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A Guassian Mixture Based Spatial Resolution Forensic Image Segmentation For Digital Multimedia Data

Gouri MS

Research Scholar, Department of Computer Science and Engineering, Noorul Islam University, Kanyakumari District gourimohans@gmail.com

RV. Sivabalan,

Associate Professor, Department of Computer Science and Engineering Noorul Islam University, Kanyakumari District rvsivan@gmail.com

Abstract
Forensic security for digital multimedia data has been extensively identified as a promising paradigm to overcome the cyber crime activities during digital data transfer. The technology persons across the earth are spending enormous amount of time on securing the information with security related mechanisms. Modern convex optimization based approach is a popular type of forgery detection algorithms in the image forgery system. However, in most existing approaches, the choice of spatial dependencies mainly depends on the whole image without considering the smaller forgeries at the pixel level. Many real-world problems deal with lossy compression using pseudo random permutation with flexibility in obtaining the compression ratio. Often such pseudo random permutation does not employ effective forensic security method compromising the security aspect. To attain an effective forensic security on digital multimedia image a mechanism called, Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) is employed. Initially, Fast Expectation Maximization Proof Identification algorithm is extensively used for estimating the maximum likelihood and considerably improving the digital data security. Segmentation operations are applied to the maximum likelihood features obtained to determine the number of changeable components and parameters of mixture pixels. GM-SRFIS mechanism improves the forensic security legal proceedings for changeable spatial components using the Bayes Digital Image Rule. The Bayes Digital Image Rule relates the odds of events to the calculus probability and maintains the legal proceedings to improve the spatial resolution level. Finally, Maximum a posterior is estimated (i.e., present receiver end digital data) based on the reference posterior probability (i.e., past digital data send from sender side) in order to ensure interpolated forensic secured digital image. Extensive experiments and performance evaluations of the investigated mechanisms is reported using Digital Media Database that includes high resolution files for performing forensic security. Finally, the proposed mechanism is evaluated using Manuscripts and Archives Digital Images Database in terms of computational time, security while transferring digital multimedia image, noise ratio and forensics system legal proceeding efficiency.

Keywords: Forensic security, Cyber crime, Lossy compression, Guassian mixture, Expectation Maximization.

1. Introduction
Digital images have been used in several fields of researches in order to make efficient decision making. This includes forensic security, crime pattern identification and detection and so on. Photo Response Non Uniformity (PRNU) [1], a method for detection of image forgery used sensor pattern noise to detect forgery. However, smaller forgeries with respect to spatial resolution remained unaddressed.

Lossy Compression and Iterative Reconstruction (LCIR) [2], a pseudo random permutation for encrypting images produced quality image on the receiving end through spatial correlation reducing the noise ratio. But, security was compromised though compression ratio and quality of reconstructed image was improved. To address the issues related to security while sending digital images, in [3], scaling factor was applied by fitting a Markov chain model. Another method in [4] used Least Significant Bit replacement and matching to improve the aspects related to security. Forgery detection remained unsolved issue. Detection of forgery using noise level function and maximum a posterior was performed in [5] and applied to different videos improving the mean posterior and variance.

With the advancement in the field of digital image processing, forgeries affects the mankind heavily where the digital images can be easily manipulated and modified affecting the digital image being sent. In [6], pixel based techniques was introduced to verify the digital images authenticities using format and geometry based forgery detection. However, the major drawback was the time complexity involved in detecting the forgeries. To address time complexity, Non Aligned [7] double JPEG compression was introduced improving the detection ratio. Another integrated method using Block and Feature based method [8] provided measures against image tampering through Scale Invariant Feature Transform (SIFT). However, authentication of images was not ensured. To provide authentication, blind forgery detection technique [9] was introduced using image slicing.

