© 2019 IJSRSET | Volume 6 | Issue 4 | Print ISSN: 2395-1990 | Online ISSN : 2394-4099
Themed Section : Engineering and Technology
DOI : https://doi.org/10.32628/IJSRSET196446

# Gamma Distribution of FAST Feature for Statistical Image Modelling in Fingerprint Image Classification

**Hnin Yu Yu Win**[*1], **Htwe Htwe Pyone**[2]
[*1]Faculty of Computer Science, University of Computer Studies (Taungoo), Myanmar
[2] Faculty of Computer Science, University of Computer Studies (Myitkyina), Myanmar

## ABSTRACT

A unique method for modelling Features from accelerated segment test (FAST) with the Gamma distribution for statistical image data is introduced. Instead of using an image's FAST feature instantly; we design the FAST function to decrease the other global extraction function. The method of moment is used to predict Gamma distribution parameters. FAST's mathematical depiction is the depiction of matrix and is too complicated to be implemented in the ranking of images. We are therefore proposing a fresh statistical function to display the picture in a few dimensional numbers. Our proposed feature utilizes FAST method of Gamma distribution that can be used directly in the identification of fingerprint images. We demonstrate that the Gamma distribution works with FAST and has been effectively implemented in the identification of fingerprint images. To show the benefits of the proposed feature, Shivang Patel Fingerprint Database is used on which classifier evaluation and state-of - the-art comparison are performed.

**Keywords :** Features from Accelerated Segment Test (FAST), Gamma Distribution, Statistical information of an Image, Fingerprint Image Classification.

## I. INTRODUCTION

A strong statistical system is essential in machine science and image processing to describe image data in a tiny amount of dimensions. The characteristics of FAST have many benefits that are typically applied to match the image and match the item. The FAST characteristics are stable when it comes to different types of image transformation, but the real numerical depiction of the FAST characteristic is very complicated and requires a considerable time for training and identification. The significant issue is how to use the FAST feature for image modelling successfully. The Gamma distribution method is used to leverage a FAST feature statistical data of fingerprint image. In this paper, Fingerprint identification system is developed based on FAST feature and Gamma distribution method. The input of the Fingerprint identification is the fingerprint image and the output is the name of person corresponding to the input fingerprint image.

The structure of the paper is: Related Work is presented in Section2. The FAST feature and its mathematical representation for an image are reviewed in Section 3. The statistics of FAST feature are observed, and the Gamma is proposed for modelling FAST feature in Section 4. The experiments on proposed features are presented in Section 5. The conclusion for our proposed feature is presented in Section 6.

## II. RELATED WORK

A high-speed feature is needed where function numbers have been applied in actual-time frame rate applications. Feature detectors such as SIFT, Harris, and SUSAN are excellent techniques that deliver high-quality characteristics, but they are too algorithmically costly to be used with any difficulty in actual-time applications. Machine learning is implemented to obtain a feature detector that can use less than 7 cents of the accessible handling moment to fully handle existing PAL audio. By contrast, neither the Harris sensor (120%) nor the SIFT tracking phase (300%) can function at complete video speed. Based on this criterion, a review of corner detectors applicable to 3D scenes is carried out to promote a number of allegations created elsewhere regarding current corner detectors and to outperform current feature detectors according to this comparison. [5].

It is suggested to combine point-based and edge-based monitoring technologies to fix the real-time 3D model-based monitoring issue. Analysis of the characteristics of these two sensor systems is provided and this contributes to some non-trivial layout decisions that generate incredibly elevated efficiency jointly. By combining the position projections, a technique for incorporating the two schemes is provided robustly. Online training can increase function monitoring efficiency. To assist in real-time results, a FAST feature detector is implemented that can execute 400Hz full-frame feature detection. The combination of these methods leads to a system capable of monitoring median forecast mistakes and very fast movements according to camera shake [7].

For event-based sensors, a learning method is suggested that is robust even under rapid and sudden movements. High temporal resolution, energy efficiency applied for high dynamic range of event-based sensors. However, in comparison with conventional depth pictures, the characteristics of event-based information are very distinct, and easy combinations of corner detection techniques intended for these pictures do not work well on event-based information. It introduces an efficient way to calculate a moment curve that invariants the velocity of the items. A Random Forest is trained to acknowledge shifting angle occurrences. For event-based detectors, a high-resolution dataset is implemented that is appropriate for quantitative assessment and contrast of corner detection techniques. For Speed Invariant Learned Corners, the SILC method is being suggested and feature comparison is being conducted with comprehensive tests [8].

