applications like law-enforcement and the medical diagnosis, it is very critical to inverse marked image back to the actual cover image after hidden data are recovered for few considerations. In another applications like high-energy particle of the physical experimental investigation and the remote sensing is also desire the actual cover image that can be retrieved of needed high-precision-nature. The marking methods are satisfying the requirement that are referred to as transformation-free, reversible, lossless and invertible data-hiding methods. The RDH (reversible data hiding) simplifies the immense possibility of the applications to link 2 types of data in such a way that cover image can be losslessly retrieved after the extraction of hidden data. Lately, several data-hiding methods are irreversible. For example, generally used (Spread-Spectrum) SS based data-hiding techniques [3-4] are not the invertible that owing to the truncation error and round-off error. The most demanding LSB based methods are not loss-less that owing to the bit-replacement without the help of memory. Another techniques like data hiding and (Quantization-Index-Modulation) QIM based methods [5-6] are not the transformation-free that owing to the error of quantization. Whereas, in few last decades the data-hiding methods are reversible for hiding the data in the encrypted images. In this technique [7], the image is encrypted by the help of PKC (Public-Key-Cryptography) algorithm. The histogram shifting and histogram expansion has been done to embed the extra data without the help of content owner. When, receiver obtains the image that can decrypt by utilizing his-own private-key. Afterwards, the data recovery and image extraction has been done. In [8], introduces the integrated loss-less and the technique of RDH (reversible-data-hiding) for data-hiding utilizing the technique of public-key-cryptographic. In this technique, the owner of content encrypted the image and hide the data with the help of key of data-hiding. Who has sent the data, the receiver has hide the key then remove embedded data and the image can be recovered utilizing the private-key. The values of pixels and cipher-text are replaced by novel-values for embedding the extra data that utilizes the wet-paper code. The embedded data can be extracted from the domain of encryption.

This paper introduces the problem of stenographic rate-transformation under the multi-transformation matrix and represents the unified framework in order to evaluate corresponding DPE, which consists framework under the consistent transformation matrix and treated as the special case. Afterwards, we integrate the multiple histogram from the histogram and create the multi-transformation matrix as the transformation matrix, which can convert the stenographic problem under the multi-transformation matrix under into the transformation matrix. The introduced framework can be utilized to enhance the stenographic in different applications and also assume the stenographic in the reversible stenographic to represent the benefits of introduced framework. This research work is organized in such a way that section- represents the related work on the basis of data hiding methods, section-3 represents the problem of rate transformation matrix under the multi transformation matrix and define the solution of this problem, and section-4 represents the performance evaluation and finally concludes our research work.

II. RELATED WORK

In last few decades, several data hiding methods has been introduced [9]. These hiding methods can be parted into 2-classes on the basis of subject in which the messages are embedded into the cover image. One of the method is utilized for the transmission of secret message [10], and other one is utilized for ownership –claim which is also known as the scheme of watermarking. In order to carry the cover image as the secret message that can be video, text and audio. Presently, the images are the main media in order to conceal the secret messages that can be easily found through the internet. In order to embed the secret message into the cover images as three alternatives such as compression, spatial and frequency domain . For the compression based data-hiding, the secret messages are embed into cover image's compression codes that are generated by the help of compression algorithm like JPEG, VQ [11], BTC (Block Truncation coding) [12] and SMVQ [13]. Whereas, the spatial based data-hiding methods conceal the secret message into the cover-image by modifying the cover image's pixel values. The typical example is the substation of LSB (Least-Significant-Bit) [14]. Finally, the frequency based data hiding methods require to transform the cover-image into the domain of frequency by the help of DCT (Discrete Cosine Transform) [15] and DWT (Discrete Wavelet Transform) [16]. The coefficient of frequency is modify to carry the secret message. Among the all three data-hiding methods, the frequency methods are relatively higher protection when compared to the other methods. On the basis of reversibility feature of data-hiding methods, this methods can be parted into reversible [17] and irreversible [18] data hiding. This can only extract the data and the data are embedded in media. Introduced the methods in [19], generates the utilization of RDH is accomplished by the help of LSB-modification. Initially, actual image cover can be encrypted by using the encryption-algorithm and few of them embeds the data into each block in such a way that just flipping the previous three LSBs. The spatial-relationship presents in the interfered block and natural images, the interfered-block should be lesser smooth than the actual block. Thus, the actual cover can be recovered along the secret data. If block selection falls in unsuitable size of block because of data extraction and the errors of image recovery may happen. The size of block is the factor that decides the embedding rate of data method. Few methods like RDH utilizes the modification of histogram [20]. The n-nary and histogram modification of data hiding method utilized to embed the secret data into the encrypted image. At the receiver side, the actual image cover is totally recovered and the extra data is extracted with the encryption key and embedding key. In [21], another approach has been proposed in order to use Slepian-Wolf encoding for data-hiding. This approach is basically inspired by the help of DSC (distributed source coding) [22]. Initially, the image encryption is done by the help of stream cipher method then utilizing the lower-density of the parity heck codes and the spare-room is created to include the secret data in vacated form. The image recovery and data extraction utilizes the technique of DSC. With the help of RDH in the encrypted images reserving the room before the encryption method [23]. This method has been given the amazing amount of the reversibility that is image recovery and data extraction aren't containing the error. In [24], the method of DE (difference expansion) computes the values differences of neighboring pixel for DE chooses few difference values. This can be applicable for video as audio as well. This data about the actual content restoration, message authentication code and the additional data implements into difference values. In [25], introduces the efficient compression of the encrypted-grayscale images for the efficient-compression of the encoded grayscale-imageries. The compression of resolution is utilized to compress the encrypted-images. One sider the sender transmits the sampled cipher-text and other side the receiver decrypt and decodes the image with low-resolution from image with higher-resolution obtain by the prediction of intra-frame. This image integrates with the encryption key, utilized as side-data to the decipher level of subsequent resolution. This can be repeated until the images are deciphered. The decorrelation pixel is very difficult for encoder so that it can be shifted to the decoder side. Thus, decode is capable to know the information about local data. This method reduces the complexity and maximizes the coding efficiency. Whereas in paper [26], introduces the algorithm of reversible watermarking utilizing the prediction and sorting, introduced the method which consists the scheme of rhombus pattern prediction. In this method, the value of one pixel can be predicted by using 4-neighbouring pixel. All of the pixels are utilize together to embed the bit. Two types of pixel sets are utilized as cross set and dot set, the cross sets is utilized for hide the data while dot set is use for computing the predictors. In any set the variation is not affect other set. The PE (prediction error) is calculated from the original pixel and predicted value and this can be extended to embed the data. The embedding data can be varied. The introduced system reduces the size of location map and this generates the capacity maximization.