Digital images can be easily edited using several software and tools by which even a novice forger can also easily fake the image without leaving any traces for visual tampering clues. As a result, several image forgery detection techniques have been designed to maximize the image reliability while sending multimedia images. In [10], block matching algorithm was introduced to address time complexity by applying sequential block clustering. However, the noise introduced while sending multimedia image was not detected. Generalized Likelihood

Ratio Tests (GLRT) [11] was applied to reduce the false alarm rate and maximized the detection performance for multimedia images.

In this work, an efficient mechanism called, Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) is presented. The contributions of GM-SRFIS include the following:

1. To attain an effective forensic security on digital multimedia image a mechanism called, Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS)
2. To reduce the computational time to perform image segmentation through Guassian Mixture based Spatial Resolution.
3. To improve security while transferring digital multimedia image by applying Fast Maximization Image Segmentation algorithm
4. To reduce the noise ratio for the segmented images being sent for forensic legal proceeding through Bayes Digital Image Rule

The paper is organized as follows. Section 2 describes the forensic security methods provided by different researchers. Section 3 details the methodology for effective forensic security on digital multimedia image called, Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) with the help of neat diagram. Section 4 presents the experimental setup required for the design of Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS). Section 5 discusses the numerical results of Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) and compared with two state-of-the-art methods on natural images. Finally, Section 6 concludes the paper.

2. Related Work

With the sophisticated standardization and cost efficient measures in sending and storing digital multimedia images, the JPEG compression has received significant popularity. In [12], Quantized Discrete Cosine Transform (QDCT) was applied with the motive of improving the accuracy of the image being sent. Though accuracy measure was ensured, little efforts were paid for image forgery detection. Methods involving active and passive were introduced in [13], for efficient detection of forgery in digital images using image manipulation operations. However, differences between malicious activities and innocent retouching were not differentiated. Least Significant Bit Matching [14] scheme provided measure for detecting information being hidden in digital data through Generalized Likelihood Ratio Test (GLRT). However, the authenticity with respect to forgery was not included. An integrated method [15] involving Scale Invariant Feature Transform (SIFT) and Discrete Cosine Transform (DCT) was introduced to reduce the noise and improve the detection rate of forgery for digital images.

Several image forgery techniques were designed by different research communities to improve the rate of detection of portions affected in digital images. Copy move forgery detection [16] was presented with the objective of detecting the duplicated regions at early stage through radix sort algorithm. But the time taken to detect reduced with the increase in the size of digital images. To speed up the operations, in [17], hypothesis testing theory was applied with the motive of detecting the hidden forger data at early stage by using Least Significant Bit matching scheme. However, optimality was not ensured. An optimal detection method called as Local Adaptive Model [18] was designed with the objective of reducing the false alarm probability rate.

In addition to hypothesis testing, statistical techniques were applied in [19] to provide an optimality test on the basis of acquisition principle that resulted in the efficiency of the digital multimedia image being detected with minimum forgery rate. In [20], a decision tree model was integrated with quantized samples to minimize the false alarm probability through weighted stego model.

Based on the methods discussed above, design of guassian mixture based spatial resolution forensic image segmentation for digital multimedia image is provided in the forthcoming sections.

3. Overview of Guassian Mixture based Spatial Resolution Forensic Image Segmentation

Digital data multimedia forensics measures the significant of computer crimes due to illegal users or un-authorized activities performed by authorized users. While sending digital multimedia data, one of the most important factors to be ensured is the trustworthiness of the digital multimedia data to be sent. This specifies that given a digital multimedia image, it has to be authenticated to ensure that it has not been changed and represents a valid image.

The proposed mechanism Guassian Mixture based Spatial Resolution Forensic Image Segmentation achieves effective forensic security for digital multimedia data. In this a fast mechanism for measuring the Gaussian Mixture based on the Spatial Resolution to a set of digital multimedia data, with applications to image segmentation is performed. The process is divided into three parts where the digital multimedia image is obtained from The Manuscripts and Archives Digital Images Database and is shown in Figure 1.