In order to search for paper images, a Markov Random Field (MRF) method has been suggested and showed to be efficient in finding random data for English comics, Telugu and Ottoman scripts[6]. The primary phases in the suggested strategy are: (a) effective graphic characteristics handling and pairing, and (b) a separate Markov Random Field (MRF) recovery algorithm to classify appropriate term pictures with a speech request. These methods were used in degraded historical records to quest the text. But, if the word image is accessible, a user cannot check for random data.

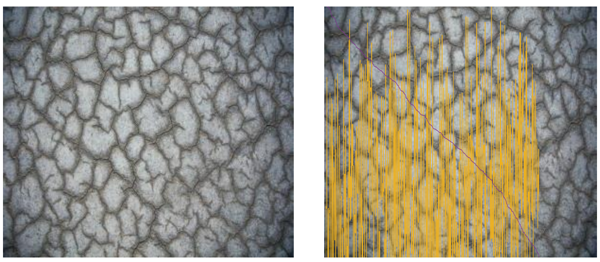
For comprehensive analysis of multi-dimensional, big volume storage devices, for example broadband video processing devices in wavelengths, the latest modelling method is proposed. The emitted and distributed fields have been calculated separately for target and sensor by implementing full-wave mathematical algorithms in the proposed modelling methods. Then use conjugate domain binding to correctly combine the fields [1].

Models of allocation from Mises, Vonn and Wrapped Cauchy have been suggested to depict the comparative stages of texture image and different type of image [4] [2]. Gamma distribution has been proposed to model the descriptor of the SIFT feature. The obtained characteristic is entered into Gamma model [3] after SIFT has been conducted on the texture image.

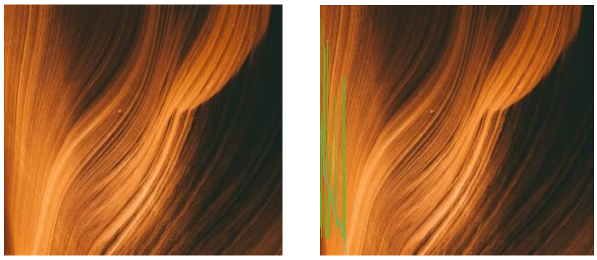
A simple continuous distribution, the Gamma is proposed to capture statistics properties of FAST. The parameters of the model are estimated by moment function. We perform state-of-art comparison for our proposed feature by using Shivang Patel Fingerprint.

## III. FAST feature and its mathematical representation

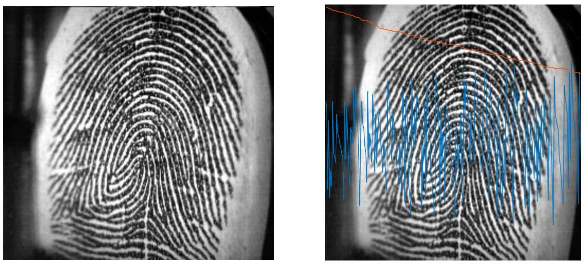
Features from accelerated segment test (FAST) are a corner detection technique that could be used in many computer vision operations to obtain function locations and subsequently to monitor and display items. In 2006, FAST is originally created by Edward Rosten and Tom Drummond [5]. The FAST angle detector's most successful benefit is its computing effectiveness. Referring to its feature, it is actually quicker than many other well-known techniques of removal of features, such as the Gaussian Differences (DoG) used by sensors SIFT, SUSAN and Harris. The mathematical representations of the FAST feature are location, matrix and count. The structure of location describes (x, y) coordinates of each corners in an image. The structure of matrix is vector and its length equals to the number of corners in an image. The count is the number of corners in an image. Figure1 shows the FAST features extraction from four images: Dry Cracked Soil Texture image, Orange Curved Walls of Sandstone at antelope Canyon Texture image, Person 18 fingerprint image and Person 12 fingerprint image. There are 709 and 96 corners Dry Cracked Soil Texture image and Orange Curved Walls of Sandstone at antelope Canyon Texture image respectively. There are 459 and 256 corners for Person 18 fingerprint image and Person 12 fingerprint image.



