Image Quilting in Steganography using Reversible Texture Formation

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Abstract - *It is an exclusive method or approach for a steganography, which is used for communication or sharing the private data with the help of multimedia carriers. There are many stenographic approaches available. The main goal of using stenography is to hide the data or secret data from the striker. This paper explains steganography in texture image. Texture formation or syntheses is a process in which we are first taking large texture image from a smaller texture image, we then merge texture synthesis image with steganography data to embed secret message and generate arbitrary size image and by using Image Quilting we can enhance the quality of the image and a simple image-based method of generating novel visual appearance in which a new image is synthesized by stitching together small patches of existing images. We call this process image quilting. First, we use quilting as a fast and very simple texture synthesis algorithm which produces surprisingly good results for a wide range of textures. Second, we extend the algorithm to perform texture transfer rendering an object with a texture taken from a different object. More generally, we demonstrate how an image can be re-rendered in the style of a different image. The method works directly on the images and does not require 3D information.*

Key Words: Steganography, Texture image, Data embedding, Texture synthesis, Image Quilting.

1. INTRODUCTION

Steganography is a method which is use for hiding a message, video, image, and file within another file, image, video or message. This word steganography is a combination of two Greek words steganos means protection and grapheins means writing. Benefit of steganography on cryptography is that the secret message does not attack the attention of the attackers by simple observation.

The cryptography protects only the content of the message, while steganography protects the both messages and communication environment. In most of the image stenographic methods, uses the existing image as their cover medium. This leads to two drawbacks. Since the size of the cover image is fixed, embedding a large secret message will results in the distortion of the image. Thus a compromise should be made between the size of the image and the embedding capacity to improve the quality of the cover image. The distortion of the image results in second drawback, because it is feasible that a steganalytic algorithm can defeat the image steganography and thus reveal that a hidden message is conveyed in a stego image.

This paper propose a good approach for steganography using reversible texture synthesis based on edge adaptive and tree based parity check to improve the embedding capacity. A texture synthesis process is of creating a big digital image with a similar local appearance of the original image and has an arbitrary size. And the paper is also using another two methods named edge adaptive and tree based parity check to improve the embedding capacity. In this paper steganography fabricates the texture synthesis procedure into secret message as well as the source texture. In particular, this procedure can be used on existing cove image to hide message. This algorithm uses process called as texture synthesis, in which secret message is embedded into the input source texture image. With the help of this process we can separate input source texture and secret message. The proposed approach offers three advantages. First, since the texture synthesis can synthesize an arbitrary size of texture images.

Until the Human Visual System (HVS) is less effective to changes in sharp regions compared to smooth regions, edge adaptive methods has been proposed to find the edge regions and hence improve the quality of the stego image as well as improve the embedding capacity and TBPC to hide the secret data into the cover image. Secondly, a steganalytic algorithm is not to defeat the steganographic approach since the texture image is composed of a source texture rather than by changing the existing image contents. Third, the reversible capability used in the project results in the recovery of the source texture so that the same texture can be used for the second round of message redirect.

2. REVIEW OF LITERATURE

2.1 Line-Based Cubism-like Approach

Currently, most popular theme is dynamic generation of art images which is creating images automatically. This type of methods produces an interest in computer operator[2]. Line based cubism, explains the algorithm known as stroke based rendering. This method is involuntary use to make the non-photo realistic type of imagery, and also uses the paint stroke and strippers methods to generate art images.

In this method we are using little or small tiles for examples circle, triangle, square and so on. All this type of small tiles is called as mosaic images. There are many types of art images, but mosaic image is one of the automatic generating art images, now the ting to arrange the tiles which belongs to the mosaic image, there is various type of arrangement available to create dynamic mosaic images. One of the methods is the stationary pattern method, but in this paper writer explains the arrangement of tittle by placing or by ordering the edges of input images.

This method generate the asphyxiate type of image. By using this method we can generate smooth image. When we try to paint the source images by using cubism method then that method is called cubism like line based method, and after this step there are other functions also ie. a) Extraction with help of prominent line. b) Extraction and recoloring of the tiles.

