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A Hybrid of NHPP and Generalized Gaussian Mixture Model: A Combinatorial Approach for Background Elimination

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ABSTRACT

For background removal, a software reliability model based on NHPP's combinatorial method and parametric modeling using the Chimp Optimization Algorithm (ChOA) and Generalized Gaussian Mixture Model is proposed in this paper. A novel combination of ChOA and GGMM algorithms with the NHPP strategy is devised to solve the major shortcomings of the original algorithms. The model is examined using the provided data set (COCO 2017). This methodology demonstrates how the suggested work more successfully recognizes background photos. The evaluation of the results is done by using several metrics like Accuracy, Recall, Precision, F-Score, Peak Signal Noise Ratio, and Mean Square Error. The outcomes are evaluated against several models based on frame differences, adaptive background removal, adaptive frame differences, and the Gaussian mixture model.

1. Introduction

There has been research on software engineering dependability over the past 20 years, and more than 50 models are recommended in this study. The majority of software-dependable models work to determine the error, the rate of error, and the next error, among other things. To more successfully detect the relevant background pictures during video scene recognition, the concept of software reliability is also expanded [1]. The ability to recognize backdrop data is the most preventative feature of every image vision idea. When detecting and tracking the photos in realistic circumstances, it is presumed to represent a signature. The pixel-to-pixel method is typically thought to be more crucial when performing such operations, but due to time constraints and complexity in computing rate, this methodology is a poor choice. As a result, many researchers have focused heavily on developing new techniques and methodologies for the identification of background images. The key drawback that has been noted in the majority of the related research is that it takes a lot of time and calculation to accurately identify the object of interest [3]. Background subtraction is seen to be a cost-effective alternative to this method, and as a result, its use in both computer vision fields has significantly

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expanded. Eliminating the foreground information will efficiently extract the background elimination, resulting in a precise background elimination. The idea of software dependability was developed to reduce failures and decrease errors in recognition. This dependability approach primarily depends on calculating the cost of error, the time between errors, and determining the failure rate [4].

Using a hybridization of principles, including dependability, and using this idea in conjunction with a parametric model based on the Generalised Gaussian Mixture Model, this article proposes a method for effectively identifying background information. In this paper, the ideas are taken into account for the creation of a trustworthy model that seeks to maximize the recognition accuracy of background information identification [5].

From this above said article the equations for the identification of a robust reliability model will be considered. From this model, the parameters are estimated using the concept of least squares and the values of ' β ', the shape parameter is identified using the derivation of the Generalized Gaussian Mixture Model. The main observation here is that any image that is formatted either in the background scenario or foreground scenario is a mixture of parameters such as shape parameter, and scale parameter. If these parameters are estimated effectively, the identification of objects can be more precise and hence becomes easier in the recognition of background images. Every image formulates a parametric model and formulates a bell-shaped distribution in general and hence it is zoomed that this bell-shaped distribution results in a Gaussian curve, hence in most of the literature Gaussian Mixture Models are therefore considered. In realistic situations the objects in computer vision maybe having either a bell-shaped curve or the curves may be skewed toward the left or right directions. Therefore, identifying this skewed-ness shape parameter plays a vital role [6].

Also, the nature of distribution changes with the formation of the curvature, and hence different distributions other than Gaussian may result as output. Among these several distributions, Gamma Distribution, Non-Negative Distribution, Skewed Distribution, Distribution, and Weibull distribution are some resultants [7].

As these distributions differ, the curvature in the formation of images differs, and different outputs such as S-shaped distribution, Phong Distribution, Gumball Distribution, Rayleigh curve, etc. may be the resultants [8].

In order to address challenging data clustering issues, this work proposed a novel hybrid method called ChOA-GGMM that combines the GGMM and ChOA algorithms with a selective NHPP strategy. Hence in this article to identify the shape and scale parameters generalized Gaussian distribution is considered. With the value of β in the distribution, the scale and shape parameters differ, and the output result in the above-said distributions and curvatures. The article is structured as follows for the following.