In next section we will discuss about stenographic algorithm.

III. PROPOSED WORK

1.1 Preliminaries

The stenographic algorithm consists of two phases. Initially, 1st phase contains cover image with the smaller entropy, which can usually achieved by the help of sorting methods and Prediction errors. Next phase is to embed the messages into the cover images. The main difficulty of the stenographic algorithm concerns and identifying the payload of UB (Upper Bound) with the help of given transformation-constraint. We find independent embedding rate and equal transformation of cover image to find UB and it is represented as:

$$\Delta = Max\{\mathbb{H}(\mathcal{B})\} - \mathbb{H}(\mathcal{A}), \quad (1)$$

Where $\mathcal{A}$ and $\mathcal{B}$ is represented as the random-variables of marked and host sequence. The entropy can be increased over all of the transition-probabilities $\mathcal{P}_{\mathcal{B}|\mathcal{A}}(\mathscr{b}|a)$satisfying the constraint of transformation.

$$\sum_{a,\mathscr{b}} \mathcal{P}_{\mathcal{B}}(a) d(a,\mathscr{b}) \mathcal{P}_{\mathcal{B}|\mathcal{A}}(\mathscr{b}|a) \leq \Delta, \quad (2)$$

Where, $\mathcal{P}_{\mathcal{A}}(a)$ is defined as the PD (probability distribution) of $\mathcal{A}$, and $d(a,\mathscr{b})$ is defined as the modifying cost from a to $\mathscr{b}$.

In order to evaluate the capacity of stenographic algorithm within the transformation-constraint we compute the differential probability estimates (DPEs) $\mathcal{P}_{\mathcal{B}|\mathcal{A}}(\mathscr{b}|a)$, which implies optimal-modification X. Some of the recent methods have introduced to get the rate-transformation-bound. The DPEs is very important to decoding and coding processes by the help of DIDC (Data Index dependent code). For transformation matrix, L_1-NDM (Norm transformation matrix) $d(a,\mathscr{b}) = |a - \mathscr{b}|$ or SED (Square error transformation) $d(a,\mathscr{b}) = (a,\mathscr{b})^2$, the DPEs has the property of NCE (non-crossing-edges). Be relaying the property of NCE, the DPEs $\mathcal{P}_{\mathcal{B}|\mathcal{A}}(\mathscr{b}|a)$ is analytically derived from marginal distributions $\mathcal{P}_{\mathcal{A}}(a)$ and $\mathcal{P}_{\mathcal{B}}(\mathscr{b})$. Therefore, the PE (Probability Estimation) of DPE is converted to estimate $\mathcal{P}_{\mathcal{B}}(\mathscr{b})$ optimal.

The TM (transformation matrix) is utilized to define cost incurred in the cover element, We refer position-dependent metric as the inconsistent and position-independent metric as consistent transformation matrix. We assume the cover image that consists of two-pixel as $\wp_1$ and $\wp_2$. When adapting the pixels by the help of magnitude k, we define cost on $\wp_1$ as $d_1(m)$ and cost on $\wp_2$ as $d_2(m)$. If cost function satisfy $d_1(m) = d_2(m)$, then we call the metric of consistent transformation. Although, many algorithms has been introduced for estimating the DPEs and all transformation matrix is consistent that significantly limiting the applications of DIDC. For the DIDC, all elements of the cover image e.g., the pixel of host image is require to share similar transformation matrix.

1.2 Problem definition

In this subsection, the sender transmits the message K bits into the cover-image as $\mathcal{A} = (a_1, \ldots, a_L)$ by modifying the elements to produce the stegno image $\mathcal{B} = (\mathscr{b}_1, \ldots, \mathscr{b}_L)$. The embedding rate is defined as;

$$\mathbb{R}_e = K/L \quad (3)$$

Where, the length of cover image is L . The methods are constructed to reduce average transformation among $\mathcal{A}$ and $\mathcal{B}$ for given embedding-rate $\mathbb{R}_e$. The change cost x to y is defined as $d(a,\mathscr{b})$ that could be the metric of SED (square-error-distribution) $d_s(a,\mathscr{b}) = (a - \mathscr{b})^2$, L_1 Norm-transformation matrix $d_1(a,\mathscr{b}) = |a - \mathscr{b}|$or by the help of user specific-transformation matrix is defined. $\mathcal{A}$ and $\mathcal{B}$ is denoted as random-variables of stegno image and cover image respectively; the PD of the cover image $\mathcal{P}_{\mathcal{A}}(a)$ is estimated by the help of histogram of cover image $\mathcal{A}$. Afterwards, in order to define the entropy $\mathcal{A}$ by $\mathbb{H}(\mathcal{A})$ and conditional-entropy $\mathcal{B}$ by the help of $\mathbb{H}(\mathcal{B}/\mathcal{A})$.

