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Cavernous Erudition Hierarchical Representations for Image Steganalysis

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ABSTRACT

The prevailing detectors of Steganography communication in digital images mainly consist of three steps. Residual computation, feature extraction and binary classification. The alternative approach to Steganalysis using digital images based on alternative approach to Steganalysis using digital image based on Convolutional neural network (CNN). The proposed CNN has a different structure from the ones used in conventional computer vision tasks (CVs).this to replicate and optimize these key steps in unified framework and learns hierarchical representation from raw images. Steganalysis using three state of the art steganographic algorithms in spatial domain e.g. HILL is better than WOW and S-UNIWARD. Selection channel aware [SCA TLU-CNN] overcome the TLU-CNN methods.

Key words: Steganalysis, Convolutional Neural Networks.

I. INTRODUCTION

Image Steganography is the science and art to conceal secret messages in the image through slightly modifying the pixel values or DCT coefficients. Steganalysis using three state of the art steganographic algorithms in spatial domain e.g. HILL is better than WOW and S-UNIWARD. Corresponding to the development of image Steganography, substantial progress has also been made in steganalysis, with the aim of revealing the presence of the hidden message in images. Recently, to better cope with the emerging content-adaptive steganographic schemes with ever-increasing security, some selection-channel-aware Steganalysis feature sets, based on the rich media model and by utilizing the selection channel, the maxSRM improved the detection of all content-adaptive steganographic schemes in spatial domain to a varying degree. Currently the best image steganalyzers are built using feature-based steganalysis and machine learning and share the same pipeline: namely, noise residual computation, feature construction and binary classification. We are implemented the deep convolution neural network using pipeline steganalysis. This paper important property of CNN is that it can extract complex statistical dependencies from high-dimensional sensory input and efficiently learn deep (hierarchical) representations by re-using and combining intermediate concepts, allowing it to generalize well across a wide variety of computer vision (CV) tasks, including image classification, face recognition, and many others. We develop a supervised CNN model specific to Steganalysis applications. (1) The first layers in the proposed CNN serves as the pre-processing module for noise residuals computation. (2) we employ a set of hybrid activation functions in the proposed CNN , where, in addition to the conventional ReLU function, a new function called truncated linear unit(TLU) is introduced to the first few layers of the network.(3) we finally further boost the Steganalysis performance by making use of the selection channel in training of the proposed CNN. The effectiveness of the proposed CNN is verified with evidence from thorough experiments using several state-of-the-art steganographic tools for a wide variety of payloads.

II. PRELIMINARIES

A. The Framework of Prevailing Image Steganalysis Methods

The well-established paradigm of image Steganalysis consists of three major steps, noise residual computation, feature extraction and binary classification.

1) Noise Residual Computation

The embedding operation in Steganography can be viewed as adding extremely low amplitude noise to the cover. Therefore, it is wiser to model the noise residuals instead of raw pixels in steganalysis. This can be used to generate different residuals and capture different dependencies among neighboring pixels. The diversity of residuals is fundamental to the success of the so call Rich Media Models (RM).Residuals appear in many areas in mathematics, including iterative solvers such as the generalized minimal residual methods, which seeks solutions to equations by systematically minimizing the residual. The residual can be considered as a measure of deviation.

2) Feature Extraction

This is critical in steganalysis. With more discriminative features, it would be much easier to distinguish cover images from stego ones. In this step, the joint or conditional probability distributions of neighboring residuals are modeled through histograms or co-occurrences.for SRM and its several variants, the features are built on the basis of fourth order co-occurrence matrixes. In machine learning ,pattern recognition and image processing, feature extraction starts from an initial set of measured data and builds derived values intended to be informative and non redundant, facilitating the subsequent learning and generalization steps and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.

$$c^{h}_{d_0 d_1 d_2 d_3} = \sum_{i,j=1}^{n_1,n_2-3} \left[r_{i,j+k} = d_k, \forall k = 0,1,2,3 \right] \cdot \varphi(\beta_{i,j}),$$

$$d_k \in \{-Tq, (-T+1)q, \cdots, Tq\}$$

----------------------------------- eq.1

Many data analysis software packages provide for feature extraction and dimension reduction. In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning. Feature extraction is related to dimensionality reduction. The selected features are expected to contain the relevant information from the input data.

