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# Improvement in Secure Mosaic Image Using Style Transfer

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## Abstract:

A secure transmission of Secret image method is proposed in which the style image is the target image and it is used for secret fragment visible mosaic image. The size of the Mosaic image is same as that of secret image. Style image is obtained by mixture of two images. Style image is obtained by Texture Synthesis. We follow the Michael Elad et al. process and to improve the quality of Style image Dual Domain Filter (DDF) is used. Mosaic image is created by dividing the secret image and target image into fragments of equal size and fitting these secret tile blocks into target blocks. For tile image hiding, a mapping sequence is generated using Genetic Algorithm (GA). This provides better clarity in the retrieved secret image. The quality of the original target image remains preserved while embedding the secret image. Therefore better security and robustness is assured. Embed these tile fragments into the target image based on the mapping sequence by genetic algorithm and permuted the sequence again by KBRP with a key. Color transformations are performed to make the mosaic image similar to the target image. After color transformation rotation is performed. Rotating each tile block into an optimal rotation angle with minimum root mean square error (RMSE) value with respect to its corresponding target blocks. For the recovery of the secret image from the mosaic image embed relevant information into the created mosaic image. Overflows/underflows in the transformed color values can also be handled by using this method. By using the same key and the mapping sequence, the secret image can be recovered.

*Keywords* **—**Image hiding, Mosaic image, Genetic Algorithm, Style transfer, texture synthesis, image segmentation, Dual Domain Filter, Key Based Random Permutation, Color Transformation.

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## I. INTRODUCTION

Style transfer is the process of migrating a style from one image (the Style-Image) to another (the Content-Image). The goal is to synthesize a new image which is an artistic mixture of content and style. In this work a novel style transfer algorithm that relies on the texture synthesis work of Elad et al[3]. This method is chosen because of its elegance, simplicity and excellent results.

One interesting positive feature is that if our algorithm is applied to an empty content-image it reduces gracefully to be Kwatra's classic texture synthesis algorithm. The results obtained using Elad et al. are visually pleasing containing rich and diverse hallucinated parts brought from the style while keeping the style essence of the content intact. In terms of the computational complexity, the most demanding part of the algorithm is the patch-matching that takes place in the very last full-resolution iterations. The image obtained is not much quality.

Image enhancement and reconstruction are important tasks in image processing. Images may be degraded by additive white Gaussian noise, by arbitrary method noise or compression artifacts. To improve such images, specialized tools are often developed for each type of degradation. Some image processing tools are generally potent to attack such problems. The bilateral filter (BF) and its variant, the joint-bilateral filter, have become popular tools due to their simplicity and effectiveness in removing named artifacts. Knaus et al.[10] algorithm is used for enhancing the image quality. The style image is sent to a Dual-Domain Filter (DDF) which is a simple but powerful image processing filter.

Both Dual Domain Image Denoising (DDID) and DDF combine bilateral filtering with wavelet shrinkage using local, windowed Fourier transforms. Intuitively, the two steps compensate the weaknesses of each other: the bilateral kernel masks out high contrast edges that may lead to ringing in wavelet shrinkage, and the local Fourier transforms detect and preserve low-contrast repetitive structures that the bilateral kernel would tend to blur away.

DDF interprets bilateral filtering and wavelet shrinkage as robust noise estimators in two different domains. Durand and Dorsey have already made the connection of the bilateral filter to robust statistics, but they did not consider the bilateral filter as a robust noise estimator. Our approach is also related to a more recent work of Knaus and Zwicker called Progressive Image Denoising (PID), where the authors made the connection of wavelet shrinkage to robust estimation of noise differentials. The iteration in PID, however, requires many small steps. In contrast, with DDF we often obtain better results in only few iterations.

The processed image is considered as the Target image and it is useful for transmitting the secret image through the internet for variety of applications. These images contain confidential or private information. Therefore, such information should be protected from leakages while transmitting through internet.

Now a day, different methods have been proposed for secure image transmission. We propose a technique based on Surya et.al.[23]. The two common approaches are image encryption and data hiding. Data hiding that hides a secret data into a cover images. So, no one can recognize the existence of the secret data. In this method, the data type of the secret message investigated is an image. Existing data hiding methods mainly utilize the techniques of LSB substitution, histogram shifting, difference expansion, prediction-error expansion, recursive histogram modification, and discrete cosine/wavelet transformations. On the payload of the cover image, an upper bound for the distortion value is usually set, in order to reduce the distortion of the resulting image.