The Equation (1) defined the problem of optimization for limited sender as represented in Equation (4) that reduces the transformation for embedding rate $\mathbb{R}$.

$$minimize \sum_{a=0}^{i=1} \sum_{\mathscr{b}=0}^{j=1} \mathcal{P}_{\mathcal{A}}(a)\, \mathcal{P}_{\mathcal{B}|\mathcal{A}}(\mathscr{b}|a)\, d(a,\mathscr{b}) \quad (4)$$

$$\mathbb{H}(\mathcal{B}) = \mathbb{R}_e + \mathbb{H}(\mathcal{A})$$

As we can see that $\mathscr{b} \in \mathbb{B} = \{0,1, \ldots, j-1\}$, $a \in \mathbb{A} = \{0,1, \ldots, i-1\}$, $\mathbb{B}$ and $\mathbb{A}$ are denoted as the finite set of alphabets, the $d(a,\mathscr{b})$ transformation matrix is defined with the help of transformation matrix such as;

$$\mathcal{D} = \left[\begin{bmatrix} d(0,0) & \cdots & d(0,j-1) \\ \vdots & \ddots & \vdots \\ d(i-1,0) & \cdots & d(i-1,j-1) \end{bmatrix}\right] \quad (5)$$

In Equation (5), $d(a,\mathscr{b})$ has similar function for all $a = 0, i-1$ and $\mathscr{b} = 0, j-1$.

For many transformation matrix like Norm and squared error of transformation matrix has been proven that corresponding $\mathcal{P}_{\mathcal{B}|\mathcal{A}}(\mathscr{b}|a)$ can be expressed by the help of host-distribution$\mathcal{P}_{\mathcal{A}}(a)$ and $\mathcal{P}_{\mathcal{B}}(\mathscr{b})$ marginal-distribution as:

$$\mathcal{P}_{\mathcal{B}|\mathcal{A}}(\mathscr{b}|a) = \mathrm{Max}\{0, \mathrm{Min}\{\mathcal{F}_{\mathcal{A}}(a), \mathcal{F}_{\mathcal{B}}(\mathscr{b})\} - \mathrm{Max}\,\{\mathcal{F}_{\mathcal{A}}(a-1), \mathcal{F}_{\mathcal{B}}(\mathscr{b}-1)\} \quad (6)$$

$\mathcal{F}_{\mathcal{B}}(\mathscr{b})$ and $\mathcal{F}_{\mathcal{A}}(a)$are the CP (cumulative probability) of $\mathcal{A}$ and $\mathcal{B}$, defined by$\mathcal{F}_{\mathcal{A}}(a) = \sum_m^a \mathcal{P}_{\mathcal{A}}(m)$, where $a = 0, \ldots., j-1$, and $\mathcal{F}_{\mathcal{B}}(\mathscr{b}) = \sum_{m=0}^{\mathscr{b}} \mathcal{P}_{\mathcal{B}}(m)$, where $\mathscr{b} = 0, \ldots., j-1$. Note, $\mathcal{F}_{\mathcal{A}}(-1) = \mathcal{F}_{\mathcal{B}}(-1) = 0$, $\mathcal{F}_{\mathcal{A}}(i-1) = \mathcal{F}_{\mathcal{B}}(-1) = 0$, $\mathcal{F}_{\mathcal{A}}(j-1) = \mathcal{F}_{\mathcal{B}}(j-1) = 1$, function $\mathrm{Min}(x,y)$ get the Min value of x and y, and function $\mathrm{Max}\,\{x,y\}$ get the Max value of x and y.

The framework is evaluating the DPE $\mathcal{P}_{\mathcal{B}|\mathcal{A}}(\mathscr{b}|a)$ by $\mathcal{P}_{\mathcal{B}}(\mathscr{b})$ and $\mathcal{P}_{\mathcal{A}}(a)$ within the transformation matrix. According to DPE, we can reversibly embed the messages and reduces the average transformation with the help of DIDC method like RHM (recursive-histogram-modification). Below figure represents the primary steps of stenographic that approaching the bound of rate transformation.