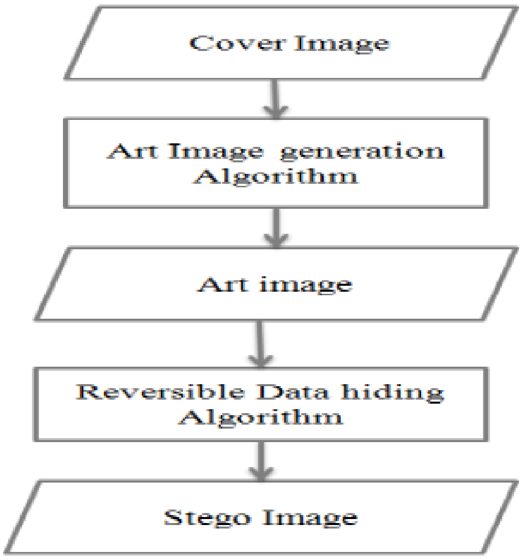

Fig -1: Diagram for Line-Based and Cubism-based approach

2.2 Markov Random Field (MRF) Method

This paper explains different type of duckbill algorithm with various texture formations. While implementing this algorithm, first the input will be any noise images and size can be change as per the user requirement. To make the sight duckbill image, this method or algorithm requires changes in dynamic nose image. This method requires sample of texture formation patches then it suit obsequious and sample to use. This method requires large time to create new texture and shape of a sample image.
In this algorithm there are two main and large pillars, first is search algorithm and other is the multi-resolution pyramid. Benefit of using this method or algorithm is to increases the speed of image processing with help of image quality:

This type of method gives many benefits like better quality of the synthesized texture image with respect to the existing techniques, it also increases the image processing speed twice and generate better order of magnitude as compare to existing results of the system. This method permits us to implement this system in application where synthesis texture is a very exclusive method. This procedure also inherits image editing and motion texture synthesis.

This procedure implements MRF method for generating texture models, since its verified that Markov Random Field is beneficial to remove the extensive type of texture forms. It does also improve the texture synthesis method to shun sampling. The Markov Random Field method uses every pixel categorized by its sets of surrounding pixels, and this method is same for every pixel in the image. While implementing MRF there are some terms and condition:

We have to check that the input image is local or stationary if the input image is local or stationary. If the input image fix between the given window size then that pattern will looks similar, then that of image is considered as stationary image and if the every pixel is simple to analyze from set of neighbouring pixels and totally different from the other image ten that image is called as local image. As based on the above condition, this method synthesis new image having same appearance and texture patch. To show the same or similar image new texture is created pixel by pixel. In the probability distribution synthesis method is not explicit and also not completely deterministic. This procedure is capable of giving high efficiency with more accelerating features.

3. SYSTEM ARCHITECTURE / SYSTEM OVERVIEW

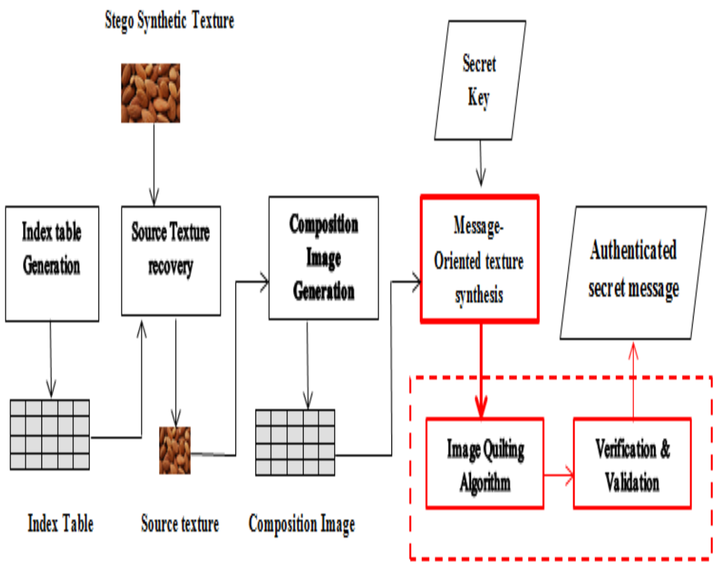

Fig -2: Architecture Diagram of the Texture Synthesis with Reversible procedure

This steganography is used to hide the secret message or post by using texture synthesis and its reversible method. The fresh texture input image is synthesized by using synthesis texture method. This process comprises o f lend of both steganography and texture synthesis process. The whole process comprises of two methods

- Embedding message method
- Message extraction method

This first method is use to separate input source image into dissimilar image block. Those chunks of images are called as patches. For recording thee location of those consistent source patches or original input patches we are taking help of index table generation method. There is also one unconditional image called as workbench, whose size is equal to the synthetic texture. And while recording the location of patches we are also allocating a patch ID. With the help of source patch ID which is been recorded into index table, we are again pasting those equivalent source patches on workbench; this procedure is called as composite image generation.