Figure 1 illustrates the architectural framework for efficient design of Guassian Mixture based Spatial Resolution Forensic Image Segmentation achieves to obtain an efficient forensic security while sending digital multimedia image. The first part namely, Guassian Mixture based Spatial Resolution reduces the computation time by applying spatial resolution through which the changeable components are obtained. The second part called as Fast Expectation Maximization Image Segmentation model is designed with the objective of improving the security while transferring digital multimedia data by effective extraction of two posterior values. Finally, the third part introduced Bayes Image Digital Rule to reduce the noise by measuring two posterior values namely, the reference posterior probability and maximum a posterior estimation.

Figure 1 shows the efficient design of information sharing with multimedia contents. The objective of Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) is to reduce the cyber crime activities while digital multimedia image transfer through an extensive forensics analysis. The elaborate details regarding the design of GM-SRFIS are explained in the forthcoming sections in detail.

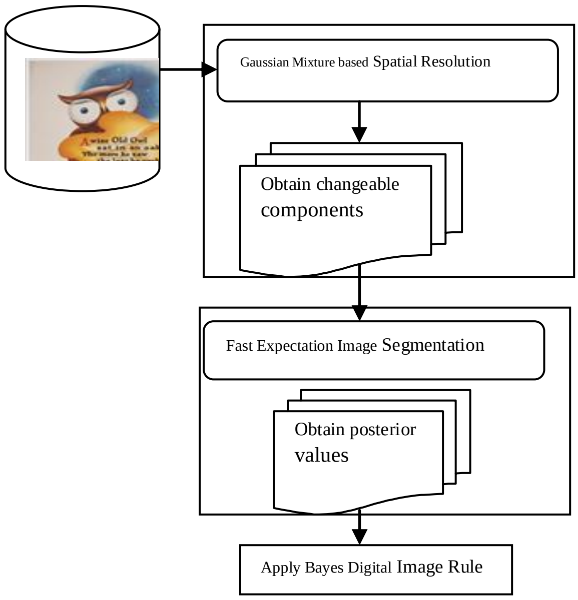

Figure 1 Architectural framework of Guassian Mixture based Spatial Resolution Forensic Image Segmentation

3.1 Design of Guassian Mixture based Spatial Resolution (reduces computational time)

In this section a detailed description of design of Guassian Mixture based Spatial Resolution to reduce the computational process by applying spatial resolution is explained. Most of the existing approaches concentrated on identifying the components through repeated iterations until optimality arrived. This involves a time consuming process. On the other hand, the Guassian Mixture based Spatial Resolution (GM-SR) model determines the number of changeable components and the parameters of the mixture pixels through segmentation operations.

The main focus of our GM-SR model is to initiate from one changeable component while deliberately modifying the mixture pixels by separating changeable components when necessary. Markov Random Field using Bayes estimation [1] initiates the process of computation with maximum mixture pixels. Though, the approach was proved to be more effective, it becomes computationally expensive for performing image segmentation applications that starts with number of mixture pixels, iteratively performing the process until the entire potentialities has been analyzed. On the other hand, in the GM-SR model, the process starts with a single component by applying spatially resolution Fast Expectation Maximization Image Segmentation algorithm (FEMIS) (as discussed in 1.2) and iterates until good achievement is obtained.

In conventional form of image segmentation applications, the pixels comprise of the color space and coordinates with spatial resolution. During image segmentation, pixels involving color space extend along one another whereas the spatial resolution are of unique in nature and do not extend along one another.

So, the proposed mechanism, GM-SRFIS is based on spatial resolution.

The Fast Expectation Maximization Image Segmentation algorithm is designed in such a way that the posterior probability is simultaneously applied through an averaging process. As a result, the GM-SR model helps in organizing spatial resolution for image segmentation. The current likelihood 'CL_X' of each single changeable component as given below

$$P(CL_X) = \sum_{i,c=1}^{n} \log W_c * X_i \quad (1)$$

From (1), $X_1, X_2, \ldots, X_i$ refers to the history of pixel values and is modeled by a mixture of 'n' changeable components and 'W_c' measures the weight of maximum a posterior value.