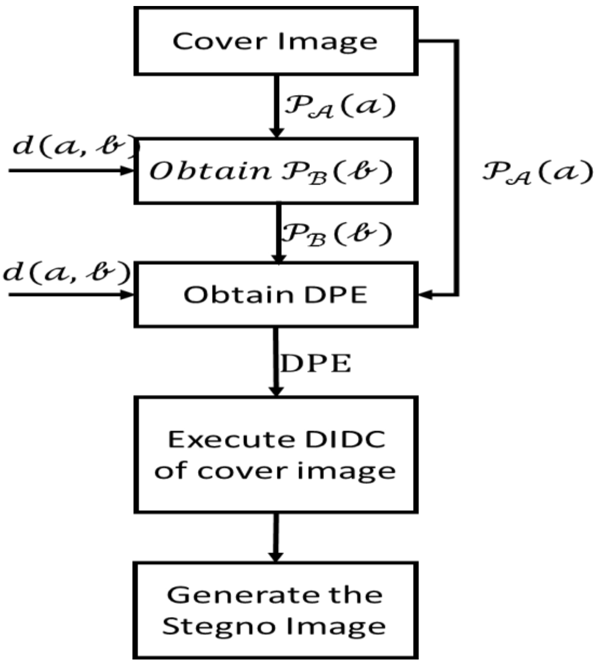


Figure 1: Primary steps of stenographic algorithm

In order to estimate the DPE, the transformation matrix is consistent and expressed as the single transformation matrix which is defined in Equ (5). In several applications, the transformation matrix is usually in-consistent and metrics of in-consistent transformation is quantified as the multi-transformation matrix. Therefore, it is very eminent to evaluate the DPE and implement optimal that embedding the RDH under the multi-transformation matrix.

1.3 Multi-Transformation Matrix

This subsection defines the transformation caused by modifying every single host-element that should be related with its point and the neighboring-elements. Considering the transformation matrix for jth element a_n is $d_n(a, \mathscr{b})$, where $a_n \in \mathbb{A} = (a_1, a_2, \ldots, a_L)$ and $1 \leq n \leq L$, the corresponding transformation matrix D_j is defined by:

$$\mathcal{D}_n = \begin{bmatrix} d_m(0,0) & \cdots & d_m(0, j-1) \\ \vdots & \ddots & \vdots \\ d_m(i-1,0) & \cdots & d_m(i-1, j-1) \end{bmatrix} \quad (7)$$

There is L number of in-consistent transformation matrix, and denoted by the help of $\big(d_1(a, \mathscr{b}), d_2(a, \mathscr{b}), \ldots, d_L(a, \mathscr{b})\big)$. If N number of transformation matrix are equal then the model have the consistent transformation matrix.

The spatial region such transformation matrix in the classes of $S - (S \leq L)$. Accordingly, the cover image $\mathcal{A}$ can be parted into the sub-images K, which is denoted as $a_m = a_m, 1, a_m, 2, \ldots, a_{m,} L_m$, where N_i is denoted as length of a_m. All of the elements in sub-images a_m share similar transformation matrix defined as $d_m(a, \mathscr{b})$, which can be defined with single transformation matrix $\mathcal{D}_m$, where $1 \leq m \leq S$. Furthermore, the cover image $\mathcal{A}$ consists S histogram and sub-images with $\mathcal{P}_{\mathcal{A}m}(a)$ showing the PD (Probability Distribution) $\mathcal{A}_m$, where $1 \leq m \leq S$. Anyways, the transformation matrix and histogram shape may vary. Various histogram perform while selected for the embedding for the fixed payload as $\mathbb{R}_e$. Moreover, if we get the rate of allocated embedding that is denoted by the $\mathbb{R}_{e_m}$ for each sub-images $\mathcal{A}_m$, then we compute corresponding DPE defined as $\mathcal{P}_{\mathcal{B}_m|\mathcal{A}_m}(\mathscr{b}|a)$ utilizing the existing techniques for the consistent transformation matrix and modify the histogram in order to get the stegno image which is denoted as $\mathcal{B}_m$. The total transformation caused by the embedding $\mathbb{R}_{e_m}$ payload into $\mathcal{A}_m$.

$$n_m = L_m \sum_{a,\mathscr{b}} \mathcal{P}_{\mathcal{A}_m}(a) \mathcal{P}_{\mathcal{B}_m|\mathcal{A}_m}(\mathscr{b}|a) d_m(a, \mathscr{b}) \quad (8)$$

For the single sub-images

$$\mathcal{A}_m = \frac{L_m \times \mathbb{R}_{e_m}}{L} \quad (9)$$

The total payloads of sub-images K is equivalent to total payload $\mathbb{R}_e$, i.e.,

$$\mathbb{R}_e = \frac{\sum_{m=1}^{S} L_m \times \mathbb{R}_{e_m}}{L} \quad (10)$$

By the help of (10), the given payload is defined as $\mathbb{R}_e$, reasonably distribution n problem of payload $\mathbb{R}_e$ among the sub-images S reduces the average embedding-transformation.

$$minimize \frac{\sum_{m=1}^{S} L_m \sum_{a=0}^{i=1} \sum_{\mathscr{b}=0}^{j-1} \mathcal{P}_{\mathcal{A}_m}(a) \mathcal{P}_{\mathcal{B}_m|\mathcal{A}_m}(\mathscr{b}|a) d}{L} \quad (11)$$

$$\frac{\sum_{m=1}^{S} L_m \times \mathbb{H}(\mathcal{B}_m)}{L} = \mathbb{R}_e + \frac{\sum_{m=1}^{S} L_m \times \mathbb{H}(\mathcal{A}_m)}{L}$$

The rate-distortion bound of the stenographic algorithm is under the multi-transformation matrix that matching the Equation (3) if $S = 1$. In order to reduce the average transformation, every single optimal allotted the payload R_i such as sub-DPE $\mathcal{P}_{\mathcal{B}_m|\mathcal{A}_m}(\mathscr{b}|a)$ is required for $m = 1,2,, \ldots .S$ that can be utilized to modify the S sub-images and embed the messages into the cover-image.

