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StegNet: An Efficient CNN based Steganlyzer

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Abstract— The objective of Image steganalysis is the detection of presence of hidden content in any given image. Steganalysis is a binary classification problem for classifying a given image into one of two classes either Stego or Cover. Conventional Steganalysis consisted of a two step method, feature extraction followed by classification using machine learning. This feature extraction process required an in-depth knowledge of image statistics which are affected by hiding the secret data. With the advent of Deep Learning, Convolution neural networks(CNN) are being widely used for image classification, with an advantage of automatic feature learning. CNN based Steganalysis methods have made the feature extraction step simple as the steganalyzer does not need to specify the features which are affected by data hiding. Added to this feature extraction step and classification step are integrated into a single step. In this paper we have reviewed the existing CNN based steganalysis methods and proposed a novel CNN architecture customized for the task of steganalysis named StegNet. StegNet is built based on deep residual learning. And each feature map is assigned a weight to determine the priority by using global average pooling.

Keywords—Steganalysis, feature leaning, CNN, Steganography, residual learning,

I. INTRODUCTION

Steganography is the process of hiding a secret message in any carrier. After the Internet revolution, due to the proliferation of Social media networks digital images are being widely used as the carriers for sending secret messages. The reason for use of images as carriers is that the images contain redundant information in their pixels, which can be readily manipulated to hide the information. The aim of steganography is to conceal the very presence of secret information.[1][2]. Steganalysis is the counterpart of steganography, which aims at detection of the presence of steganographic content in a given cover or carrier such as image, text, video etc.,[3]. Steganalysis techniques can be broadly divided into two categories, Targeted steganalysis techniques and Universal steganalysis techniques. Targeted steganalysis techniques are designed to attack a particular steganographic scheme, whereas Universal steganalysis techniques are designed to detect stego content in images irrespective of steganogrpahic method used to embed the secret data. Inevitably Targeted steganalysis techniques are more efficient in detection accuracy but they are limited in their applicability and scope. Universal steganalysis techniques which are also called Blind steganalysis techniques, though less efficient in comparison, they are supposed to perform well against any sort of steganographic scheme.

In this article we have :

1. Reviewed various steganalysis techniques based on Convolutional Neural Networks; and
2. Proposed a customized CNN architecture based on enhanced residual learning named it as StegNet.

Rest of the paper is organized as follows, Section II contains the overview of traditional steganalysis, Section III contain the limitations of conventional steganalysis, Section IV introduces the Convolutional neural networks followed by section V reviewing the CNN based steganlysis schemes, Section VI describes the proposed StegNet Architecture, Section VII presents the experimental details and results and Section VIII concludes the proposed research work.

II. CONVENTIONAL STEGANALYSIS

In general Steganalysis can be viewed as a binary classification problem which deals with classifying a given image belonging to one of the two classes, cover or stego. Huge number of techniques have been proposed for the image steganalysis problem in the literature. Most of these methods fall into a two step process. The first step is generally called as feature extraction step. In this step a set of features are handpicked by the steganalyzer, which are supposed to be sensitive to the data embedding. Selection of these features and design of this feature extraction requires a great deal of domain knowledge of image statistics and steganographic schemes. These features are assumed to be capable of capturing the noise created by the steganography. Some of the features that were used for steganalysis in the recent past are Image Quality Metrics[4], wavelet based statistics [5] [6] [7] [8] [9] [10] [11][12][13] [14], cooccurence matrices[15] [16] [17], Histogram features[18], features from DFT of the histogram of differential image[19], Histogram Characteristic function [20], Binary similarity measures[21], contourlet transform features[22], statistical moments of contourlet transform featues[23], Markov and DCT feature set [24]. Subtractive Pixel Adcency Matrix(SPAM)[25] used second order Markov features of adjacent pixels to reliably detect the LSB Matching steganography(LSBM). Spatial Rich Model(SRM) combining various cooccurence matrices to form a feature vector[26] and has proven to be the most effective model for steganalysis surpassing the efficiency of all other previous models. Project Spatial Rich Model(PSRM)[27] projects noise components into many predefined directions to capture various histogram features.

The second step in conventional steganalysis, is classification based on machine learning. Classification involves training a classifier with the features extracted. Various classifiers used for the task of steganalysis are Support Vector Machine(SVM)[40], Bayesian, Artificial Nerual Network, Fisher Linear Discriminator, Linear Discriminant Analysis, etc. Combination of SRM and Ensemble of base classifiers[26] is proved to be the most effective classifier in conventional steganalysis domain with the combination of SRM model for feature extraction.