The parameters of the mixture pixels is given as below

$$Pixels_X = (w_X, \mu_X, \sigma_X, \alpha_{final(X)}, \alpha_{initial(X)}) \quad (2)$$

From (2), 'w_X' refers to the posterior probability of mixture pixels with 'μ_X' and 'σ_X' representing the mean and standard deviation values for fast expected mixture pixels, whereas '$\alpha_{final(X)}$' and '$\alpha_{initial(X)}$' represents the fast expected maximum likelihood at iteration '$n-1$' and 'n'respectively.

Followed by this, the fast expectation maximization for image segmentation applies the following two processes as part of the FEMIS model.

3.2 Design of Fast Expectation Maximization Image Segmentation (improves security while transferring digital multimedia image)

Image level segmentation help in increasing the resolution where the number of pixels is in the order of hundreds to thousands and finding the best components is a challenging task. The application of Fast Expectation Maximization Image Segmentation improves security while transferring digital multimedia data through forensic security method.

To implement segmentation process, singular value decomposition is used with the objective of improving the security while transferring digital multimedia data and is given as below

$$CM_X = (UM_X) * (\sum i, j) * (VM_X) \quad (3)$$

Where 'CM_X' involves a complex matrix which is the product of unitary matrix 'UM_X' (i.e.,$a * a$), diagonal matrix '$\sum i, j$' (i.e., $a * b$) and conjugate matrix '(VM_X)' (i.e., $b * b$)respectively. The 'a' columns of 'UM_X' and 'b' columns of '(VM_X)' are referred to as the left singular and right singular vectors respectively. The proposed mechanism, GM-SRFIS with the objective of improving the security only measures the UM_Xvalue. Now, the two segmented new Gaussian factors $X\ and\ Y$ with two posterior value is as given below

$$W_i^X = \frac{1}{2} * UM_X \quad (4)$$

$$W_j^Y = \frac{1}{2} * UM_Y \quad (5)$$

Where W_i^X and W_j^Y represents the posterior values for pixels 'i and j'respectively. The Fast Expectation Maximization then produces a sequence of estimates by invariable updating the following two steps. We optimize over W_i^X for a pixel 'i' assuming W_j^Y and $\theta$are fixed. Then the expected value $ExpVal$ with the help of log likelihood function from (6) and maximize the expectation using $ARGMAX$ function from (7) is given as below

$$Q(\theta, \theta^i) = E[\log P\,(W_i^X, W_j^Y \mid W_i^X, \theta^i) \quad (6)$$

$$\theta^{i+1} = ARGMAX\ Q(\theta, \theta^i) \quad (7)$$

Algorithm 1: The proposed Fast Expectation Maximization for Image Segmentation

Step 1: Initialize the parameter current likelihood for each changeable component
Step 2: Initialize the parameter current likelihood for mixed pixels
Step 3: Apply segmentation using singular value decomposition
Step 4: Obtain expectation value for pixel 'i'
Step 5: Obtain maximization value for pixel 'i'
Step 6: Evaluate CM_X
Step 7: If convergence of CM_X then
Step 8: Stop the process
Step 9: else
Step 10: Go to step 4
Step 11: end if

Fast Expectation Maximization Image Segmentation is used for estimating the maximum likelihood and considerably improves the digital data security level. The design of Fast Expectation Maximization Image Segmentation algorithm is given above in Algorithm 1. The initialization of the parameter current likelihood for each changeable component and current likelihood for mixed pixels is obtained from the digital multimedia image. The process of digital multimedia image segmentation is performed using Singular Value Decomposition. In order to improve the digital multimedia image security, maximum likelihood of pixel 'i' is obtained through the Expectation and Maximization functions. The algorithm stops when log likelihood converges to CM_X.