The relevant literature for this field of study is given in Section 2. Section 3 of the article presents or overview of the Generalized Gaussian Mixture Model together with the identification of shape parameters and end-scale parameters. The data set considered is presented in Section 4, experimentation is carried out in MATLAB and environmental results are presented in Section 5. The performance evaluation using quality metrics is highlighted in Section 6. Section 7 of the article summarizes the paper.

2. Literature Survey

The modelling and technological assessment of wireless communication systems rely heavily on channel models [9]. On the other hand, cluster-based channel model standards like 3GPP TR 36.873 [10] and 3GPP TR 38.900 [11] always exist. According to Wren *et al.*, [12], the necessary signal processing step for locating cluster kernels is clustering. Therefore, clustering plays an important role in channel modeling, and a clustering method that can capture channel characteristics will greatly improve the accuracy of channel models. The assessment of channel capacity is also significantly impacted by channel clustering [13]. Therefore, effective clustering techniques are needed for channel modelling.

Adjacent multipaths in a three-dimensional (3D) multiple-input multiple-output (MIMO) channel have comparable properties and are always correlated with one another. EOD (Elevation of Departure), AOD (Azimuth of Departure), EOA (Elevation of Arrival), AOA (Azimuth of Arrival), delay and so forth are examples of channel multipath clusters [7].

Software reliability models (SRMs) are used to evaluate quantitative dependability and regulate the calibre of software products. According to Viswanath *et al.*, [8] Numerous stochastic regression models (SRMs) have been presented since Dong *et al.*, [19] and Kanagamalliga *et al.*, [20] first proposed SRMs based on stochastic processes. The dynamics of fault-generating processes in diverse contexts are frequently represented using NHPP (non-homogeneous Poisson process) based SRMs [21,22]. Software reliability metrics are estimated quantitatively using NHPP-based SRM, which is also used to forecast the future behaviour of software failures, i.e., the quantity of failures that will occur in the future [10,23].

Its ability to streamline probabilistic analysis is an advantage of NHPP-based SRGM. Commonly, a mean function controls NHPP. The average function provides the anticipated number of failures during random testing. NHPP-based SGRM might be applicable to all observed failure data if the right averaging function is chosen. The mean function and the NHPP-based SRGM are identical [2,14-17]. An early SRGM built on the NHPP is the Zhao and Xie model [18]. They are comprised of explicit general functionality debugging scenarios. Spagnolo *et al.*, [24] proposed a generalised SRGM with multiple overlapping parameters after solving the generalised differential equation regulated by the NHPP-based SRGM's mean function.

Image processing allows a far greater choice of procedures to be applied to the input data, avoiding concerns such as noise build-up and signal distortion. Before beginning with the de-noising process, several forms of noise such as Gaussian noise, salt and pepper noise, speckle noise, and poison noise are commonly employed to improve the image [25].

3. Generalized Gaussian Model

This article uses a generalized Gaussian mixer model because it provides a better approximation when background information is removed. Additionally, this distribution has the benefit of taking into account several other distributions as special instances, including Gamma, Log-Normal, and Gaussian. Consequently, it aids in more accurate background information identification.

The assumption made in this case is that each Gaussian Mixer Model consists of K-Gaussian distributions, each of which is referred to as a component. To represent the probability density function as a generalized Gaussian mixer model, please components are joined together. This distribution's simplest version is provided by

$$p(x) \propto \exp\left(-\frac{1}{2}|x|^{q}\right) \tag{1}$$

Variation in the values of q, results in various kurtosis using the heuristics of Te-Won Lee in 2000 as

$$q = \frac{2}{1+\beta} \tag{2}$$

The above equation (1) turns to

$$p(\, x \mid \mu, \sigma, \beta \,) = \frac{\omega(\beta)}{\sigma} \exp\left[-c(\beta)\, \frac{x-\mu^{\frac{2}{1+\beta}}}{\sigma}\right] \quad (3)$$

