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An Effective Object Detection and Background Elimination Using Image Retrieval Method in Surveillance

Ch Lavanya Ratna *[1], Y. Srinivas [2]

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Abstract: Surveillance systems employing closed-circuit television (CCTV) cameras are extensively used in various security applications, including traffic monitoring, airports, and object tracking areas. Object tracking plays a crucial role in continuously monitoring objects of interest in an environment. The development of an effective object tracking system requires consideration of aspects such as object recognition, detection, and background elimination. Among these, object detection through CCTV cameras primarily relies on background subtraction techniques. This two-step approach involves building a statistical representation of the background scene and identifying the foreground by subtracting it from the image. However, the widespread use of CCTV cameras for security purposes has resulted in significant storage space requirements, raising concerns regarding global monitoring applications. To address these challenges, efficient models are needed to rapidly extract relevant images. However, data acquisition limitations due to illumination techniques, weather conditions, changing backgrounds, camera jitter, and baselines pose challenges to the effectiveness of retrieval systems, particularly in thermal cameras commonly used for background image acquisition in surveillance. This paper proposes a statistical model-based approach using the Pearsonian family of distribution, including its extensions, to enhance the efficiency of image retrieval and background identification. Considering the asymmetric nature of surveillance camera data, various families within the Pearsonian distribution are explored for effective background modeling in this study.

Keywords: *Background subtraction, foreground identification, Gaussian Mixture model, Pearsonian family of distribution.*

1. Introduction

The areas of computer vision comprise of various sub areas of science and technology and provide an effective approach for identifying the objects of interest. In terms of technology computer vision is considered to be a theory for creating a synthetic system in order to extract valuable information from the images including audio, video and multimedia as well as other multidimensional perception force [1]. In some ways, biological vision and computer vision can be seen as mirror images of each other. In biological vision, the research of visualization in relation to humans and animals is carried out, and the proper models are built to comprehend this physiological behavior. Contrarily, in computer vision, numerous components of human visual perception are investigated together with suggested software and hardware mechanisms that can aid in a clearer perception of the item[2]. Every computer vision task is thought of as starting with image segmentation. The goal of image segmentation is to remove irrelevant details from photograph and retain just the information that is absolutely necessary. To comprehend the finer points of the photograph, numerous methods have been developed[3]. Certain procedures, such enhancing techniques that aid to increase the output images' clarity, should be used in order to comprehend images in depth.

Generally speaking, it is believed that humans may accurately interpret images that either use low-level features or high-level features. A portion of the information related to high level picture interpretation is typically disregarded by the lowest level perceptions, and the opposite is generally believed to be true for high level perception[5] .The same crucial information is therefore thought to be absent in both circumstances. The semantics can be used to understand how people interpret visual content. As a result, a number of approaches are suggested in the literature for improving image perception based on semantic descriptors. It is vital to distinguish, between the image's foreground and background details in order to conduct a more thorough examination of the picture[6] . One of the most fascinating areas of research in computer vision is background subtraction. It mostly aids in populating the techniques for differentiating between fixed objects (background) and moving objects (foreground). Most notable researchers have been aware of background subtraction during the past two decades, with the key benefit being that it can more effectively enable security-related reasons[7]. As a result, these ideas are more frequently used in surveillance applications, which aid in the analysis of image data from cameras pointed at security points to spot security flaws in locations like public malls, airports, train stations, highways, secure borders, and in nearly all other locations

*[1 *]Department of Computer Science Engineering, Dr Lankapalli Bullayya College of Engg, Visakhapatnm, 530013, India*
[2] Department of Computer Sscience Engineering, GITAM University, Visakhapatnm, 530013, India
** Corresponding Author Email: lavanya2.kowmar@gmail.com*

that require security. When such systems are installed, nevertheless. Background subtraction is one of the most exciting fields of computer vision research. It mostly assists in populating the methods for identifying moving items from background objects that are fixed in place (foreground). Since it can more effectively enable security-related reasons, background subtraction has been known to most eminent researchers for the previous 20 years. These concepts are therefore increasingly used in surveillance applications, which help in the analysis of image data from cameras pointed at security points to spot security flaws in places like open malls, airports, train stations, highways, secure borders, and in nearly all other locations that require security[8].