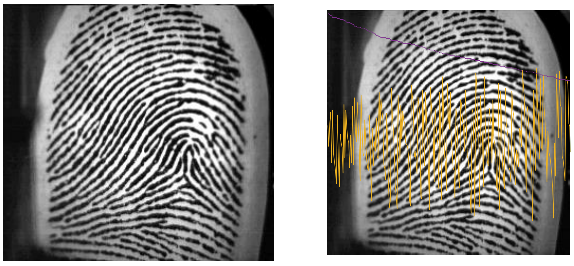
(i)



(ii)



(iii)



(iv)

**Figure 1.** (i) Dry Cracked Soil Texture image and 709 corners in FAST (ii) Orange Curved Walls of Sandstone at antelope Canyon Texture image and 96 corners in FAST (iii) Person 18 fingerprint image and 459 corners in FAST (iv) Person 12 fingerprint image and 256 corners in FAST

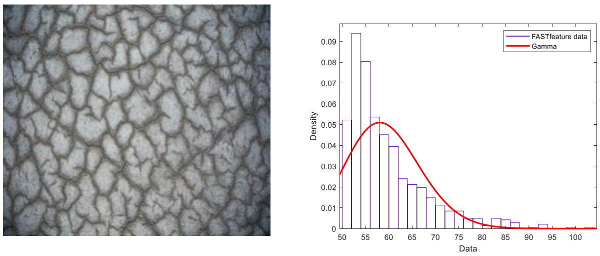
## IV. Statistics of FAST feature and proposed Gamma for modeling fast feature

Our primary objective is to present a distribution model that can correctly model FAST feature and can also describe an image properly. Histogram matching and goodness of fitting test are two hypotheses for discovering the appropriate model for FAST feature. We then develop the statistical system for the FAST feature according to the research of these two theories.

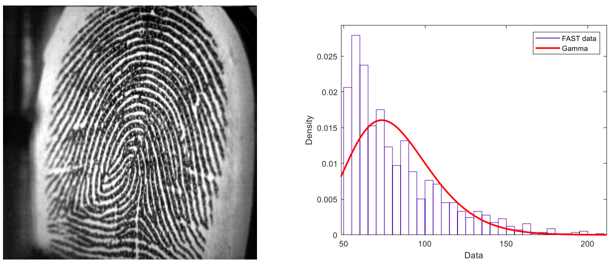
### A. Histogram Matching

Histogram matching in image processing is the generation of an image's histogram to match its histogram to a defined histogram. Figure 2 shows the observation for corresponding histogram outcomes. The FAST feature histograms are produced for 2 fingerprint images. We find out that the FAST feature has the defined histogram, which is distributed uniquely, according to the study of these histograms. We also derive the histogram of the Gamma distribution that is designed for 45000 random numbers with the value of mu (μ) is 1.0659 and the value of sigma is 0.4679.

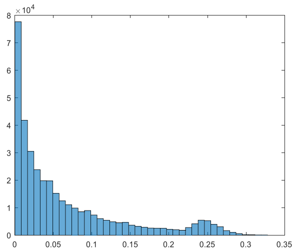
The histograms of the FAST feature for 2 fingerprint images match the histogram of Gamma probability distribution. According to the histogram matching results in figure 2, we find out the fit probability model for FAST feature.




(i)




(ii)



(iii)

**Figure 2.** (i) Dry Cracked Soil Texture image and histogram of its FAST feature (ii) Person 18 fingerprint image and histogram of its FAST feature (iii) Histogram of Gamma distribution that is calculated for 350000random numbers with the parameters: mu (μ) = 1.0659, sigma (δ) = 0.4679

### B. Goodness of Fitting (GOF) Test

GOF test calculates the compatibility of a random sample with a proposed theoretical mechanism of distribution of probability. The fitness god (GOF) experiment illustrates how well our information suits the allocation. Our study job is using the Kolmogorov-Smirnov to check out the FAST descriptor fit model. The Kolmogorov-Smirnov test statistics (D) are based on the greatest vertical difference between empirical distribution functions and the cumulative theoretical:

$$D = \underset{1\le i\le n}{\mathrm{MAX}}\left(F(x_i)-\frac{i-1}{n},\frac{i}{n}-F(x_i)\right) \tag{1}$$

where F ($x_i$) is the empirical cumulative distribution function. Assume that we have a random sample $x_1$... $x_n$ from some distribution with CDF $F(x)$.