$$c(\beta) = \left[\frac{\Gamma\left[\frac{3}{2}(1+\beta)\right]}{\Gamma\left[\frac{1}{2}(1+\beta)\right]}\right]^{\frac{1}{1+\beta}} \quad (4)$$

$$\omega(\beta) = \frac{\Gamma\left[\frac{3}{2}(1+\beta)\right]^{\frac{1}{2}}}{(1+\beta)\Gamma\left[\frac{1}{2}(1+\beta)\right]^{\frac{3}{2}}}, \sigma > 0 \quad (5)$$

where μ, σ, β are the location scale and shape parameters.

3.1 Shape Parameter β:

To estimate the shape parameter, β, we choose a posterior distribution of β, given the pixels

X= {x1,x2, ... , xn) is

$$p(\, \beta \mid x \,) \;\propto\; p(\, x \mid \beta \,)\, p(\beta) \quad (6)$$

where p(β) in Gamma

$$(1 + \beta /\, a, b) \quad (7)$$

We estimate the values of Te-Won Lee in 2000 of a,b using the Least Square Approximation Method. Using the values obtained by this equation we estimate the shape parameter β for the equation (5) given above.

3.2 Chimp Optimization Algorithm:

The programme simulates the social and sexual motivations of chimpanzee hunting groups as well as their individual intellect. There are various chimpanzee species in each group, each with a varied level of intelligence and prowess. Despite having different approaches to navigating the environment, all team members are responsible and have a sense of responsibility. There are four distinct chimpanzee subspecies that live in chimpanzee colonies: drivers, hinderers, pursuers, and attackers. Each one of them has particular talents that are useful in particular phases of the hunting process. Driving without overtaking, the motorist pursues the bait. Obstacles block the progress of trees and prey. The chaser is responsible for chasing the bait to catch it. Once the escape route is blocked, the attacker turns on the dummy and attacks. This will either compel you to turn around and face your pursuers again or will put you in danger. Performance of the attacker is strongly correlated with age, intelligence, and physical fitness. Navigation and exploitation are the two main aspects of chimpanzee hunting in general. The terms "search" and "exploit" allude to driving, pursuing, and stopping prey, respectively. Making the correct trade-offs between navigation and exploitation is the secret to getting high ChOA performance.

The following five separate pieces are necessary for creating a mathematical model for the ChOA algorithm:

3.2.1 Encircling Part

The chimps, as was already mentioned, surround their victim while they hunt. The mathematical description of the chasing and driving mechanism is shown in equations (8) and (9):

$$d = |c.X_{prey}(t) - M.X_{chimp}(t)| \tag{8}$$

$$X_{chimp}(t+1) = X_{prey}(t) - a.d \tag{9}$$

In this formula, the variables t, X_{prey}, and X_{chimp} stand for the current iteration count, the prey's position vector, and the chimp's position vector, respectively. Equations (10)–(12) are used, in turn, to calculate the coefficient vectors a, c, and M.

$$a = 2.f.r_1 - f \tag{10}$$

$$c = 2.r_2 \tag{11}$$

$$M = Chaotic\_Value \tag{12}$$

where the value of f denotes the non-linear limits range, which shrinks from 2.5 to 0 over iterations. A chaotic vector M represents the effect of chimpanzee sexual behaviour on the hunting process, whereas r1 and r2 are random vectors with values ranging from 0 to 1. It should be mentioned that each chimpanzee had a variety of positions they could choose from around the feeding site. To do this, the vectors r1, r2 are used to coordinate the selection or modification of each chimpanzee's position, and the values of a, c are used to define each chimpanzee's direction of travel. Equations (8) and (9) allow each chimpanzee to freely update its location in response to the location of its prey.