3.3 Bayes Digital Image Rule (reduce noise or PSNR)

Finally, to reduce the Peak Signal to Noise Ratio of the segmented images being sent for forensic legal proceeding, pixel labeling corresponding to the previous examined true digital multimedia images' pixel is verified. This is performed by applying Bayes Digital Image to show that each segment of digital multimedia images' pixel is similar in the receiving end as sent by the sending end.

Bayes' Digital Image Rule relates the odds of events with the calculus probability and maintains the legal proceedings that shows that the segmented digital multimedia image reduce the noise or PSNR. The Bayes' Digital Image Rule in Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) uses the maximum a posterior estimation (i.e., present receiver end digital data) are computed based on the reference posterior probability (i.e., past digital data send from sender side) in order to effectively reduce the noise and therefore ensures forensic secured digital image.

The two posterior values obtained from (4) and (5) W_i^X and W_j^Y represent the reference posterior probability and maximum a posterior estimation respectively. The reference posterior probability W_i^X represents the digital multimedia image sent whereas a maximum a posterior estimation is made for effective forensic evaluation.

$$if\ W_i^X \le W_j^Y\ 1 \quad (8)$$

$$if\ W_i^X = W_j^Y\ 0, Otherwise \quad (9)$$

From (8), both the reference and maximum posterior probability are checked and if the result of the condition returned in 1, it shows that few noises are introduced whereas if the result of the condition is 0, then there ensures secured forensic multimedia image.

4. EXPERIMENTAL EVALUATION

In this section, we present the results obtained by applying the proposed algorithm using the Manuscripts and Archives Digital Images Database (MADID) to conduct the experimental result. The Manuscripts and Archives Digital Images Database (MADID) comprises of digital reproductions of photographs, posters, drawings, text documents, and other images taken from the research collections of Manuscripts and Archives, Yale University Library. The proposed mechanism Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) is implemented using MATLAB.

The performance of the Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) is compared to that of the Photo Response Non Uniformity (PRNU) [1], a method for detection of image forgery and Lossy Compression and Iterative Reconstruction (LCIR) [2], a pseudo random permutation for encrypting images. The tests on MADID were conducted to evaluate four parameters: computational time, security while transferring digital multimedia image, noise ratio and forensics system legal proceeding efficiency.

5. Discussion

In this work, we efficiently evaluated the proposed mechanism to attain an effective forensic security on digital multimedia image. The table given below table and graph describes the performance of the proposed GM-SRFIS mechanism for digital multimedia data and compared with the existing Photo Response Non Uniformity (PRNU) [1] and Lossy Compression and Iterative Reconstruction (LCIR) [2].

5.1 Impact of computational time

Computational time for obtaining changeable components is the time taken to perform segmentation process by modifying the mixture pixels. It is measured in terms of milliseconds. It is the product of changeable components 'n' obtained for segmentation and the time '$Time$' taken to modify mixture pixels (i.e., ms). It is given as below

$$CT = n * Time \tag{10}$$

The mathematical evaluation for computational time using (10) is given below with respect to five images using GM-SRFIS, PRNU and LCIR respectively:

CT (using GM-SRFIS) = 3 * 0.05 = 0.15
CT (using PRNU) = 3 * 0.08 = 0.24
CT (using LCIR) = 3 * 0.09 = 0.27

In order to gain deeper insight on the influence of computational time, in table 1, the number of images and computational time required to obtain changeable components using MADID database is recorded.

Figure 2 shows the computational time for different forensic security methods as a function of different number of images. Compared to the existing Photo Response Non Uniformity (PRNU) [1] and Lossy Compression and Iterative Reconstruction (LCIR) [2], the proposed GM-SRFIS mechanism consumes less computational time through segmentation operations. This is because by applying Guassian Mixture based Spatial Resolution (GM-SR) model for determining the number of changeable components and the parameters of the mixture pixels through segmentation operations, the computation time decreases using GM-SRFIS mechanism by 5 – 62 % compared to PRNU. In addition, with the application of spatially resolution Fast Expectation Maximization Image Segmentation algorithm, resulting in minimized computation time by 12 – 75 % compared to LCIR respectively.