1.4 Embedding the transformation Matrix

According to the transformation matrix, the cover image $\mathcal{A}$ is parted into the S sub-images, while each sub-images has its own transformation matrix and the PD (probability distribution). Assume that, the sub-image histogram a_m is indicated by $\mathbb{H}_i$; the we allocate it an the offset value $oa_m (m = 1,2, \ldots, K)$. By translating the sub-histogram $\mathbb{H}_m$by the help of corresponding offset oa_m, then we integrate the sub-histograms $\mathbb{H}_i$ into the larger histogram based $\mathbb{H}_w$. In our method, $oa_m = (m-1)m$. Each of the sub-histogram $\mathbb{H}_i$, and the sub-images $\mathcal{A}_m$ is transformed by the help of corresponding offset ox_i.

The transformed $\mathcal{A}_i$ is defined by the help of $\mathcal{A}_m^t$, with its elements that being in the range of $\{(m-1)m, (m-1m+1, ..., im-1$. The $\mathcal{S}$ is transformed as sub-images that is integrated to create the images as $\mathcal{A}_c$ is defined as;

$$\mathcal{A}_w = [a_1^t \;\; a_2^t \;\; .....a_S^t] \tag{11}$$

In order to normalize the histogram $\mathbb{H}_w$, the host of PD (Probability Distribution) $\mathcal{P}_{\mathcal{A}_w}(a)$ is achieved. After translation, the range of a is increased by the K factor and $x \in \mathcal{X}^c = \{0,1,2, ..., km-1\}$. In order to define the host of PD $\mathcal{P}_{\mathcal{A}_w}(a)$ in the form of vector which is defined as;

$$\mathcal{P}_{\mathcal{A}_w} = \mathcal{P}_{\mathcal{A}_1^t}, ..., \mathcal{P}_{\mathcal{A}_S^t}, \tag{12}$$

Where,

$$\mathcal{P}_{\mathcal{A}_1^t} = [\mathcal{P}_{\mathcal{A}_w}((m-1)i), ..., \mathcal{P}_{\mathcal{A}_w}(mi-1)], \quad 1 \le m \le S \tag{13}$$

The PD $\mathcal{P}_{\mathcal{A}_w}$ outcomes are normalizing from the given histogram $\mathbb{H}_w$, then we get,

$$\mathcal{P}_{\mathcal{A}_1^t} = \frac{L_m}{L}\mathcal{P}_{\mathcal{A}_m}, 1 \le m \le S \tag{14}$$

The range of stegno image $\mathscr{b}$ is increased by the help of S factor, and $\mathscr{b} \in \mathbb{Y}^w = \{0,1,2, ..., sl-1\}$. Then, we define the PD of stegno image as;

$$\mathcal{P}_{\mathcal{B}_w} = \mathcal{P}_{\mathcal{B}_1^t}, ..., \mathcal{P}_{\mathcal{B}_S^t} \tag{15}$$

Where,

$$\mathcal{P}_{\mathcal{A}_1^t} = [\mathcal{P}_{\mathcal{B}_w}((m-1)j), ..., \mathcal{P}_{\mathcal{B}_w}(mL-1)], \quad 1 \le m \le S \tag{16}$$

In order to modify the host sub-images $\mathcal{A}_m^t$ to create the stegno sub-images as $\mathcal{B}_m^t$ for $m = 1,2, ..., S$. Note that, $\mathcal{B}_m^t$ is generated only form $\mathcal{A}_m^t$ otherwise the modification will be the meaningless. In order to modifying the elements as $\mathcal{A}_m^t$ to create $\mathcal{B}_m^t$ elements while $m \ne n$, then we define the modification cost as an infinite. The transformation matrix for cover image under the multi-transformation matrix is represented in Equ. (17) and $d_w(a, \mathscr{b})$ shows the element in ath and $\mathscr{b}th$ of row and column of $\mathcal{D}_w$.

$$\mathcal{D}_w = \begin{pmatrix} \mathcal{D}_1 & \cdots & \infty \\ \vdots & \ddots & \vdots \\ \infty & \cdots & \mathcal{D}_S \end{pmatrix} \tag{17}$$

Where, $\mathcal{D}_m$ is defined in Equ. (18).

$$\mathcal{D}_m = \begin{bmatrix} d_m((m-1)i, (m-1)j) & d_m((m-1)i, (m-1)j+1) & ... & d_m((m-1)i, mj-1) \\ d_m((m-1)i+1, (m-1)j) & d_m((m-1)i+1, (m-1)j+1) & ... & d_m((m-1)i+i-1, mj-1) \\ \vdots & \vdots & \vdots & \vdots \\ d_m(mi-1, (m-1)j) & d_m((mi-1), (m-1)j+1) & d_m(mi-1, mj-1) & \end{bmatrix} \tag{18}$$

By creating the histogram based transformation matrix, we convert the stenographic problem under the multi-transformation matrix. The created transformation matrix can be represented in the single transformation matrix as $\mathcal{D}_w$. The optimization problem is converted by the help of equ (11) into the equ (19).