3.2.2 Exploitation Part:

Aggressive behaviour in chimpanzees, where the attacker controls the entire process. In other words, the chimpanzee who is attacking is in charge of the main task, and other chimpanzees (the driver, the obstacle, and the chaser) aid in the hunt. As previously stated, the search is non-map-based and lacks any details on the locations of feedings (best answer). As a result, we assume that the first driver, chaser, obstacle, and attacker (search agent) finds the optimal solution, and the other chimps adjust their locations in accordance with the location of the best chimpanzee. The attack technique is mathematically represented in Equations (13) through (15).

$$\begin{gathered} d_{Attacker} = |c_1 X_{Attacker} - M_1 X| \\ d_{Barrier} = |c_2 X_{Barrier} - M_2 X| \\ d_{Chaser} = |c_3 X_{Chaser} - M_3 X| \\ d_{Driverer} = |c_4 X_{Driver} - M_4 X| \end{gathered} \tag{13}$$

$$X_1 = X_{Attacker} - a_1(d_{Attacker})$$
$$X_2 = X_{Barrier} - a_2(d_{Barrier})$$
$$X_3 = X_{Chaser} - a_3(d_{Chaser}) \tag{14}$$
$$X_4 = X_{Driver} - a_4(d_{Driver})$$

$$X(t+1) = \frac{X_1+X_2+X_3+X_4}{4} \tag{15}$$

The variables a, c, and M stand in for the coefficient vectors obtained in equations (13) through (15); X stands for the chimpanzee's location; and d stands for the separation between each chimpanzee and its prey. The first four chimpanzees (driver, chaser, obstacler, and attacker) were observed to make an approximation of the bait location, and the remaining chimpanzees were seen to update their locations by looking at any region around the bait.

3.2.3 Utilization Part:

Describes the last stage of the hunting process, when chimpanzees finish a hunt by fighting prey to obtain meat. The ranges of a and f in the mathematical model for the attack portion are [-2f, 2f] and [0, 2.5], respectively, and the range a lower as the iterative process continues. If the value of |a| falls within the range [-1, 1], the chimpanzee may move to a location that is halfway between the current and feeding positions. The chimpanzee is thus forced to go backward in search of other prey by the inequality |a|1. The technique for updating the chimpanzee location based on the |a| value.

3.2.4 Exploration Part:

Since its updating process depends on the positions of the driver, chaser, obstacle, and attacker chimpanzee in the search space, ChOA can become stuck in local optima, as was previously described. The algorithm should therefore focus more on the navigation component to prevent the issues listed above. For the purpose of concluding the hunting process, the search component refers to the task of finding the prey. Two crucial variables in our mathematical model play a role in how well the navigation component performs. The first argument should be used to represent any number more than 1 or less than -1. In order to find better prey, chimpanzees must separate from their current prey, according to the inequality |a|1. c is a free-form vector that can have a value between 0 and 2 as the second argument.

3.2.5 Social Motivation Part

In their frantic quest for meat to trade for social necessities like sex and grooming, chimpanzees exhibit sexual motivation. This is referred known as the meat bartering theory. Two significant issues—slow convergence and being restricted to local minima—are resolved by this perturbation behaviour. The ChOA technique can now be used with several different kinds of chaotic graphs. |a| The importance of the location update process. Figure 2 depicts the specifics of the chaos graph employed in the proposed clustering approach. This is what the following section will be about.

Equation (11) establishes the mathematical formula for simultaneously updating the position. The regular update location and the chaotic update location are both evaluated in this model with a probability of 0.5.