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3) Binary Classification

The final step of steganalysis is to classify an image as a cover or a stego using an elaborately designed classifier, which needs to be trained through supervised learning prior to practical application. It is the task of classifying the elements of a given set into two groups on the basis of a classification rule.

III. CONVOLUTION NEURAL NETWORK (CNN)

Convolution neural network is a class of deep feed forwarding artificial neural network that has successfully been applied to analyzing visual imagery. It operations convolution is a mathematical operation on two functions to produce a third function, that is typically viewed as a modified version of one of the original functions. The input and output of a Convolutional layer are sets of arrays called feature maps, while each Convolutional layer usually produces feature maps by a three-step process, convolution, non –linear activation and pooling. Pooling is the grouping together of resources for the purposes of maximizing advantages or minimizing risk to the users. The term is used in finance, computing and equipment management.

$$F^n(X) = \text{pooling}\,(f^n\,(F^{n-1}(X)_* W^n+B^n)),\text{---------------------Eq.2}$$

Imaging, image metadata an image is a visual representation of something. In information technology, the term has several usages. An image is a picture that has been creation or copied and stored in electronic from an image can be described in terms of vector graphics or raster graphics. An image stored in raster from is sometimes called a bitmap .An image map is a file containing information that associates different location on a specified image with hyper text link.

1) Image Resolution

Resolution refers to the number of pixels in an image. Resolution is sometimes identified by the width and height of the image and well on the total number of pixels in the image.

2) Hierarchical Representation

Having a structure consisting of multiple levels a hierarchical business structure would mean that the chain of command looks like a pyramid with a large base of workers, who are directly supervised by the smaller level above them who are in turn supervised by the level above them. Digital image represented to raster image or bitmapped image

Drawback of Existing System

Embedding in test image is the low performance of the signals. The different versions of SRM using different values for maxSRM, tSRM. It indicating the SVM (support vector machine) needs to supervised learning.

IV. PROPOSED SYSTEM

It overcomes the Existing system. HILL is better than WOW and S-UNIWARD. We are using TLU in Architecture Local Response Normalization (LRN), Batch Normalization (BN) and Local Contrast Normalization (LCN).TLU-CNN will decrease in non-linearity can still have comparable performance to ReLU.