Table 1 Tabulation for computational time

No. of images	Computational time (ms)		
	GM-SRFIS	PRNU	LCIR
5	0.16	0.26	0.28
10	0.25	0.29	0.31
15	0.31	0.34	0.35
20	0.28	0.31	0.29
25	0.35	0.33	0.32
30	0.25	0.29	0.30

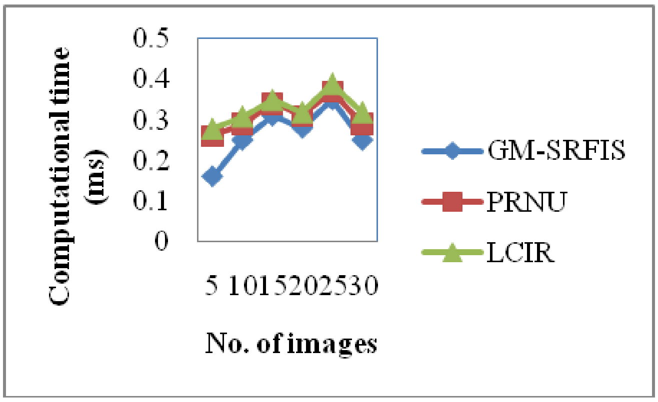

Figure 2 Measure of computational time

5.2 Impact of security while transferring digital multimedia image

The measure of robustness or security evaluates the amount of noise during retrieval of digital multimedia image. The security while transferring digital multimedia image is evaluated based on the ratio of difference between digital multimedia images sent (i.e., size in terms of KB) to the digital multimedia image received (i.e., size in terms of KB). Higher the difference more securitized the method is said to be. It is measured in terms of percentage (%).

$$R = \frac{Image\ Size_R}{Image\ Size_S} * 100 \tag{11}$$

The mathematical evaluation for robustness in terms of security while transferring multimedia image using (11) is given below with respect to five images of sizes in the range of 23.4 KB to 92.5 KB using GM-SRFIS, PRNU and LCIR respectively:

R (using GM-SRFIS) = (20.2 / 23.4) * 100 = 86.32
R (using PRNU) = (18.35 / 23.4) * 100 = 78.41
R (using LCIR) = (17.55 / 23.4) * 100 = 75

Table 2 Tabulation for security while transferring digital multimedia image

Image size (KB)	Security while transferring digital multimedia image (%)		
	GM-SRFIS	PRNU	LCIR
23.4	85.83	77.35	74.12
25.4	86.31	78.91	76.31
43.2	89.25	80.25	79.16
65.8	86.28	77.38	74.32
88.3	88.35	79.45	77.15
92.5	89.42	81.35	78.21

Numerical results for security while transferring digital multimedia image are reported in table 2. The table reveals that with the increase in the size of multimedia image, the security is also increased though a slight variance was recorded at the fourth image with a size of 65.8 KB. This is because of the noise in the fourth image that affects the security.