$$F(x_i)=\frac{1}{n}[NumberofObservation \le x] \tag{2}$$

The data of the Kolmogorov-Smirnov test (D) measured for the distribution matched with Gamma. We used this test with measurements from a constant range hypothesized by Gamma. For each of the FAST features of an image in our dataset, we assessed Kolmogorov-Smirnov test statistics (D). Table 1 shows the FAST sample calculation of the Person 18 fingerprint image. The value of D indicates how Distribution fits with FAST feature. In this test, Gamma, Gen Pereto and Generalized Gamma distribution are used for testing because their histogram shapes are matched with histogram of FAST feature.

**Table I :** Kolmogorov-Smirnov test (D) for Person 18 fingerprint image

| Rank | Fit Distribution Name | (D) |
|---|---|---|
| 1 | Gamma | 0.14990 |
| 2 | Gen. Pareto | 0.17206 |
| 4 | Generalized Gamma | 0.11788 |

In Table 1, the gamma distribution also has the sample score (D) below 0.15 in the bottom 3 positions. The range (D) spans from 0 to 1. If its D value is below 0.5, the proposed distribution will be a nice model. Gamma distribution model was selected for FAST feature based on the observer outcomes of the histogram pairing and goodness of fitting (GOG) test.

### C. Modeling FAST with Gamma

This section describes how to use moment technique to predict two parameters of Gamma distribution. The distribution of gamma is a set of two parameters of distributions used to model amounts of random variables dispersed exponentially. The Gamma probability distribution function is:

$$y = f(x|\mu,\sigma) = \frac{1}{\sigma^{\mu}\Gamma(\mu)} x^{\mu-1} e^{\frac{-x}{\sigma}} \qquad (3)$$

where $\mu$ and $\sigma$ are shape and scale and $\Gamma$ ($\mu$) is the Gamma function. We used moment method to estimate the parameters of Gamma distribution. The $k^{th}$ order moment of the distribution is defined as:

$$mk=E(x-\mu)\ k \qquad (4)$$

where E(x) is the expected value of x and the value of k is 1, 2, 3 and 4. After modeling the FAST feature with Gamma model, we get the 2 parameters of row vector to form the proposed feature vector called FAST-Gamma. The flow of proposed feature extraction is shown in Figure 3. Some examples of proposed feature vectors are shown in table 2.

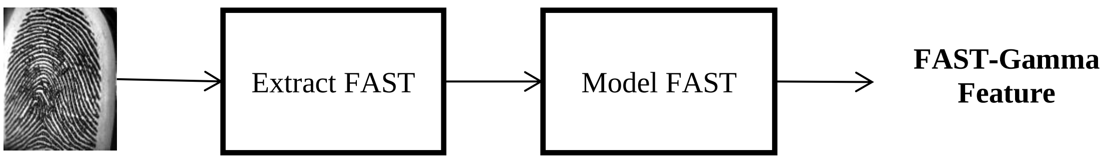



**Figure 3.** Flow of Proposed Feature Extraction

**Table II :** Example of Proposed Features for fingerprint images

| Image | Red | | Green | | Blue | | Gray Scale | |
|---|---|---|---|---|---|---|---|---|
| | μ | σ | μ | σ | μ | σ | μ | σ |
| Person_1 | 7.4969 | 11.3513 | 7.4969 | 11.3513 | 7.4969 | 11.3513 | 7.4969 | 11.3513 |
| Person_2 | 8.6363 | 9.9307 | 8.6363 | 9.9307 | 8.6363 | 9.9307 | 8.6363 | 9.9307 |
| Person_3 | 10.3170 | 7.5705 | 10.3170 | 7.5705 | 10.3170 | 7.5705 | 10.3170 | 7.5705 |

## V. EXPERIMENTAL RESULTS

Initial investigation for proposed feature and state-of-art features comparison are performed in this section. In this experiment, we use Shivang Patel Fingerprint Database to show that advantages of our proposed feature. The Shivang Patel Fingerprint Database consists of 21 labels of fingerprint image for 21 persons. For each person, eight images are available to recognize. The images are all 256x256 pixels with RGB color spaces. To extend this database, seven rotation angles (0, 30, 60, 90, 120, 150, and 200 degree) are performed for each image. Hence this database has 1176 (21 labels x 8 images x 7roations) images.