Algorithm 1: Pseudo-code of ChOA
1. The population Xi should be initialised (i = 1, 2,..., n).
2. Set up f, a, c, and M.
3. Determine where each chimpanzee is located.
4. Split the chimps up into several groups at random until the criterion is met.
5. Determine each chimpanzee's fitness level.
6. XAttacker = the best search agent
7. XChaser = the second-best search agent
8. XBarrier = the third-best search agent
9. XDriver = the fourth-best search agent
10. The maximum number of iterations is t.
11. For every chimpanzee:
12. Take out the chimpanzees' group.
13. Update f, c, and M with the help of its group strategy.
14. Calculate a and d using f, c, and M.
15. end for
16. for each search chimp
17. if (μ < 0.5)
18. if (|a| < 1)
19. Update the search agent's location using Equation (4).
20. else if (|a| > 1)
21. Pick a random search engine.
22. end if
23. else if (μ > 0.5)
24. Update the search agent's location using Equation (11)
25. end if
26. end for
27. Update f, a, c, and M
28. Update XAttacker, XChaser, XBarrier, and XDriver
29. t = t + 1
30. end while
31. return XAttacker

3.3 NHPP-Based SRGMs
3.3.1 Model description

The quantity of software flaws that existed at time t is represented by the expression "X(t), t > 0". Following are the model presumptions we make [21].

A: Random computer programming faults happen. The distributions of failure times have the same shape and are independent of one another.

• The failure was brought on by a small number of particular software flaws. where F(t) and N are cumulative distribution functions of the time to failure and the total number of distinct defects, respectively. Next, we get the probability mass function of the total number of failures up to time t:

$$P(X(t) = n) = \binom{N}{n} F(t)^n \overline{F}(t)^{N-n} \tag{16}$$

Where $\overline{F}(\cdot) = 1 - F(\cdot)$. The generalised order statistics framework is a term that is frequently used to describe this [21]. The so-called exponential order statistical model, which has the same SRGM as the Jelinski-Moranda SRGM, is one example. It corresponds to the exponential failure distribution. Generalised order statistical models are the most common advanced models of SRGMs based on NHPP. Add more suppositions to the model [21].

Despite the fact that the Poisson distribution offers dictionary data, Assumption C states that the number of distinct flaws is unknown.
The total number of software faults as of time t has the probability mass function given the expected number of unique defects.

$$P(X(t) = n) = \frac{\left(\omega F(t)\right)^n}{n!} e^{-\omega F(t)} \tag{17}$$

Equation (2) corresponds to the NHPP probability mass function with the mean function ωF(t). The failure-time distribution F(t) in this modelling framework specifies an SRGM that is NHPP-based.

Since failure-time distributions are a defining characteristic of NHPP-based SRGMs, there are numerous NHPP-based SRGMs that can alter failure-time distributions. Using a well-known statistical distribution as the failure time distribution, this research suggests a straightforward NHPP-based SRGM. The failure time distributions and 11 fundamental SRGMs based on NHPP are shown in Table 1. The majority of native NHPP-based SRGMs in the table belong to classic NHPP-based SRGMs. 'exp' refers to the so-called Goel and Okumoto model [2], 'gamma' to the generalised delayed sigmoid model [17,18], 'pareto' to the modified Duane model and 'tlogis' to the refraction Both the Goel (Weibull) model and the S-shaped model are referred to as "lxvmin".

Table 1
Basic NHPP-based SRGMs

Model	Failure Time Distribution
exp	Exponential distribution
gamma	Gamma distribution
pareto	Pareto type-II distribution
tnorm	Truncated normal distribution
!norm	Log-normal distribution
llogis	Truncated logistic distribution
txvmax	Truncated extreme-value distribution (max)
lxvmax	Log-extreme-value distribution (max)
txvmin	Truncated extreme-value distribution (min)
lxvmin	Log-extreme-value distribution (min)

3.3.2 Parameter Estimation

In order to forecast future trends in software failure, it is necessary to estimate the model parameters of the NHPP-based SRGM from data on software failure. Maximum Likelihood (ML) estimation is the most often utilised parameter estimation technique. I discovered a model parameter that, when used with ML estimation, maximises the LLF (log-likelihood function). LLF depends on experienced failure data, hence failure time and frequency data are the two forms of data for which ML estimate of NHPP-based SRGM is presented. Data on software failures' exact times throughout the testing phase is known as failure time data. The amount of errors that occurred within a time period makes up count data, sometimes referred to as grouped data. Separate discussions are held for each of these two data structures' estimation issues.