$$minimize \frac{\sum_{a=0}^{Si-1}\sum_{\mathscr{b}=0}^{Sj-1}\mathcal{P}_{\mathcal{A}_w}(a)\mathcal{P}_{\mathcal{B}_w|\mathcal{A}_w}(\mathscr{b}|a)d_w(a, \mathscr{b})}{L} \tag{19}$$

$$\mathbb{H}(\mathcal{B}_w) = \mathbb{R}_e + \mathbb{H}(\mathcal{A}_w)$$

In Equ (19), the same problem is define in Equ (3). Hence, we evaluate the DPE and optimal transformation as $\mathcal{P}_{\mathcal{B}_w|\mathcal{A}_w}(\mathscr{b}|a)$ and $\mathcal{P}_{\mathcal{B}_w}(\mathscr{b})$. By introducing the infinite transformation in optimal modification, which causes the minimal transformation, the $\mathcal{A}_m^t$ elements is not modified to $\mathcal{B}_m^t$ elements for $m \ne n$. The corresponding DPE between $\mathcal{A}_m^t$ and $\mathcal{B}_m^t$ are zero and DPE $\mathcal{P}_{\mathcal{B}_w|\mathcal{A}_w}(\mathscr{b}|a)$ has the following form as;

$$\mathcal{P}_{\mathcal{B}_w|\mathcal{A}_w} = \begin{bmatrix} \mathcal{P}_{\mathcal{B}_1^t|\mathcal{A}_1^t} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathcal{P}_{\mathcal{B}_S^t|\mathcal{A}_S^t} \end{bmatrix} \tag{20}$$

Where, $\mathcal{P}_{\mathcal{B}_m^t|\mathcal{A}_m^t}$ is defined in equ (21) and $\mathcal{P}_{\mathcal{B}_w|\mathcal{A}_w}(\mathscr{b}|a)$ shows the xth row and yth column of $\mathcal{P}_{\mathcal{B}_w|\mathcal{A}_w}$.

After getting the optimal transformation $\mathcal{P}_{\mathcal{B}_w}$ and DPE $\mathcal{P}_{\mathcal{B}_w|\mathcal{A}_w}$, the allotted payload for each sub-image is defined to optimally transform the respective S sub-images based on the DIDC methods. At the end, DIDC requires to perform the S times. Certainly, we can also implement the DIDC to the cover image $\mathcal{A}_w$ to embed the messages and create the stegno images $\mathcal{B}_w$according to the $\mathcal{P}_{\mathcal{B}_w|\mathcal{A}_w}$. After getting the $\mathcal{B}_w$, we require to retranslate each of the translated stegno sub-images $\mathcal{B}_m^t$ for $m = 1,2, ..., S$ by the corresponding off-set $o_{\mathscr{b}m}$ to generate the ultimate stegno images $\mathcal{B}$.

1.5 Optimized Embedding Message through optimal coding

We have introduced the general framework for computing the DPE of stenographic algorithm within the multi transformation Matrix, allowing us to embed the message through optimal coding. The introduced framework can be implemented in several forms as implementation of stenographic that approaching the rate distortion bound under the multi-transformation matrix the following step is given as follows:

STEP-1: In order to preserve the elements of host-signal to create the cover image and embed the auxiliary information $\mathcal{A}$ form the residual elements. The given auxiliary information embedded into LSBs (Least-Significant-Bits) of residual elements under LSBs.

STEP-2: The cover image is parted into the S classes according to the transformation matrix and get the sub-images.

STEP-3: In order to translate each sub-image by the help of corresponding offset to normalized the host-histogram to create the host-PD.

STEP-4: Create the histogram based transformation matrix as $\mathcal{D}_w$.

STEP-5: In order to embed the messages with stenographic to create the stegno image.

STEP-6: Retranslate the stegno images by the help of corresponding offset to generate the ultimate stegno image.

STEP-7: Embed the auxiliary-information into LSBs of the reserved elements, primarily underflow/overflow location map pixels as cover-histogram, number of classes and embedding rate.

1.6 Extracting the message through optimal coding

STEP-1: Remove the auxiliary information from reserved elements and consisting the underflow/overflow location-map pixels as host-histogram, number of classes and embedding rate.

STEP-2: in order to parted the stegno image into the given classes according to the transformation matrix and get the stegno sub-image.

STEP-3: in order to translate the each stegno sub-image by the help of corresponding off-set and integrate the outcomes to create the stegno image.

STEP-4: based on the embedding rate and constructed $\mathcal{D}_w$ as the parameters, compute the DPE. Utilizing decode as stegno image to restore the cover image and remove the stegno image.

Step-5: In order to retranslate each cover image by the help of corresponding off-set to reconstruct the cover image. Finally, reconstruct the reserved elements on the basis if removed LSBs.

IV. PERFORMANCE EVALUATION

In this section, the experiments were conducted on gray-scale images as 10,000 with the dimension of 512*512 pixel, which is taken from the standard database as BOSSbase 1.01 [33]. The experimental results were implemented by using Matlab. We compare out outcome with existing methods, which is totally based on BPP and the resultant value of our proposed method provides the capacity of hiding with regards to the RDB (Rate-Distortion-Bound).

1.7 BPP

The embedding-capacity of our proposed method is calculated as total-number of Secret-bits inside the stegno image. Total rate of BPP is defined in Equation (21), where $\mathcal{H} \times \mathcal{W}$ is the height and weight of the image.

$$BPP = \frac{Embedding\ Cpacity}{\mathcal{H} \times \mathcal{W}} \qquad (21)$$

The hiding capacity of our proposed method is compared with state-art-of-methods such as HUGO-BD, S-UNIWARD, WOW, MiPOD, HILL, and NMF in which our proposed method gives better quality of image after hiding the data at the embedding payloads as 0.1, 0.2, 0.3, 0.4 and 0.5 BPP. Below Table 1 and Table 2 represents the SRM based steganography and Max-SRM based steganography at various embedding payload from 0.1 to 0.5 BPP.