The main drawback of the data hiding method is that, difficulty to embed a large amount of message data into a single image. The secret image must be highly compressed in advance, in order to hide a secret image into a cover image with the same size. Data compression operations are usually impractical for many applications like keeping or transmitting legal documents, military images, medical pictures, etc.

In this method, a mosaic image steganography is used to hide the secret image based on Genetic algorithm (GA) and Key based random permutation (KBRP). Genetic algorithm (GA) is used to generate a mapping sequence for tile image hiding. Genetic algorithm (GA) provides better clarity in the retrieved secret image and reduces the computational complexity. The quality of original cover image remains same after embedding the secret image, so better security and robustness is assured.

The mosaic image is created by dividing the secret image and target image into equal number of fragments and fitting these secret tile blocks into corresponding target blocks according to the mapping sequence generated by Genetic Algorithm (GA). The mapping sequence is again permuted using Key based random permutation (KBRP) with a key to improve the security. Using the same key and the mapping sequence, the secret image can be recovered.

## II. RELATED WORKS

The earliest works related to style transfer is reported in [1]. This paper by Efros and Freeman belongs to the branch of texture synthesis based methods – algorithms that aim to synthesize textured images based on a given texture example (e.g. see [4]–[7]). This paper suggested a patch-quilting procedure for texture synthesis, and then showed how to extend it to target a closely related goal of texture transfer (rather than style transfer) [4]. Their view of the style transfer task was more conservative, assuming that general shades of the given content image are to be reproduced by tiling patches from a given texture image. Merging the patches over their overlaps was proposed to be done by finding optimal seam-curves between adjacent patches which exhibit minimum variation. Later work by Freeman in a different context (example-based super-resolution) [8], replaced this patch merging procedure with a better one based on a Belief-Propagation (BP) approach [9]. BP serves as a combinatorial approximate solver for a minimization procedure, seeking the best patch assignments among few neighbors per each location so as to get the smoothest outcome [6].

These works have been followed by many, most of which studied the problem of texture synthesis, aiming to generate a pseudo-random texture image from a given texture example with a high visual quality outcome. One of these follow-up works is the paper by Kwatra et al. [2], which proposed a very effective texture synthesis approach, relying on the same core principles as in [27] of patch matching and their fusion. Kwatra et al. adopted a global optimization point of view, of seeking an overall synthesized image that would give the minimal accumulated local distance to patches extracted from the example texture. This task has been broken into two stages, in the spirit of the EM (or K-Means clustering) algorithm [11], in the first stage freezing the current global image and seeking the best patch-matches, and in the second freezing the found matches and seeking to update the global image aggregating all these chosen patches.

In 2015 Gatys et al. proposed a brilliant and very different style transfer method that was shown to lead to very impressive results [12]. Their approach to the problem was the first to adopt a pre-trained CNN [14], as the means for extracting features from both the style and the content images. Interestingly, their work was based on earlier effort to use CNN for handling the texture synthesis problem [13], and so we see the same pattern of building a texture synthesis algorithm, and then generalizing it to obtain style transfer [5].

In 2017 Elad et al. proposed a style transfer algorithm. Many of its ingredients are borrowed directly from Kwatra et al. [28], and thus we shall clearly define the changes that brought us to handle the transfer task. An initialization of his algorithm by the content image, augmented by very strong noise, in order to both tie the result to the content in selected areas, while enabling it to depart from it elsewhere. Applying color-transfer from the style to the content within the iterative process, in order to preserve the richness of the style in the final outcome and avoid repetitive patterns, and the most important of all and merging the intermediate result with the content image in selected areas, applied in the patch-aggregation step in each iteration. This is based on a segmentation algorithm that defines the importance of content regions [7].

Ling et al. [17]. We restrict the discussion here to selected state-of-the-art techniques, focusing on their relation to our approach. Denoising approaches can be broadly categorized into spatial filtering, transform domain filtering, and dictionary learning-based methods. Spatial filtering techniques are conceptually very simple: they estimate denoised pixels by computing weighted averages of other pixels in the image. The bilateral filter [16] implements this idea by weighting pixels in a neighborhood window based on their similarity to the center pixel whose denoised value is estimated. The crux is that the weights of the bilateral filter are highly sensitive to the noise in the input, hence bilateral filtering by itself is not a very effective denoising approach, especially for larger noise levels. Recently, Caraffa et al. [15] describe an iterated version of the bilateral filter that is robust to outliers and they demonstrate how it can be used to remove non-Gaussian noise.