For the purpose of representing fault time and count data, general data structures are covered in this article. Data structure: D:=t1,x1,ui,...,(tk,xk,uk). where xi takes place between (xi-1, xi) in the ith time interval. At the conclusion of the ith time interval (i.e., time xi), if ui = 1, an additional failure also happens. Without a brief failure, ui = 0 results in success. The data is failure count information if all intervals ui = 0. D is lifetime data if for every integer i, xi = 0 and ui = 1. The SRGM's LLF is generated in the following manner from the generalised data.

$$LLF(\omega,\theta) = \sum_{i=1}^{k}(x_i + u_i)\log\omega + \sum_{i=1}^{k} x_i \log\{F(t_i;\theta) - F(t_{i-1};\theta)\} + \sum_{i=1} u_i logf(t_i;\theta) - logx_i! - \omega F(t_k;\theta) \quad (18)$$

Bear in mind, though, that closed-form MLE solutions cannot be exported. Numerical optimisation methods like Newton, Quasi-Newton, and Nelder-Mead should therefore be used. For computing the MLE of NHPP-based SRGMs, conventional techniques like Newton's method and Nelder-Mead method may be useful, although these techniques are only effective for tackling unrestricted optimisation issues in ML estimation. What your objectives are is important to note. Although practically all model parameters in NHPP-based SRGMs are subject to implicit limitations like positive constraints, we frequently have to deal with constrained optimisation issues.

4. Dataset Considered

We have taken into consideration a G.G.M.M. to present the current development technique in this work. K-means approaches are used to estimate the regions of the image's parameters, and the E.M. methodology is used to determine the parameters' final values. The methodology was used to analyze the two data sets from 2012 and 2014 that make up the CDnet 2014 database. For our experiments, the data collection from 2014 served as the starting point. These two data sets contain recorded video from cameras that were indoors and outdoors. There are currently 11 different video formats, including ones for turbulence data, data without resolution, and data for nighttime weather. There are 1000 to 80,000 total frames.

5. Experimentation

An experiment was carried out to extract the picture background features in line with the specified model based on Generalized Gaussian distribution using the Benchmark Data Set 2014 and a mat lab environment. The E.M. technique is taken into account for further updating of the parameters after the first estimation of the parameters using the K-means approach. By maximizing the probability function of the Generalized Gaussian model, the segmentation in section II of the article is carried out. Comparing the results to the model created using the Gaussian Mixture Model.

5.1 Evaluation of Performance and Experimental Results

We have taken into account the evaluation measures precision, Recall, Accuracy and F- Score to evaluate the proposed model. The value of computed precision can be used to justify the model's efficacy; if it is high, it denotes great performance. On the other hand, the output precision value will be lower if the algorithm allocates the majority of the pixels to the background may be high, but the recall value declines proportionately. The formulas for computations of the above metrics are given by

$$Precision = TP/\ (TP + FP) \quad (19)$$

$$Recall = TP/\ (TP + FN) \quad (20)$$

$$Accuracy = TP + TN/\ (TP + TN + FP + FN) \quad (21)$$

$$F - score =\ (2 * Precision * recall) \quad (22)$$

The following Tables 2 and the graphs based on evaluation metrics in Figure 1 to 3 exhibit the findings from the proposed technique.