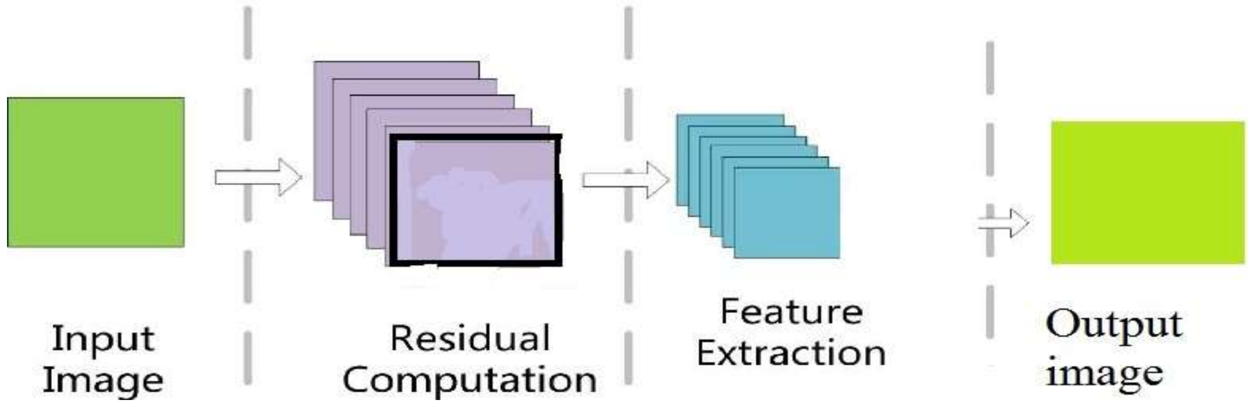

Figure 1. working process of the image steganalysis

Image Steganography is the science and art to conceal secret messages in the images through slightly modifying the pixel values (in spatial domain) or DCT coefficients (in JPEG domain). Nowadays, the most secure steganographic schemes are content-adaptive ones, which tend to embed the secret data in the regions with complex content where the embedding traces are less detectable. Corresponding to the development of image Steganography, substantial progress has also been made in steganalysis, with the aim of revealing the presence of the hidden message in images. Authentication is a process in which the credentials provided are compared to those on file in a database of authorized user's information on a local operating system or within an authentication server. If the credentials match, the process is completed and the user is granted authorization for access. The permissions and folders returned defines both the environment the user sees and the way he can interact with it, including hours of access and other rights such as the amount of allocated storage space. In machine learning ,pattern recognition and image processing, feature extraction starts from an initial set of measured data and builds derived values intended to be informative and non redundant, facilitating the subsequent learning and generalization steps and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. . The diversity of residuals is fundamental to the success of the so call Rich Media Models (RM).Residuals appear in many areas in mathematics, including iterative solvers such as the generalized minimal residual methods, which seeks solutions to equations by systematically minimizing the residual. The residual can be considered as a measure of deviation.

V. WOW ALGORITHM

We now describe our main contribution which is a new algorithm that combines the strengths of clock, a predominantly read cache algorithm, and CSCAN, an efficient write cache algorithm, to produce a very powerful and widely applicable write cache algorithm.The data structures and the algorithm. The destage operation proceeds as in CSCAN, wherein a destage pointer is maintained that traverses the circular list looking for destage victims. In CSCAN every write group that is encountered is destaged. We only allow destage of write groups whose regency bit is zero. The write groups with a regency bit of one are skipped; however, their regency bit is turned off, and reset to zero. The basic idea is to give an extra life to those write groups that have been hit since the last time the destage pointer visited them. This allows us to incorporate regency representing temporal locality on one hand, and small average distance between consecutive destages representing spatial locality. The simplicity of the algorithm is intentional so that it succeeds in real systems. The superiority of the algorithm to the current state-of-the-art should encourage its widespread use.

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```
CACHE MANAGEMENT POLICY:
Page x in write group s is written:
if (s is in NVS) // a write group hit
    if (the access is not sequential)
        set the recencyBit of s to 1
    endif
    if (x is in NVS) // a page hit
        set the recencyBit of s to 1
    else
        allocate x from FreePageQueue
        and insert x in s
    endif
else
    allocate s from
        FreeStripeGroupHeaderQueue
    allocate x from FreePageQueue
    insert x into s and s into the sorted queue
    initialize the recencyBit of s to 0
    if (s is the only write group in NVS)
        initialize the destagePointer to point to s
    endif
endif
```

Fig.2) WOW Algorithm

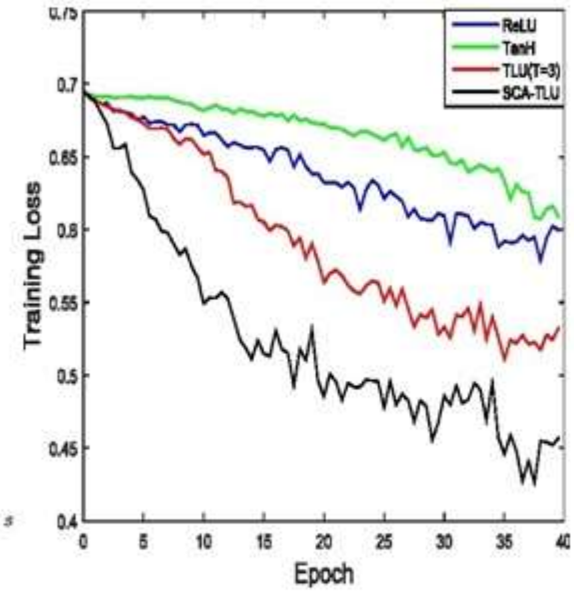

fig.3) output of wow Algorithm

Advantages of Proposed System

Selection Channel Aware [SCA TLU-CNN] overcomes the TLU-CNN method. S-UNIWARD decreases the error detection more than WOW technique. Decrease the performance loss. HILL provides the high resolution images.

VI. CONCLUSION

The steganalyzers contains residual computation, feature extraction and binary classification. It based on convolution neural network (CNN). CNN based steganalyzers able to simulate and optimize the keys in unified network architecture. It has slight different structure than designed for CV tasks. In this paper we used three algorithms. These are WOW, S-UNIWARD and HILL. This algorithm compared to SRM and its selection channel variant maxSRMD2. Here embedding signal have extremely low signal to noise ratio (SNR), a set of hybrid activation function is adopted in CNN model. TLU is introduced to first few layers of our network to adapt to distribution of the embedding signals. The performance of the proposed CNN is boosted by knowledge of selection channel.

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