### A. Initial Investigation for Proposed Feature

In the initial investigation for our proposed feature, we train only 168 (21x8) images which has the rotation angle 0. In this case, there are two test sets for this classifier:

(i) **Test set I:** 168 images with rotation angle 0 degree that were trained in classifier and test again as test set I.
(ii) **Test set II:** 1008 images with different rotation angles 30, 60, 90, 120, 150, and 200 degree.

In table 3, the classification accuracies for different classifiers are tested by using these two test sets.

TABLE III: CLASSIFICATION ACCURACIES FOR PROPOSED FEATURE USING TWO TEST SETS WITH DIFFERENT CLASSIFIERS

| **Classifier (train 208 images)** | **Accuracy (%)** | |
|---|---|---|
| | **Test set I (168 images)** | **Test set II (untrained 1008 images)** |
| Linear SVM | 87.24 | 83.41 |
| Quadratic SVM | 93.32 | 81.38 |
| Cubic SVM | 98.15 | 83.09 |
| Fine KNN | 100.00 | 79.33 |
| Median KNN | 77.96 | 80.21 |
| Cosine KNN | 65.97 | 65.22 |
| Cubic KNN | 78.49 | 80.53 |
| Weighted KNN | **100.00** | **83.49** |

In table 3, we investigate our proposed features with different classifiers to know the robustness of our proposed feature by calculating of classification accuracy. The cubic SVM, quadratic SVM and weighted classifiers are the suitable classifiers for our proposed feature because they can correctly classify untrained samples (test set II) up to 83 %. The Weighted KNN reached classification accuracy up to 83.49% for untrained 1008 images. According to this research we decided to choose Weighted KNN classifier for fingerprint recognition.

### B. Compare FAST-Gamma with state-of-art Features

The proposed feature and state-of - the-art technologies are compared after original inquiry for proposed feature. To evaluate our test outcome, we used Shivang Patel Fingerprint Database and 10-Fold-cross verification. We are extending this database in this experiment and using Weighted KNN classifier for fingerprint image identification.

Validations are conducted 10 tries in 10-Fold-cross verification. For each validation, the entire dataset is split similarly into 10 subsets in which 9 practice subsets and 1 test subsets are split. For each validation moment, the registration precision is calculated and median ranking precision is also calculated over these 10 validations. The classification accuracy for each validation is:

$$\text{classification accuracy} = \frac{correct\_classified\_samples}{classified\_samples} \tag{5}$$

The number of classified samples is:

$$numberOfClassifiedSamples = \frac{Total\_number\_of\_samples}{10} \tag{6}$$

The average classification accuracy over these 10 fold cross validations is:

$$\text{classification accuracy} = \frac{\sum_{i=1}^{k} classification\_accuracy_i}{10} \tag{7}$$

where total sum of classification accuracy is divided by 10 because we use 10-Fold-cross validation. four feature vectors for state-of-art comparison:

(i) **Normalize color space representation [10]:** It is color texture feature descriptor based on preliminary dimensionality saving of color space. After discarding the color channel, the initial image was transformed into a matrix of the complex number using the (rang / avg) variable. By calculating the normalized allocation of energy, the texture feature is obtained. The Gabor filter store has been used to obtain 32 characteristics that are relatively invariant in rotation.
(ii) **GGD-WC [4] and GGD-Vonn [2]:** model based statistical feature that modelled the wavelet

domain location information by Wrapped Cauchy and Vonn distribution.

(iii) **GGD-Ga [3]:** model based statistical feature that model the SIFT descriptor by Gamma distribution. This feature consists of GGD-MAG, which is built using two-parameters GGD and mean of the UDCT magnitude coefficients, and SIFT-Gamma.

The experimental result for comparison is shown in table 4. In table 4, our proposed feature has 86.3 % of average classification accuracy for KNN classifier in 10-Fold-cross validation. Our proposed feature has more average classification accuracy than Normalize color space representation and Average color differences feature vectors. But our proposed feature has less classification than GGD-WC, GGD-Vonn and GGD-Ga feature vectors. The length of our proposed feature (4) is better than other feature vectors' length. The previous state of art features are combined with other color statistic features to form color texture features. In our proposed feature, we only consider for texture feature of an image. For combination with other feature, the co-occurrence feature vector with our proposed feature has the 94.3 % of accuracy. The co-occurrence feature vector is statistical information of gray level co-occurrence matrix (GLCM). The statistical information of GLCM is contrast, correlation, energy and homogeneity.