Classical transform domain methods rely on image representations using sets of suitable basis functions that are chosen such that the signal can be represented accurately by few coefficients. That is, the image representation in the transform domain is sparse, and noise corrupts mostly the small coefficients. Denoising in the transform domain is the problem of estimating the basis coefficients of the denoised image, where one can exploit the sparsity of the representation. The most popular transforms are the discrete cosine transform (DCT) [19], and wavelets [20] and their many variations. Our approach is related to these techniques since it includes a transform domain filtering step based on local, windowed Fourier transforms. We combine this, however, with a bilateral kernel to avoid ringing artifacts, which otherwise often hamper pure transform domain approaches that rely on simple, data independent transforms like the Fourier transform. Our approach is related to denoising using shape adaptive DCT (SA-DCT) by Foi et al. [18]. Key differences to our work are that they use binary masks restricted to simple polygonal shapes, while we use bilateral kernels with continuous weights and arbitrary support. We directly apply the DFT to the masked data instead of using SA-DCT, and we iteratively refine the bilateral kernels and the denoising filters in several steps [38].

The problem of compression and denoising artifact removal is highly related to image denoising and often addressed with similar algorithms. For example, adaptive bilateral filtering has been proven effective for JPEG deblocking [21]. It is common to simply cast artefact removal as a denoising problem and use existing denoising methods as discussed above to solve it [22]. Similarly, we will show that our dual-domain filter is highly effective for addressing these problems too.

Lin-Yu Tseng et.al proposed an image hiding technique using Genetic Algorithm (GA) and an Optimal Pixel Adjustment Process (OPAP) [24] in the year 2008. In the image hiding methods, a secret image is embedded into a cover image. The fusion of the two images, called a stego-image, fools the attackers who cannot be aware of the differences between the cover image and the stego-image. Secret image can be transmitted securely using this method. In this method, each pixel in the secret image is disarranged and adjust them to make a suitable string of bits that could be embedded. Then these strings of bits are embedded into the cover image in corresponding locations, and resulting image would become a stego-image that hides secret data. This method proposes a new image disarranging technique. It employs an improved Genetic Algorithm (GA) and an Optimal Pixel Adjustment Process (OPAP), to improve the quality of the stego-image.

Manoj Sharma et.al proposed an image hiding technique using unitary similarity transformation [25] in the year 2011. In this technique, an efficient and different method of image hiding is proposed. This method is based on unitary similarity transformation, which involves Eigen value calculations and determining Eigen vectors of a matrix, and transforming into a diagonal matrix. Here, only the secret image needs to be transformed into diagonal matrix and embedded to the cover image. In order to recover the secret image from the stego-image inverse transformation is applied [37]. The decryption key in this is the Eigen vector matrix. This hiding algorithm is simple and can be easily implemented. This method can greatly improve robustness of image-hiding and the security of the system. The quality of the recovered secret image and stego-image can be improved by using this method [35].

The mosaic image is the result of rearrangement of the fragments of a secret image and the preselected target image. No database is required for selecting the target images. After a target image is selected arbitrarily, the given secret image is first divided into rectangular fragments called tile images, which then are fit into similar blocks in the target image, called target blocks, according to a similarity criterion based on color variations [36]. Next, the color characteristic of each tile image is transformed to be that of the corresponding target block in the target image, resulting in a mosaic image which looks like the target image. The proposed method is new in that a meaningful mosaic image is created, in contrast with the image encryption method that only creates meaningless noise images. Also, the proposed method can transform a secret image into a disguising mosaic image without compression.

## III. PROPOSED ALGORITHME

In this section we describe in detail the proposed secret image transfer with styled target image via mosaic image algorithm. Frist let us consider the style target image formation.

For the formation of style image we follow the Elad et.al.[3] algorithm that produce a better image. First the content image and the style image is selected and it is processed to obtain the style image.