1.8 Comparative analysis

1.8.1 Image based comparison

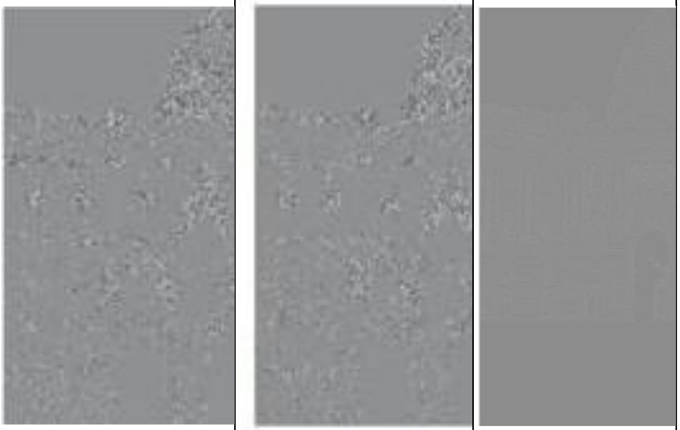
In order to evaluate the effectiveness of our proposed method, we compared with several state-art-of methods such as HUGO-BD, S-UNIWARD, WOW, MiPOD, HILL, and NMF at various embedding-payloads at 0.4-BPP. Below Table-1 shows the effectiveness of our proposed method in comparison to the other existing method and Table-2 shows better security performance in comparison to HILL and NMF. As we can see that in Figure-2, the HUGO-BP embedding too much obvious at edges, S-UNIWARD embedding is very poor at the regions of cover image by the textured regions, whereas, MiPOD embeds the secret data in both of the smooth and texture regions. HILL has higher embedding probability in the texture regions and NMF embeds the secret information in the texture regions whereas our proposed method perfectly embeds the secret data in comparison to the other methods.

(a) Cover Image

(b) HUGO-BD

(c) S-UNIWARD

(d) HILL



(e) MiPOD (f) NMF (g) Proposed method

Figure 2: the above figure represents the visualization of embedding changes that made to cover image at payloads of 0.4 BPP, (a) cover image, (b) HUGO-BD, (c) S-UNIWARD, (d) HILL, (e) MiPOD, (f) NMF and (g) Proposed Method

1.9 Feature set comparison

Further in order to evaluate the DIDC model, we consider the feature set comparison namely SRM (Spatial Rich Models) [35], SRM is steganalysis feature which is formed through the high order statistics gathered from the noise residuals (image). SRM features of different image totally differ from the other and the main characteristics of SRM feature is that the difference between the stego image and the cover image is nominal. In the above two feature set the error detection rate is considered for comparison. Higher value of error detection rate suggests higher efficiency of model. Moreover error detection rate value is comapared by varying the BPP and it is observed that DIDC model achieves the higher value than the any state-of- art technique in table 1. Meanwhile for different BPP i.e. 0.1, 0.2, 0.3, 0.4, 0.5 SRM value achieved by DIDC model is 0.4588, 0.4559, 0.3600, 0.2950, 0.2200 respectively. Furthermore, the comparative analysis shows that our model outperforms the existing model.

Table 1: SRM based steganography at different embedding payloads

Steganography methodology	Embedding payloads (BPP)				
	0.1	**0.2**	**0.3**	**0.4**	**0.5**
HUGO-BD [27]	0.3618	0.2967	0.2361	0.1949	0.1537
S-UNIWARD [28]	0.4020	0.3202	0.2609	0.2073	0.1637
WOW[29]	0.4034	0.3180	0.2555	0.2059	0.1691
MiPOD[30]	0.4150	0.3442	0.2893	0.2398	0.1969
HILL[31]	0.4319	0.3579	0.2963	0.2459	0.2061
NMF[32]	0.4326	0.3592	0.3002	0.2471	0.2067
DIDC	**0.4588**	**0.4559**	**0.3600**	**0.2950**	**0.2200**

Similarly by considering the selection CA (Channel Aware)-Feature set maxSRMd2 [34] in table 2 by varying the embedded payloads. DIDC model observes the value of 0.4529, 0.4500, 0.3400, 0.2950 and 0.2350 for 0.1, 0.2, 0.3, 0.4 and 0.5 when compared to the value of existing model 0.3797, 0.3166, 0.2644, 0.2238 and 0.1881 respectively.

Table 2: MaxSRM based Steganography at different embedding payloads

Steganography methodology	Embedding payloads (BPP)				
	0.1	**0.2**	**0.3**	**0.4**	**0.5**
HILL	0.3764	0.3094	0.2594	0.2176	0.1828
NMF	0.3797	0.3166	0.2644	0.2238	0.1881
DIDC	**0.4529**	**0.4500**	**0.3400**	**0.2950**	**0.2350**

1.10 Feature Set set ROC (Reciver Operating Characteristics)

The ROC-curve is the performance-metric which is utilized to estimate discriminative ability of the binary clasiifier. This curver is generated by plotting the TPR (true-posive-rate) against the FPR (false-positive-rate) at different types of threshold value. Below figure 3 and 4 represnts the ROC at embedding payloads at 0.3 BPP of SRM. Where as in figure 5 and figure 6 represnts the ROC at embedding payloads at 0.3 BPP of Max_SRM. Similalry Figure 5 and Figure 6 presents the ROC for maxSRMd2 with the payload of 0.3 and 0.5, the AUC observed for both payload is 0.7411 and 0.8499 respectively.