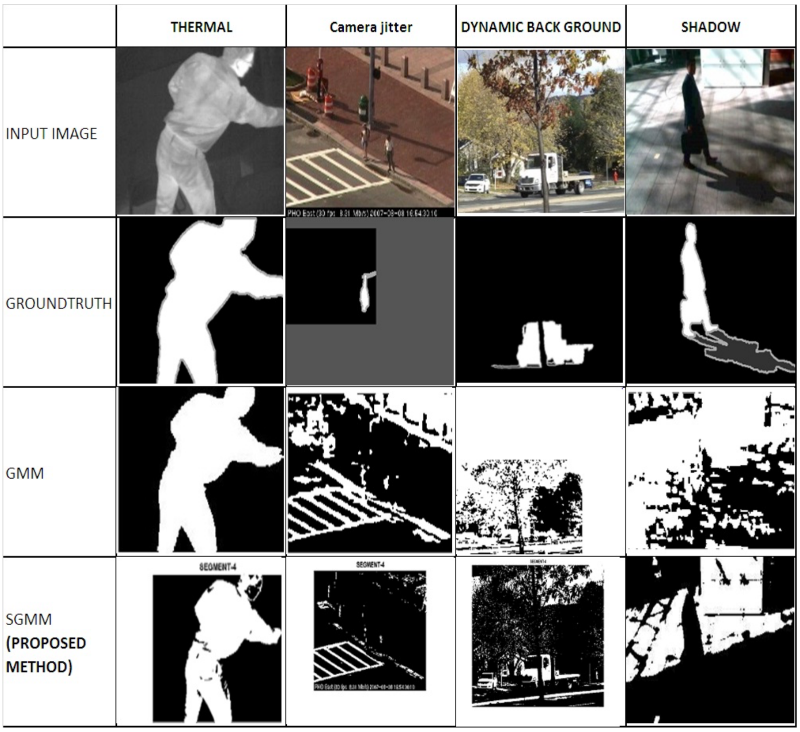

Fig. 1. Baseline from the CDNet2014 Dataset including foreground detection of thermal, camera jitter, dynamic background, shadow, and bad weather

Table 2
Metrics for evaluating various techniques on THERMAL video from CD Net DATASET

Metrics for evaluating various techniques on THERMAL video from CD Net DATASET		
Metrics\ Methods	GGMM +NHPP	GMM
PRECISION	0.0568	0.0318
RECALL	0.0237	0.173
ACCURACY	0.9912	0.9781
F-SCORE	0.0615	0.0356