As discussed earlier style image is an artistic mixture of content and style. In this work a novel style transfer algorithm that relies on texture synthesis work of Elad et.al. This is chosen because because of its elegance, simplicity and excellent results [29]. To achieve the desired results the algorithm starts in the following way

1. An initialization of the algorithm [30] by the content image, augmented by very strong noise, in order to both tie the result to the content in selected areas, while enabling it to depart from it elsewhere.
2. Applying color-transfer from the style to the content within the iterative process, in order to preserve the richness of the style in the final outcome and avoid repetitive patterns is the most important of all.
3. Merging the intermediate result with the content image in selected areas, applied in the patch-aggregation step in-each iteration. This is based on a segmentation algorithm that defines the importance of content regions [31].

The algorithm starts at the energy minimization point and for each patches in content and style the energy is optimized [33]. We are given a content image C R3Nc , and a style image S R3Ns . These two images are accompanied by a segmentation mask W [0,∞)Nc that marks the importance of pixels in the content image, in terms of its parts to be preserved. More on this mask will be brought later in this Section. Our goal is the creation of the image X that would minimize the following series of energy functional: EL,n

$$\{\underline{X}\}\frac{1}{c}\sum_{(i,j)\in\Omega L,n}\min_{(k,l)}\left\|\boldsymbol{R}_{ij}^{n}\underline{X}-\boldsymbol{Q}_{kl}^{n}\boldsymbol{D}_{L}^{S}\underline{S}\right\|_{2}^{r}+$$
$$\left\|\boldsymbol{D}_{L}^{C}\underline{C}-\underline{X}\right\|_{\boldsymbol{W}}^{r}+\lambda_{p}\{\underline{X}\}$$

The energy minimization is done with the omission of the patch sizes and the pyramid decomposition were we sequentially freeze some of the unknowns and update the others repeat this strategy for several iterations as related to the Elad et.al[3]. The results are much pleasing.

According to Elad et.al.[3] the EM process should be applied to varying patch sizes and to several resolution scales of the images involved. One could imagine merging all these energy functional together into one holistic term to be minimized, but this is not the path taken here. We deploy a sweep over the patch sizes and over the scales sequentially [32]. This has the spirit of the stochastic gradient descent approach, where each patchsize and resolution level contributes its influence to the final outcome separately, thus leading to a better steadystate final result, with better chances of avoiding local minima. The proposed sweep over the patch sizes and the scales is done only for one round, starting from the coarsest resolution down to the native one, and for each such resolution sweeping through patch sizes from the largest to the smallest. For each L (resolution level) and n (patch size) we apply a fixed number of outer iterations to update X and the patch-assignments {(k, l)}, and within each of these we apply 10 inner iterations to solve the IRLS problem [34].

Each sub-optimization problem is initialized with the output of the preceding optimization, with an option to lead to randomized overall results by adding strong noise to the temporary solution at the beginning of the process in each resolution later. The very first of all these optimization steps is initialized by the content image with very strong additive Gaussian noise (σ = 50), so as to enable the algorithm to match patches daringly.

This process serves our overall goal of getting a fast end to end style transfer process that gradually refines the result. One refinement effect is in terms of the spatial resolution of the resulting image, as we go from the coarsest to the finest resolution layer. A second refinement effect is obtained by starting with big patches (33 × 33) and moving gradually to smaller and smaller ones (21 × 21, 13 × 13, 9 × 9, and possibly going down to 5 × 5), which gives the ability to the algorithm to adopt large elements from the style image, while refining and modifying them locally. The third and perhaps the most important refinement effect correspond to the influence of the content image. The details of the content are consistently pushed into the temporary result, weighted by W, and influencing the hallucination results obtained, delicately in regions where W is low, and more pronounced in regions where W is high. This way, important regions in the result never depart too far from the content image, while less important regions are allowed to drift and hallucinate.

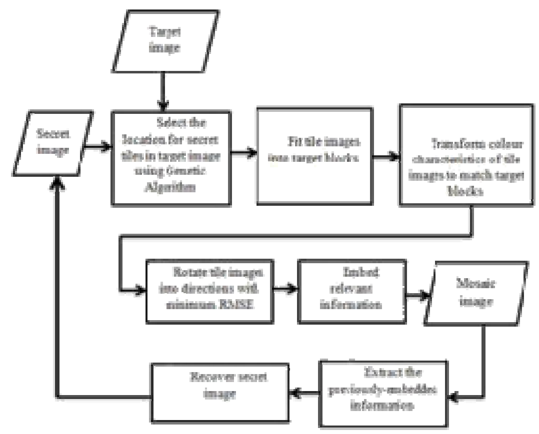
The segmentation is done as per the Elad et.al[3] process. The positive side of this algorithm is built of clear and simple building blocks, the influence of its ingredients on the final outcome is rather clear. This helps in adjusting the algorithm's parameters and providing meaningful knobs to control the results obtained [40].