III. LIMITATIONS OF CONVENTIONAL STEGANALYSIS

Though many advances can be observed in feature extraction techniques from Image quality metrics [4] to Rich Models [26], selecting the effective features which is done manually is not a trivial task and requires a great of deal of expertise and domain knowledge. As steganography leaves only a weak noise in the cover image, steganalyzer has to meticulously pick features from image statistics, which are affected by this weak noise. Selection of these image statistics as features is highly difficult because image statistics are affected by many factors such as image pre-processing, in-camera processing and contents of the image. With many advances in modern steganography it is harder to model the features that are affected by the data embedding. And as the feature extraction and classification are done separately, optimization of these two steps cannot be done simultaneously. Any inference from the classification step cannot be used to improve the feature selection process and similarly any information lost in feature extraction step cannot recovered in the classification phase[28][29]. Moreover the vast dimensionality of feature vector is another major problem with conventional steganalysis.[30]

IV. CONVOLUTIONAL NEURAL NETWORKS

Similar to Artificial Neural Networks, Convolution Neural Networks are also biologically inspired. The visual cortex of brain consisting alternate layers of simple and complex layers is the inspiration to Convolutional Neural Networks(CNN) model. The major building blocks of a typical CNN are convolution layer, pooling or sub-sampling layer, and non-linear activation layer. These are grouped into modules of CNN and all these modules are followed by one or more fully connected layers. The fully connected layer outputs the class label. The objective of convolution layer is to extract the relevant features by using convolution filters. We can define number and size of convolution filters for a single input image. And the input image is convolved with a filter kernel to obtain feature map, which combines convolutions with multiple input feature maps. Initially the weights in the convolution filter are initialized randomly. The convolutional structure consists of the concepts of local regions and shared weights. Using local regions, low level features are obtained by applying same parameters in different neighbouring input feature map. Feature maps are obtained from neurons in the convolution layers and each neuron has a receptive field and is connected neighbouring neurons from previous layers through a set of trainable weights. Weights are learned and inputs are convolved with these learned weights to compute a new feature map and the convolved features are subjected to a nonlinear activation function. The k^{th} output featuremap Y_k can be computed as $Y_k = f(Wk * X)$

Pooling or subsampling reduces the dimensionality of feature maps without much loss of the information. Pooling reduces the spatial resolution, obtaining spatial invariance to spatial translations and input distortions. Two variants of pooling are in use, one is max pooling which outputs the maximum value of each 2x2 region and average pooling which outputs the rounded average integer value of the same region.

Non-linear functions have degree more than one and have a curvature when we plot a Non-Linear function. Applying a Non-linear activation function to the output of convolution facilitates the extraction of non-linear features. Sigmoid and hyperbolic tangent functions have been the traditional choice as activation function. ReLU, rectified linear unit and its variants truncated ReLU, leaky ReLU etc., have been the most successful activation functions for classification in the recent years.

Fully Connected Layer: A stack of several convolutional, pooling layers and activation layer extract more abstract features. This stack is followed by one or two fully connected layers translate these feature representations and perform function of high level reasoning. In classification problems softmax operator is used in fully connected layer.

V. REVIEW OF CNN BASED STEGANALYSIS TECHNIQUES

Though the Deep learning and CNN based image classification techniques have been highly successful in computer vision related tasks from the year 2012, those techniques have been used for steganalysis in the year 2014 by Tan and Li [31]. They proposed the use of convolutional auto-encoders to build an effective CNN for the task of steganalysis. They designed a nine layer, three stage CNN with Stacked Convolutional Auto Encoders (SCAE) for blind steganalysis. In spite of pre-training by SCAE the detection error rate observed in this method was relatively too high(31%) when compared to the state of art SRM method(14%) [15].