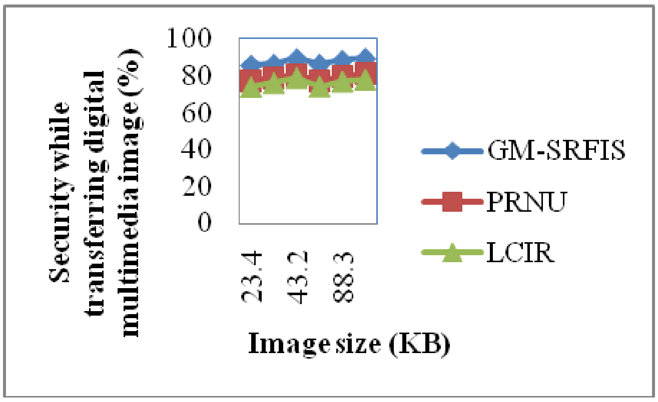

Figure 3 Measure of security while transferring digital multimedia image

To illustrate how different image sizes affect security while transferring digital multimedia image, figure 3 plots as a function of difference between digital multimedia images sent to the digital multimedia image received. The results are consistent which shows that security increases with the increase in the size of the image. The figure shows that with the increase in the size of images, the security also gets increased. Also, there is a steep increase in security using the proposed GM-SRFIS mechanism when compared to the existing Photo Response Non Uniformity (PRNU) [1] and Lossy Compression and Iterative Reconstruction (LCIR) [2]. This is because of the application of Fast Expectation Maximization Image Segmentation that uses singular value decomposition for effective segmentation of images. In addition, the GM-SRFIS mechanism though uses the products of unitary, diagonal and conjugate matrices, to emphasize security, only the values obtained from unitary matrix is used which increases the security by 8 – 10 % compared PRNU [1] and LCIR [2] respectively.

5.3 Impact of noise ratio

The noise ratio or PSNR (i.e., peak signal-to-noise ratio) in the proposed work is used as a quality measurement between the original digital multimedia image sent and the received image. It is measured in terms of decibels. To compute the PSNR, mean-squared error is first calculated using the following equation:

$$MSE = Image\ Size_S - Changeable\ Component_S \quad (12)$$

$$PSNR = \frac{R^2}{MSE} \quad (13)$$

In the previous equation, R denotes the maximum fluctuation in the input multimedia image where the size of R is 255.
The mathematical evaluation for noise ratio using (12) & (13) is given below with respect to five images of sizes in the range of 23.4 KB to 92.5 KB using GM-SRFIS, PRNU and LCIR respectively:

MSE (using GM-SRFIS) = $(23.4 – 17.55)^2 = (5.85)^2$ = 34.22
PSNR (using GM-SRFIS) = (255 / 34.22) = 7.45
MSE (using PRNU) = $(23.4 – 18.35)^2 = (5.05)^2$ = 25.50
PSNR (using PRNU) = (255 / 25.50) = 10
MSE (using LCIR) = $(23.4 – 10.23)^2 = (4.17)^2$ = 17.3889
PSNR (using LCIR) = (255 / 17.3889) = 14.66

Table 3 Tabulation for noise ratio

Image size (KB)	Noise Ratio (db)		
	GM-SRFIS	PRNU	LCIR
23.4	7.95	11.25	14.66
25.4	11.23	15.35	18.39
43.2	17.43	21.28	22.35
65.8	20.25	25.89	27.21
88.3	19.31	22.14	25.22
92.5	23.16	25.33	28.32

Numerical results for noise ratio are recorded in table 3. In this case, the noise ratio obtained through GM-SRFIS is comparatively lesser than the two other methods namely, PRNU [1] and LCIR [2] respectively.