This algorithm operates fully on RGB domain. One may envision modifying it to work only on the luma channel, while modifying the chroma channels independently. Color transfer is done according to the style image considered.

The image is further sent for Dual-Domain Filter for enhancing the quality of the image, DDF as a robust noise estimator in two domains, the spatial and frequency domain. Typical image denoising filters estimate a signal x directly from a noisy input y, attempting a decomposition y = x + n, where n is the noise. In contrast to such filters, our filter first estimates the noise n which is then subtracted from the noisy signal y to obtain x. This seemingly subtle difference allows us to directly express noise estimation in both domains in an analogous fashion using robust kernels [39]. While we make no assumptions about the signal, we assume to know the noise statistics. The noise statistics are used to robustly estimate the noise first in the spatial domain, then in the frequency domain [41].

Dual-Domain Filter is done as per the Knaus et.al[10]. Every pixel is sent to the filter which removes the noise in two steps. DDF first uses a bilateral filter in the spatial domain to obtain an intermediate noise estimate ¯ in the pixel value yp. The bilateral filter is defined over a square neighborhood of pixels q ∈ Np, where Np is a filter window, centered around pixel p and limited by radius r. DDF then re-estimates the noise ˆ in the frequency domain using the frequencies f ∈ Fp, where Fp is the frequency domain implied by the neighborhood Np. The Dual-Domain Filter performs the noise estimation in the Spatial Domain, Frequency Domain and removes the noise. This produces the better enhanced image.

The better enhanced style image is target image where secret image is transferred using it through mosaic image to other user.




The proposed method consist of two main phases as shown by the block diagram

1) Mosaic image creation 2) Secret image recovery.

In the first phase, a mosaic image is yielded, which consists of the fragments of an input secret image with color corrections conforming to a similarity criterion based on color variations [47]. The phase includes four stages:

1. Fitting the tiles of the secret image into the target blocks of a preselected target image using genetic algorithm
2. Transforming the color characteristics of tile images in the secret image to become that of the corresponding target block.
3. Rotating each tile image into a direction with the minimum RMSE value with respect to its corresponding target block
4. Embedding relevant information into the created mosaic image for future recovery of the secret image. In the second phase, the information that is embedded is extracted to recover nearly loss

lessly the secret image from the generated mosaic image. The phase consists of two stages:

1. Extracting the embedded information for secret image recovery from the mosaic image
2. Recovering the secret image using the extracted information.

### A. *Mapping of Tile Images into Suitable Target Blocks:*

The Secret image is divided into rectangular shaped fragments called tile images of equal size and they are fitted into the blocks of target image that are selected arbitrarily [43]. Mapping of tile images into target blocks are done using Genetic Algorithm. The population size and maximum number of generation is set as 10. First, an initial population of 10 mapping sequences is created. The next generations are created by the operations selection and crossover [51]. The crossover probability is set to 0.6. PSNR values are considered as the fitness values. PSNR is peak signal to noise ratio. The threshold fitness value (PSNR value) is set as 40. Create mosaic image by fitting the tile images based on the optimal mapping sequence [42].

### B. *Color Transformations between Blocks*

The color distributions of tile image T in the given secret image and target block B in targets image are changed to make them look alike. T and B be described as two pixel sets {p1, p2, . . . , pn} and {p´1, p´2, . . , p´n}, respectively. Let the color of each pi be denoted by (ri, gi,bi) and that of each p´i by (r´i, g´i, b´i). At first, the means and standard deviations of T and B are computed respectively, in each of the three color channels R, G, and B by the following formulas

$$\mu_c' = \frac{1}{n}\sum_{i=1}^{n} C_i'$$

$$\sigma_c = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(C_i - \mu_c)^2}$$

$$\mu_c = \frac{1}{n}\sum_{i=1}^{n} C_i \sigma_c' = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(C_i' - \mu_c')^2}$$