After doing the above procedure we have to find Mean square error (MSE) of those regions where the images are overlapped. Mostly overlapped areas are found between patch which we have insert into the workbench. And after that all the patches are rearranged as per the order of Mean square error (MSE). Finally the patch image is selected with respect to the given list in such a way that the patch rank is equal to the decimal value. This decimal value is also called as n- bit value of conceal or secret message.

At client location there is a creation of index table by using secrete key, that key client already have for every size of the input source texture we can also called as patch region and its equivalent order is directly mentioned in index table. After taking the block size manage a s per the equivalent order.

Authentication is the next step, where we are assuming the current location of workbench and equally the located of stego synthetic texture to analyses the block region of stego. This block region of stego is use to predict or to search the candidate list and to verify that is there any patch from candidate list having equal kernel region as the corresponding block region of stego. If such alike region of patches is originated, then the matched patch is given a rank. We can show the secrete bit value in a decimal value format. This above mentioned procedure is also called as extraction of message.

3.1 PROCESSING STEPS FOR THE SYSTEM

This reversible texture synthesis scheme has following steps:

1) Data collection (Consists any type of host medium),
2) Pre-processing (Index table generation, composition, message orientation)
3) Similar stego synthetic texture,
4) High-image quality (Image quilting, verification and validation)

1) Input Data Collection

All type of multimedia used for Reversible Texture Synthesis Systems are: Images (JPEG,GIF,PNG), Videos (MP4,MKV, FLV). Our main input which is given by user is a single Image as a query.

2) Index Table Generation

The first process is the index table generation where we produce an index table to record the location of the source patch set SP in the synthetic texture. The index table allows us to access the synthetic texture and retrieve the source texture completely.

3) Patch Composition Process

The second process of the algorithm is to paste the source patches into a workbench to produce a composition image. First, we establish a blank image as our workbench where the size of the workbench is equal to the synthetic texture. By referring to the source patches ID stored in the index table, we then paste the source patches into the workbench.

4) Message-oriented texture synthesis process

We will embed our secret message via the message oriented texture synthesis to produce the final stego synthetic texture.

5) Image Quilting

All these steps are applied on single query image. A simple image-based method of generating novel visual appearance in which a new image is synthesized by stitching together small patches of existing images. We call this process image quilting.

6) Output: Stego synthetic texture

After applying all the algorithms which are listed above, the output will be a Query image with same texture and embedd data into host medium

3.2 MATHEMATICAL MODEL

Let S be a system having Input (I), Functions(F) and Output(O).

$$S= \{ I; F;O \}$$

Where, I is a set of all types of multimedia files.

$$I = \{Images; Videos / Kw * Kh \} \text{ --(1)}$$

O is the set of Steganography Texture Synthesis

$$O = \{ MKw * MKh \} \text{ ---(2)}$$

F is the set of functions used for steganography using Reversible Texture Synthesis.

$$F= \{ F1; F2; F3 \}$$

F1 is a function for Index Table Generation

- Input: Patch Image / Kw * Kh
- Output: No. of patchs with Index values (TPn)
- Functions:

Where,
Tpw is the width dimensions of Index Table.
Tph is the height dimensions of Index Table.
F2 is a function for Patch Composition Process.

- Input:Tpw _ Tph
- Output:TPn ⍰ SPn
- Function:
  - EPn = TPn - SPn —-(4)

Where,
EPn is the Embeddable patches in the setgo synthesis texture.
TPn is the No. of patches in the synthetic texture.
SPn is the No. of source patches sub divided in the source texture.

F3 is a function for Message-Oriented texture synthesis.