Because feature learning is done automatically in deep learning the steganalyzer's task may seem to be trivial in deep learning based steganalysis. But there are subtle differences between classification in computer vision tasks and steganalysis tasks. The CNN models used for general image classification tasks were not much successful in capturing the weak noise created by steganography, as these models focused more on capturing the image content rather than the noise content. Qian et al.[28] developed a customized CNN for steganalysis named as Gaussian-Neuron CNN(GNCNN). Images of size 256X256 are used as input to the CNN. A high pass filter is used for input images to enhance the stego noise. The 5X5 KV kernel is used for image pre-processing. The convolution operation in each convolution layer hierarchically captures dependencies among a large neighbourhood making an accurate prediction. The Gaussian function $f(x) = e^{\frac{-x^2}{\sigma^2}}$ is used as non-linear activation function followed by average pooling. Bossbase v1.01 is used and 256 features are obtained in total and passed into a series of three fully connected layers. Though the detection error rate was 2-5% higher than the SPAM and SRM steganalysis models this attempt has changed the whole scenario of steganalysis and opened many doors for more effective steganalysis techniques.

Xu et al. [35] introduced CNN architecture which incorporated domain knowledge of steganalysis in training. They used the same high pass filter which was used by Qian et al. [28]and Tan and Li [31]. Five groups of convolutions are used in this architecture. Each group contained convolution, non-linear activation and average pooling. Hyperbolic tangent (TanH) non-linear activation function is used for the first two groups and Rectified Linear Unit(ReLU) is used for the next three groups of convolutions. Batch Normalization was employed before the non-linear activation in each group to avoid poor local minima. Group-5 uses global average pooling, producing 128-D features and passing them to the fully connected layer. Stego images from HILL and S- UNIWARD[34] were considered for training and testing. The proposed CNN performance was superior compared to the state of the art SRM[26]model with 0.4bpp stego images. Qian and Dong[36] used the feature representation learned with high payload steganographic images to improve the learning of feature representation in case of low payload steganographic images. By using this transfer learning they could achieve better detection rate for WOW steganographic images. The CNN architecture proposed by Qian et al.[28] is used in this case. [37] Couchot et al. [37] have taken up a peculiar scenario of steganography where the same stego key is reused in embedding process. Qian[29] in 2017 published an extensive work on CNN based Steganalysis. Domain knowledge of Steganalysis is incorporated in the CNN by enhancing the stego noise by high pass filtering and by exploiting the inter pixel dependencies.

VI. PROPOSED STEGNET

We have proposed a novel CNN architecture which we named as StegNet, which is customized for the task of Steganalysis. This architecture is built based on residual learning. Though the CNNs were highly successful in computer vision related tasks from the survey in the previous section it was evident that CNNs were not that successful in case steganalysis. Many CNN based steganalysis techniques were inferior in their performance, when compared to the machine learning based traditional SRM model[26]. This may be the result of the fact that CNNs were successful in recognizing the image content but could not capture the weak noise signal created by steganography. He et al.[38] proposed a deep CNN frame work with less computational complexity to train, using identity mapping. This was called residual learning. It was proved that residual learning facilitates large number of layers in the CNN with less computational complexity [38]. Residual is the offset we should add so that our prediction matches the actual value. Let H(x) be the output of a block in ordinary CNN consisting a cascaded of convolution, non-linear activation function, pooling or batch normalization.

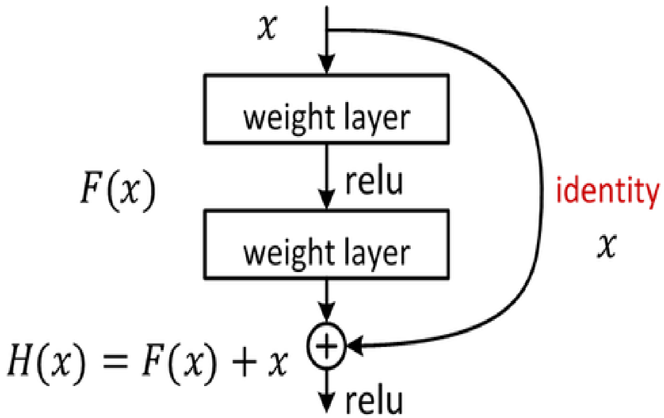

Figure 1. *Residual mapping*

In residual learning instead of directly approximating H(x), residual learning fits the residual F(x) such that F(x)= H(x)- I(x) where I(x) is identity mapping I(x)=x and F(x) is the mapping the network layers could achieve according to their inputs. This architecture resembles the phenomena of Steganalysis in which

Stego image = Cover Image + Secret message
Pure image = Cover Image + 0

Cover image can be considered as an identity mapping function and the residual may be fitted as either secret message or zero. And Secret message can be detected with higher certainty in case residual learning than in other CNN based steganalysis techniques. As the residual network architecture is strongly similar to the steganalysis, we firmly believe that these residual networks yield better performance for detection stego images than any other convolutional neural networks such as LeNet, AlexNet, inception, VGGnet, etc., which are in use for image classification .