In which ci and c´i denote the C-channel values of pixels pi and p´i, respectively, with c = r, g, or b and C=R, G, or B. Next, we determine new color values (r´´i , g´´i ,b´´i) for each pi in T by

$$C \quad i$$

$$q_c = \sigma_c'/\sigma_c$$

In which is the standard deviation quotient where c = r, g, or b. It can be verified easily that the new color mean and variance of the resulting tile image T´ are equal to those of target block B, respectively. To compute the original color values (r´i, g´i, b´i) of pi from the new color values (r´´i , g´´i ,b´´i) ,we use the following formula which is the inverse of the above equation [49].

$$C_i = (1/q_c)(C_i'' - \mu_c') + \mu_c$$

After the color transformation process is conducted as described, some pixel values in the new tile image T´ might have overflows or underflows. To deal with this problem, such values are converted to be non-overflow or non-underflow ones and record the value differences as residual values for use in later recovery [50]. Specifically, we convert all the transformed pixel values in T ´ which are not smaller than 255 to be 255, and all those values not larger than 0 to be 0. Next, we calculate the differences between the original pixel values and the converted values as the residuals and keep them as part of the information associated with T ´. The residuals are encoded in order to reduce the number of required bits to represent them [44].

### C. *Rotating the Tile Images*

After the color characteristic of T is transformed, a further improvement on the color similarity between the resulting tile image T´ and the target block B is made by rotating [45].

T´ into one of the four directions, 00, 900, 1800 and 2700, which yields a rotated version of T´ with the minimum root mean square error (RMSE) value with respect to B among the four directions for final use to fit T into B [50]. Embedding the Secret Image Recovery Information To recover the secret image from the mosaic image, relevant recovery information has to embed into the mosaic image. Here, the information embedded is the index of the target block and the optimal rotation angle [48].

The information that is to be embedded is encrypted with a key. For embedding, a technique proposed by Coltuc and Chassery [26] was adopted and is applied it to the least significant bits of the pixels in the created mosaic image to conduct data embedding. Other than the classical LSB replacement methods, which substitute Least Significant Bits with message bits directly, the reversible contrast mapping method applies simple integer transformations to pairs of pixel values. Specifically, the method conducts forward and backward integer transformations as follows, respectively, in which (x, y) are a pair of pixel values and (x', y') are the transformed ones

$$x' = 2x - y , y' = 2y - x$$

$$x = \left\lceil \frac{2}{3}x' + \frac{1}{3}y' \right\rceil , y = \left\lceil \frac{1}{3}x' + \frac{2}{3}y' \right\rceil$$

The method yields high data embedding capacities close to the highest bit rates and has the lowest complexity reported so far.

### *D. Extracting the Secret Image Recovery Information and Recovering the Secret Image*

The mosaic image is segmented for extracting the secret image recovery information that was embedded into it by reversible contrast mapping. The information embedded is the index of the target block and the optimal rotation angle [46]. The extracted information is then decrypted using the same key that was used for encrypting it. Using the extracted information, compose all the final tile images to construct the desired secret image as output.

## IV. CONCLUSIONS

Images from different sources are utilized and transmitted through the internet for variety of applications. These applications include confidential enterprise archives, military image databases, document storage systems, online personal photograph albums and medical imaging systems. These images contain confidential or private information. Therefore, such information should be protected from leakages while transmitting through internet. Now a day, different methods have been proposed for secure image transmission. The two common approaches are image encryption and data hiding. Image encryption is the process of encoding secret images in such a way that only authorized parties can view it. Data hiding is the process of embedding the secret data into the cover images. The Image encryption technique is based on the natural property of an image like high redundancy and strong spatial correlation. By using these properties, the encrypted image is obtained. The encrypted image is a noise image, so without the correct key the secret image cannot be decrypted. The encrypted image is a meaninglessly that cannot provide additional information before decryption. It also makes an attacker's attention to the encrypted image during transmission because of its randomness in form. A new secure image transmission method has been proposed using GA and KBRP, which can create meaningful mosaic images and also can transform a secret image into a mosaic image with the same size of the secret image. This method provides more clarity to the image and more security is provided. Secret fragment- visible mosaic images with very high visual similarities to selected target images can be created by using color transformations and the scheme for handling overflows and underflows in the converted values of the pixels colors. There is no target database is required to select the target images. Also, the original secret images can be recovered nearly losslessly from the created mosaic images.

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