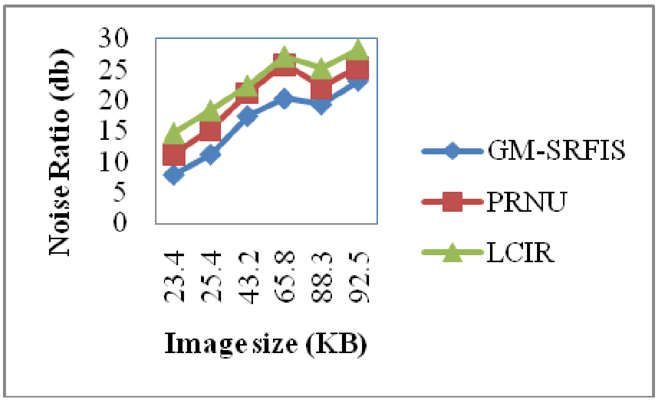

Figure 4 Measure of noise ratio

To better understand the noise ratio of the proposed mechanism, GM-SRFIS, five digital multimedia images of different sizes were used extracted from MADID database. For experimental purposes, image size in the range of 23.4 KB to 92.5 KB from MADID database is used. Compared to the existing Photo Response Non Uniformity (PRNU) [1] and Lossy Compression and Iterative Reconstruction (LCIR) [2], the noise ratio in the proposed GM-SRFIS mechanism is lower. This is because of the application of Bayes' Digital Image Rule that significantly relates the odds of events with the calculus probability and maintains the legal proceedings and therefore increases the security using GM-SRFIS mechanism. Furthermore, to have a significant impact of noise ratio, the proposed GM-SRFIS mechanism, uses the reference posterior probability for effective forensic evaluation. This extensively reduces the noise ratio using GM-SRFIS mechanism by 9 – 41 % compared to PRNU and 22 – 84 % compared to LCIR respectively.

5.4 Impact of forensics system legal proceeding efficiency

To measure the effectiveness of the proposed Fast Expectation Maximization Image Segmentation algorithm, the impact of forensics system legal proceeding efficiency with respect to three different methods, GM-SRFIS, PRNU and LCIR is shown in table 4. The results are obtained by using six different images extracted from MADID image database with the size in the range of 23.4 KB to 92.5 KB.

Methods	Efficiency of forensics system
GM-SRFIS	87.38
PRNU	75.88
LCIR	71.32

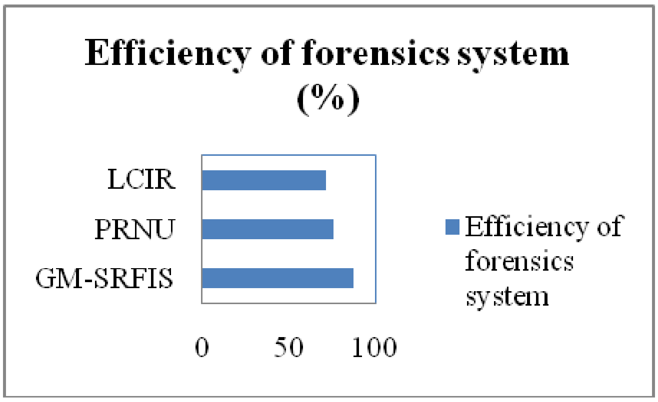

Figure 5 Measure of forensics system legal proceeding efficiency

Lastly the forensics system legal proceeding efficiency is measured via different number of images and sizes for implementation purpose. From the figure 5 it is illustrative that the proposed GM-SRFIS mechanism potentially yields better results than the existing LCIR [1] and PRNU [2]. The significant results achieved using the GM-SRFIS mechanism is because of the application of Guassian Mixture based Spatial Resolution to obtain higher forensic proceeding efficiency during digital multimedia image using GM-SRFIS by 13.16 % when compared to LCIR. As a result, the forensic security rate is improved to a coarser construction, because the Fast Expectation Maximization Proof Identification algorithm estimates the maximum likelihood and thereby increasing the forensic system legal proceeding efficiency by 6.01 % when compared to PRNU [2].

Conclusion

Digital multimedia image forensic security is becoming more challenging, due to the unrelenting advancement in the Internet community. In this work, Guassian Mixture based Spatial Resolution Forensic Image Segmentation (GM-SRFIS) mechanism is designed with the objective of attaining an effective forensic security on digital multimedia image. The resulting Forensic Image Segmentation problem has been formulated as a Guassian Mixture based Spatial Resolution and solved through a novel Fast Expectation Maximization Proof Identification algorithm. The initially selected images from MADID database obtain changeable components using Gaussian Mixture based Spatial Resolution. The proposed Fast Expectation Maximization for Image Segmentation algorithm by estimating maximum likelihood enhances the security aspect while transferring digital multimedia image. Finally, the noise in the segmented images being sent for forensic legal proceeding is reduced by applying Bayes Digital Image rule based on the reference posterior probability. Experimental results demonstrate the high efficiency and robustness in terms of security using the FEMIS algorithm with the digital multimedia image obtained through MADID database.

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