The proposed architecture consisted three major blocks. 1. Pre-processing of Input Images 2. Convolution Phase 3. Classification with fully connected layers.

In pre-processing phase a high pass filter is used to capture the weak noise created by steganography. The purpose using this kernel is to capture the stego noise so that detection of stego signal will become easy for Network. The steganographic methods introduce only a slight change in the pixel values of cover image. Hence the stego noise pattern is very weak and hard to capture. The use of high pass filter for pre-processing suppresses the image content and enables the CNN to capture the noise component. By this the learned feature representations will be more sensitive to the stego noise. Without the mandatory high pass filtering, it was found that CNN would not converge.

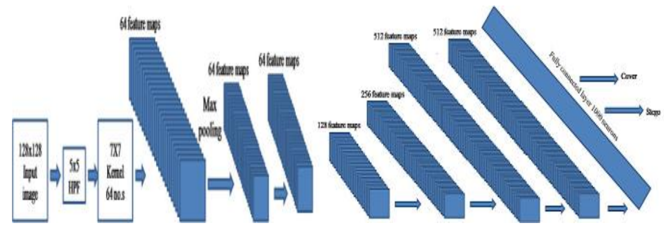

Figure 2. *StegNet Archiecture*

The proposed StegNet consists of five blocks. Each block consists of convolution, Batch Normalization and ReLU activation. In the first block convolution is performed with of 64 kernels of size 7x7. ReLU activation, maximum pooling and Batch Normalization follow the convolution. Each pair of convolutions has a skip connection with identity mapping. he second block consists of three pairs of convolution layers with 64 kernels, each of size 3x3. In the third block four pairs of convolutions with 128 kernels of size 3x3. The fourth block contains the 12 convolutional layers with each with 256 kernels. And finally block of the CNN consists of 6 convolutional layers each with 512 kernels of size 3x3. There are two categories of blocks one is ordinary block where the dimensions of output are same as input. In the second category dimensions increasing blocks the output dimensions are doubled using padding. In normal CNN all the feature maps are given equal weight where as in our proposed network with a queue from Squeeze and Excitation networks[39], we have added a weight to each feature map by global average pooling. The idea here is to add weight to the feature maps produced from convolutional layers so that the network uses this weight of each channel effectively. Each channel is added a weight adaptively. Then each cannel is squeezed into a single numeric value using average pooling and two fully connected layers one with ReLU non linear activation function another with Sigmoid activation function. At each non-identity residual each feature map is associated with a weight which is calculated by performing max pooling over the entire feature map. This value is used as a descriptor to indicate the weight of a feature map in the network. These channel descriptors are subjected to ReLU activation function followed by Sigmoid activation function. Based on these values the input is scaled back to original dimensions as from the residual block. This modification to regular residual CNN is expected to learn the features effectively as only the feature maps that are effective are selected for training.

VII. EXPERIMENTAL RESULTS

The image dataset used for the experimentation and results is BOSSbase1.01version, because this database is the most widely used in the recent years by all the steganalyzers. It consists of 10000 gray scale images. we have generated

160000 non overlapping images, each of size 128x128 using crop function. We generated 120000 stego images using Highly Undetectable steGO (HUGO) with 0.4 bit-per-pixel payload. StegNet is trained with 120000 pairs of cover and Stego images and remaining 40000 pairs are used for testing. The learning rate is fixed at 0.001, momentum at 0.9 and weight decay 0.0001. SGD with mini batch size 10 is used. All the experiments are performed on NVIDIA GPU machine. The detection accuracy of the proposed StegNet is given in the table in comparison with state of art SRM model and DRN model for steganalysis[41]. It is clearly evident that the proposed StegNet performs better than the other two techniques.

Table 1. Detection Error rates at 0.4bpp payload

Method of Steganography	***SRM method***	***DRN method***	***StegNet***
WOW	20.1	4.3	2.8

VIII. CONCLUSION

We have built a customized deep CNN architecture for Steganalysis. Because of the novel modifications made to the regular CNN which includes residual learning and indexing feature maps with a weight the StegNet shows a better performance than the existing CNN based steganalyzers as well as conventional state of art SRM model. The detection error was reduced to about 65% compared to the error in residual learning method.

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