Table IV: Average classification accuracy over 10-Fold-cross validation with KNN classifier

.

| **KNN classifier (10-Fold-cross validation)** | | |
|---|---|---|
| **Feature Vector** | **Length** | **avgAC (%)** |
| Normalize color space repress: [9] | 32 | 71.40 |
| GGD-WC [4] | 48 | 87.33 |
| GGD-Vonn [2] | 48 | 89.77 |
| GGD-Ga [3] | 38 | 94.79 |
| **Proposed Feature (FAST-Gamma)** | **8** | **86.30** |
| **FAST-Gamma + GLCM feature vector** | **16** | **94.30** |

## VI. CONCLUSION

FAST feature is based on the Gamma distribution model for image feature according to the outcomes of the histogram matching experiment and the outcomes of the goodness fitting test. The test output demonstrates the characteristics of the proposed feature called FAST-Gamma. The experiment on Shivang Patel Fingerprint Database shows that the proposed feature is independent of rotation and scaling, and our proposed feature achieves a nice trade-off between quality and efficiency of identification. While our proposed feature can effectively design the FAST function and be implemented in the classification of fingerprint images, we must attempt to enhance our proposed feature by studying and cooperating with other image attributes. The distribution of Gamma probability and the technique of moment efficiently model the FAST function and it can be implemented in other applications depending on implementation fields for image processing.

## VII. REFERENCES

[1]. P. C. Theofanopoulos and G. C. Trichopoulos, "Modeling of mmW and THz Imaging Systems Using Conjugate Field Coupling,", IEEE Antennas and Wireless Propagation Letters,2017 Dec 6, vol. PP, no. 99, pp. 1-1, doi: 10.1109/LAWP.2017.2780803

[2]. Vo A, Oraintara S and Nguyen N, "Vonn distribution of relative phase for statistical image modeling in complex wavelet domain", Signal Processing, 2011 Jan 31; pp.114-25.

[3]. Zeglazi, Oussama, Aouatif Amine, and Mohammed Rziza. "Sift descriptors modeling and application in texture image classification.", Computer Graphics, Imaging and Visualization (CGiV), 2016 13th International Conference on. IEEE, 2016 Mar 29 pp. 265-268.

[4]. Vo A and Oraintara S., "A study of relative phase in complex wavelet domain: Property,

statistics and applications in texture image retrieval and segmentation",. Signal Processing: Image Communication, 2010 Jan 31;25(1), pp.28-46.

[5]. Rosten, E. and Drummond, T., 2006, May. Machine learning for high-speed corner detection. In European conference on computer vision (pp. 430-443). Springer, Berlin, Heidelberg..

[6]. I. Z. Yalniz and R. Manmatha, "Dependence models for searching text in document images," in IEEE Transactions on Pattern Analysis and Machine Intelligence, 2014, vol. PP, no. 99, pp. 1-1, doi: 10.1109/TPAMI.2017.2780108

[7]. Rosten, E. and Drummond, T., 2005, October. Fusing points and lines for high performance tracking. In ICCV (Vol. 2, pp. 1508-1515).

[8]. Manderscheid, J., Sironi, A., Bourdis, N., Migliore, D. and Lepetit, V., 2019. Speed Invariant Time Surface for Learning to Detect Corner Points with Event-Based Cameras. arXiv preprint arXiv:1903.11332.

[9]. Vertan, Constantin, and Nozha Boujemaa. "Color texture classification by normalized color space representation.", Pattern Recognition, 2000. Proceedings. 15th International Conference On, vol. 3,2000, pp. 580-583.

[10]. Hanbury, Allan, Umasankar Kandaswamy, and Donald Adjeroh, "Illumination-invariant morphological texture classification.", Mathematical Morphology: 40 Years On, 2005, pp.377-386.

**Cite this article as :**

Hnin Yu Yu Win, Htwe Htwe Pyone, "Gamma Distribution of FAST Feature for Statistical Image Modelling in Fingerprint Image Classification", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Online ISSN : 2394-4099, Print ISSN : 2395-1990, Volume 6 Issue 4, pp. 353-360, July-August 2019. Available at doi : https://doi.org/10.32628/IJSRSET196446

Journal URL : http://ijsrset.com/IJSRSET196446