- Input: TPn - SPn
- Output: TC
- Function:
  - TC = BPP * EPn * Eij —-(5)

Where,
TC is the Total Message embedding capacity Image Quilting Algorithm.
BPP is the Bit per Patch.
EPn is the No if embeddable patches in the stego synthetic texture.
Eij is the Minimum Error Boundary Cut.

3.3 THE IMAGE QUILTING ALGORITHM

The complete quilting algorithm is as follows:

- Go through the image to be synthesized in raster scan order in steps of one block (minus the overlap).
- For every location, search the input texture for a set of blocks that satisfy the overlap constraints (above and left) within some error tolerance. Randomly pick one such block.
- Compute the error surface between the newly chosen block and the old blocks at the overlap region. Find the minimum cost path along this surface and make that the boundary of the new block. Paste the block onto the texture. Repeat.

The size of the block is the only parameter controlled by the user and it depends on the properties of a given texture; the block must be big enough to capture the relevant structures in the texture, but small enough so that the interaction between these structures is left up to the algorithm. In all of our experiments the width of the overlap edge (on one side) was 1/6 of the size of the block. The error was computed using the L2 norm on pixel values. The error tolerance was set to be within 0.1 times the error of the best matching block.

4. SYSTEM ANALYSIS

4.1 DataSet

- First stored the admin face image into the database. Then create a training set of face images. The Capture images are the training set. It contains no. of images (M) for each person.
- Data is in the form of .jpg format
- Size of image : 0-10 KB

4.2 Hardware

1) Memory: 8GB
2) Processor: Intel (R) Pentium (R) CPU B950 @2.10 GHz
3) Hard disk: 64 GB

4.3 Software

1) Operating System: CentOs
2) Eclipse 4.2.2 and above

D. Performance Parameters

There are several mechanisms to determine or to analyze the image quality of the stego texture synthetic. In this paper we are using the following type of algorithm to define the performance parameters-

1) Mean squared error of the overlapped (MSEO)
2) Pearson Product Moment Correlation(PPMC)
3) Structural SIMilarity (SSIM)

4. RESULT

We collect our experimental results on a personal computer with an i7-2600 3.4GHz CPU and 4GB memory. We adopt four source textures for the results of our collection. Table III presents the total embedding capacity our algorithm can provide when different resolutions of the synthetic texture are produced by concealing various BPPs. It is interesting to point out that given a fixed number of BPP, the larger the resolutions of the source texture SwSh (9696 vs. 192192), the smaller the total embedding capacity (TC) our algorithm will offer (6160 bits vs. 5890 bits for 10 BPP). This is because the larger source texture will contain more source patches SPn (9 vs. 36) that we need to paste which cannot conceal any secret bits. This will reduce the number of embeddable patches (EPn) on the composition image (616 vs. 589), thus reducing the total embedding capacity. Nevertheless, we can employ larger BPP (11 vs. 14) in order to convey more secret messages (6776 bits vs. 8246 bits).

The maximal capacity provided by our algorithm is 34398 bits.

Capacity	PURE	4 BPP	5 BPP	8 BPP	10 BPP
192*193	1562	1680	1557	1680	1541
96*96	141	141	141	141	136
128*128	385	402	385	402	385

TABLE : COMPUTING TIME (SECOND).