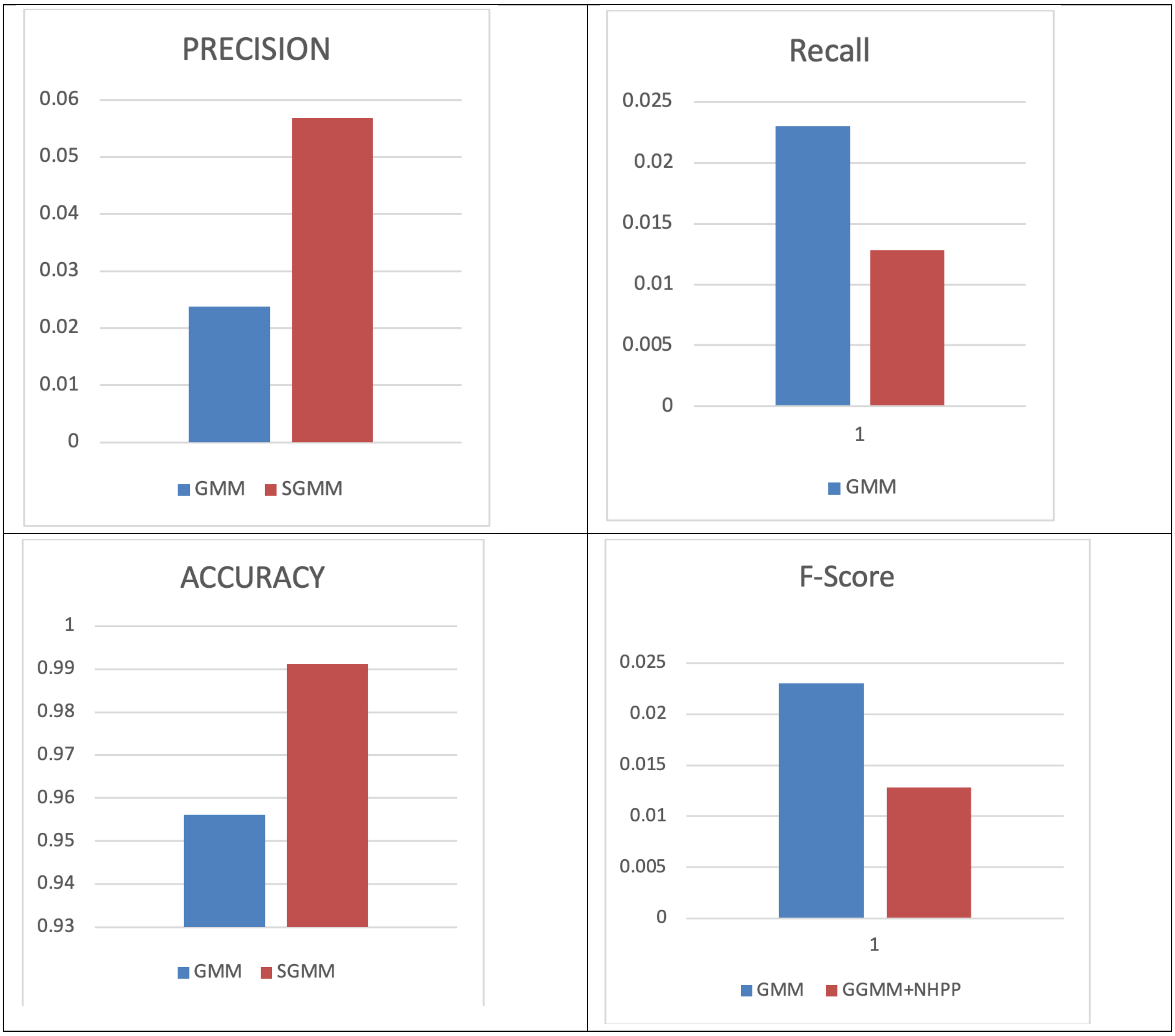

Fig. 2. Performance analysis on THERMAL video from CD Net DATASET

Table 3
Evaluation Metrics of different methods on CAMERA JITTER video from CD net DATASET

Evaluation Metrics of different methods on CAMERA JITTER video from CD net DATASET		
Metrics\ Methods	GGMM +NHPP	GMM
F-SCORE	0.0587	0.0255
ACCURACY	0.9876	0.9652
RECALL	0.0657	0.083
PRECISION	0.0868	0.0346

Fig. 3. Performance analysis on CAMERA JITTER video from CD Net DATASET

Performance Evaluation:

In Table 4, the findings of the proposed research are presented in comparison to the accuracy, sensitivity, and accuracy of the (GMM-ChOA) method that is being suggested. Comparing the proposed study to earlier research DE-EM, SVM and GMM-ChOA graphic analysis reveals that it achieves the highest ratios in terms of accuracy, sensitivity, and accuracy range. The proposed work's values for accuracy, sensitivity, and precision are therefore 97.5%, 97.9%, and 90.4%, respectively. Our suggested GMM-ChOA approach offers greater accuracy, sensitivity, and precision when compared to conventional techniques. This demonstrates that the proposed model is more reliable and efficient for monitoring images.

Table 4
Comparison of Accuracy, Sensitivity and Precision

Comparison	DE-EM	SVM	GMM	GMM-ChOA
Accuracy	93.48%	95.76%	82.4%	97.5%
Sensitivity	73.21%	96.22%	78.67%	97.9%
Precision	83.64%	73.59%	88.4%	90.5%

6. Conclusion

This article proposes a paradigm for the efficient segmentation of photos based on contextual data. Using the E.M. algorithm, the convergent values are produced by processing the initial parameter values. The results of the experiment are compared to data from the current models built on the Gaussian distribution, as shown in Tables 3 and 4, using performance measures like Precision, Recall, Accuracy and F-score. The fact Presented above and shown in the tables and graphs make it clear that the recommended technique works well in terms of all the parameters and results. The vast majority of segmentation-related applications may be particularly well suited for the suggested technique.

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