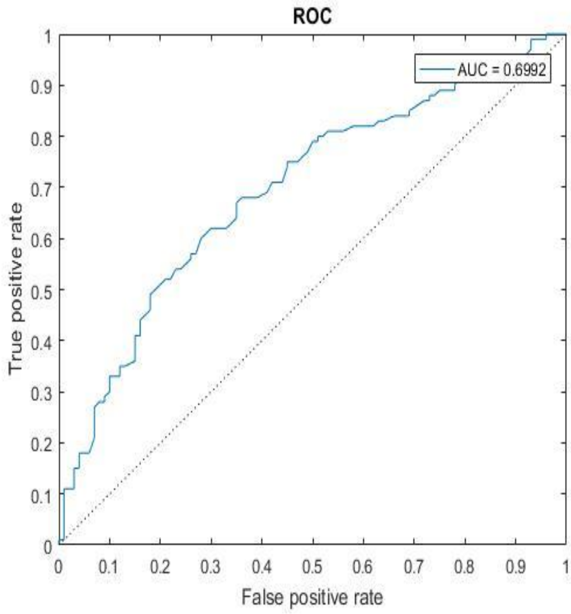


Figure 2: ROC at embedding payloads at 0.3 BPP of SRM

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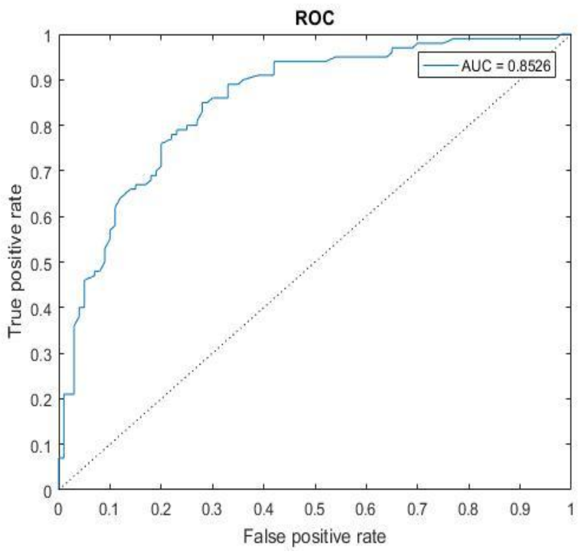

Figure 3: ROC at embedding payloads at 0.5 BPP of SRM

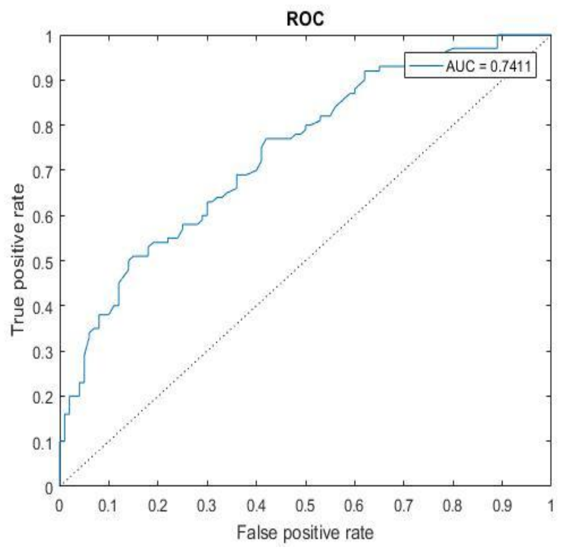

Figure 4: ROC at embedding payloads at 0.3 BPP of Max_SRM

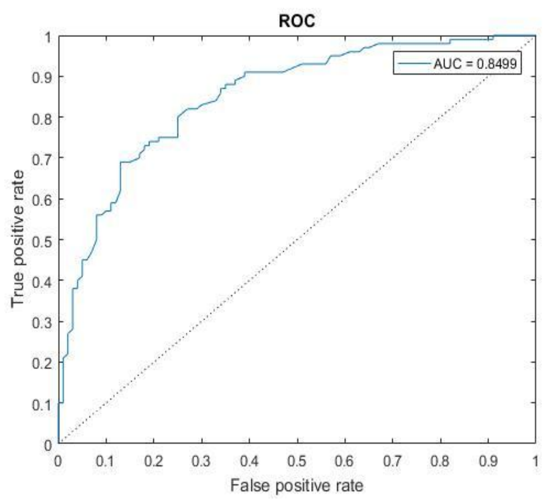

Figure 5: ROC at embedding payloads at 0.3 BPP of Max_SRM

V. CONCLUSION

In the research work, we propose an adaptive steganography technique named as DIDC, the proposed framework helps in the problem of stenographic rate-transformation under the multi-transformation matrix and represents the unified framework in order to evaluate corresponding DPE, which consists framework under the consistent transformation matrix and treated as the special case. Further, the proposed model is evaluated by considering standard database as BOSSbase 1.01. the comparison takes place in three different segment, at first we compare the setgno image later by considering the two distinctive feature set i.e. SRM and maxSRMd2 we compare the error detection rate by varying BPP value of 0.1, 0.2, 0.3, 0.4 and 0.5 and . The comparison analysis shows the in terms of error detection rate; proposed DIDC model outperforms the state-of-art technique along with existing NMF model. At last, we also plot AUC by varying payload value as discussed earlier, the AUC value observed for 0.3 and 0.5 is 0.6992 and 0.8526 for SRM feature set. In case of feature set MaxSRMd2 the AUC observed for 0.3 and 0.5 is 0.7411 and 0.8499. Image steganography plays an important part in transmission of data, our proposed does achieve the significance growth, however still there are lot of areas that needs to be focused and can be optimized further.

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