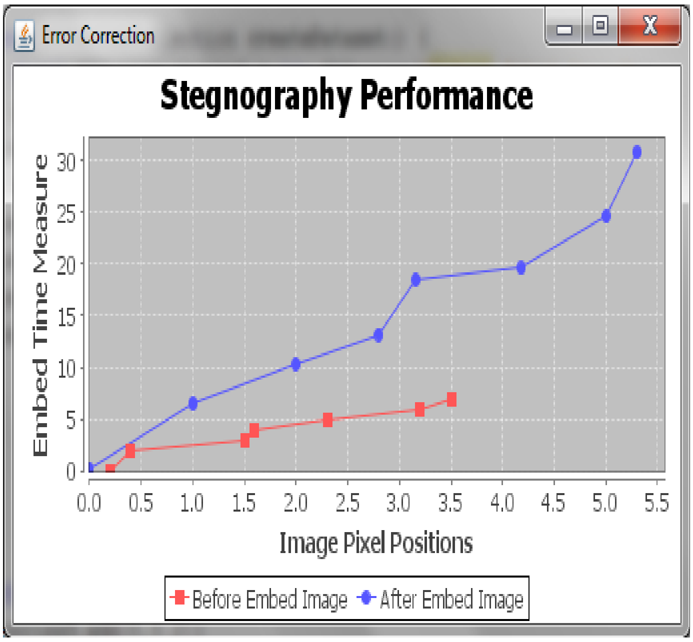

Chart -1: Stegnography Performance and Error Correction

The computing times of are shown in Table I. The range of the computing time is 6.8 percentage to 8.7 percentage more than that needed for pure texture synthesis. Nevertheless, our algorithm is flexible enough to provide a different embedding capacity by simply altering the patch size, satisfying the desirable capacity or texture quality demanded by users. Also, our algorithm can retrieve the source texture, making possible the second round of message embedding using the recovered source texture.

Algorithms	Rope Net	Metal	Peanuts	Ganache
MSEO	1565.3	1391.1	1236.9	556.2
PPMC	0.9991	0.9984	0.9974	0.9955
SSIM	0.28	0.26	0.07	0.15

TABLE : Algorithm Parameters For Image Quality Dataset

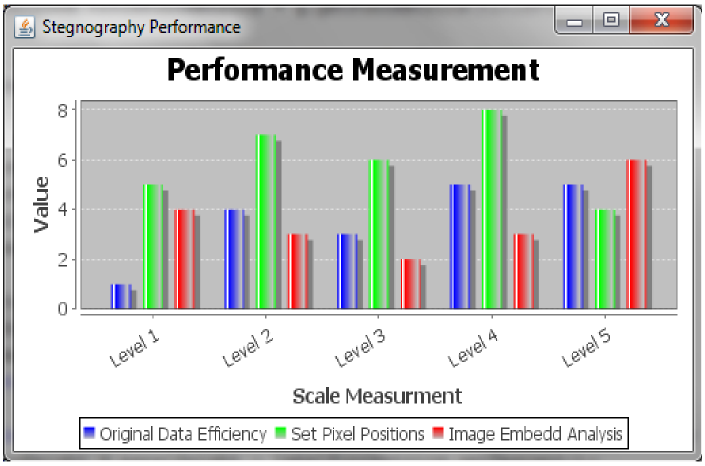

Chart -2: Parameters Measurement for image quality dataset

We use several mechanisms to determine the image quality of the stego synthetic texture. We define the first measurement, which is called the mean squared error of the overlapped area (MSEO) to determine the image quality of the synthetic results. MSEO reflects the similarity between the candidate patch and the synthesized area where we will specifically operate image quilting technique during the message-oriented texture synthesis process. Consequently, the MSEO has a nonzero value even in the case of the pure patch-based texture synthesis. If the MSEO produces a small value, it implies that the synthetic texture shows a high image quality of the overlapped area.

The second scheme we adopt for measuring the image quality is the Pearson Product Moment Correlation (PPMC). It is employed as a measure of how well two variables are related. The Pearson coefficient values that this scheme produces are between 1 and -1. A result of 1 means that there is a perfect positive correlation between the two variables, while a result between 0.5 and 1.0 represents a high correlation.

Next, we employ the SSIM (Structural SIMilarity) index to quantify the similarity between the pure and stego synthetic textures. The SSIM is an image quality assessment method for measuring the change in luminance, contrast, and structure in an image. The SSIM index is in the range of [-1, 1] and when it equals to 1, the two images are identical.

5. CONCLUSIONS

In this paper, there are some methods which are directly or indirectly meant for texture formation or texture synthesis. Few of them shows above, which uses art image techniques. Synthesis data or information and patches used for art images or in patch, different methods uses edge-graph which includes unlimited or infinite number of resolution which give advantage to big or large data into texture like spatial image. While doing or following the whole procedure there might be some exemplar in which, chance of using same data multiple time then this will be a drawback. Therefore this approach proposed have additional and more advantages capabilities like reversibility to extract the original image from given stenographic texture. We can also use this whole procedure on a single source image many time. The original image recovery is possible by using the above approach.

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