Background information plays a vital role in recognition of any image of interest. It is considered to be the primitive step of object recognition and object tracking. In general methodologies based on pixel-to-pixel comparisons are used for detection or tracking of the objects, however this methodology leads to a lot of computational effort and time[9]. Therefore, to overrule this disadvantage new methodologies are proposed for identification of background subtraction. In general background subtraction methods aim at minimizing the cost of preprocessing during image acquisition. Hence background subtraction methods play a predominant role In the area of computer vision and in particular recognition of objects. As it has strong roots in the process of extracting the vital information from the images[10]. However, the main consideration in this regard is that these background elimination modeling required to face challenges encompassing both dynamic and non-static background. Also lightning conditions, motion in objects also influence the recognition accuracy. In general lot of research has been driven in this area of research and methodology based on gaussian distribution are mostly considered. However, there are certain limitation using gaussian mixture model which include,

1. It is a pixel wise based algorithm and it fails to consider the relation between pixel. In general there is a strong correlation between the neighboring pixels and gaussian mixture model does not consider this factor.

2. The output of gaussian mixer model is mostly noisy and generally the results are derived from the false classification results, because of the condition in the input video sequence such as fluctuating trees, ripple in water and changes in illumination.

3. Generally in the application, the identification of background images from the object sequences, images will be exhibiting asymmetric nature of distribution and in contrary gaussian mixture model assumes the data to be in a symmetric form.

Hence approaches are to be designed for development for effective identification of background images in a most effective manner. In this paper an attempt is made by considering various limitations which come along the process of background elimination such as illumination changes, camera jitter, angle of acquiring the image etc.

2. Methodology

2.1 Pearsonian Family of Distributions

There is a well-known family of distributions called the Pearson family of distributions, named after the British mathematician and statistician Karl Pearson. The Pearson family encompasses a wide range of probability distributions that are commonly used in statistical modeling and analysis.The Pearson family includes distributions such as the normal (Gaussian) distribution, the beta distribution, the gamma distribution, the chi-square distribution, and many others. Each distribution in the Pearson family has its own set of parameters and characteristics, making them suitable for different types of data and modeling purposes.

The normal distribution, for example, is often used to model continuous data that is symmetric and bell-shaped. The beta distribution is frequently employed to model data that falls within a bounded interval, such as proportions or probabilities. The gamma distribution is commonly used for modeling skewed, positive-valued data, such as waiting times or income. The choice of a specific distribution from the Pearson family depends on the characteristics of the data being analyzed and the assumptions made about its underlying distribution. Researchers often rely on statistical techniques, such as maximum likelihood estimation, to estimate the parameters of the chosen distribution and make inferences about the data.

The Pearson family of distributions, including the normal, chi-square, beta, and others, has been extensively studied and applied in various fields such as economics, finance, engineering, and environmental sciences. Known for their flexibility and ability to capture a wide range of data patterns, the Pearson family distributions offer a versatile modeling approach[11]. The normal distribution, a prominent member, plays a fundamental role in statistical inference and the central limit theorem. The chi-square distribution is commonly used in hypothesis testing and confidence interval construction, while the beta distribution finds applications in Bayesian statistics and modeling proportions. Moments, skewness, and kurtosis characterize these distributions, providing insights into data shape and characteristics[12]. Parametric estimation methods, such as maximum likelihood estimation, are employed for parameter estimation, and the distributions' mathematical properties facilitate the development of statistical methodologies and computational algorithms. With their wide accessibility in statistical software, the Pearson family distributions serve as a common language for statisticians and researchers[13]. Goodness-of-fit tests, such as the chi-square test, assess their suitability for specific datasets. Moreover, they are widely used in regression analysis, time series analysis, and simulation studies, enabling the modeling, analysis, and generation of data with specific characteristics. Overall, the Pearson family of distributions remains a cornerstone of statistical analysis and modeling, providing a comprehensive toolkit for understanding and interpreting data across diverse fields[14-20].

In summary, while there is no widely recognized "Pearsonian Family of Distributions," the Pearson family of distributions comprises a diverse set of probability distributions that are extensively used in statistical modeling and analysis[21-24].

2.2 Pearsonian Probability Distribution Of Family

2.2.1 Updated equations for Pearsonian Family of Distribution

$$P\alpha_l = \frac{1}{N}\sum_{i=1}^{N} P\left(\frac{l}{x_i}, \theta^g\right)$$

$$(l/x_i, \theta^g) = \frac{\alpha_l f_l\,(x_i,\theta^g)}{\sum_{k=1}^{M} \alpha_k f_k \binom{x_i,\theta^g)}{\mu_i,\sigma_k^2}}$$

Where N is the number of sample observations

M is the number of classes

θ^g is the initial set of parameters

For a Pearsonian Family of Distribution

$$\sum_{K=1}^{M} \alpha_k f_k\,(x_i, \theta^g) = \alpha_1 \frac{a_1^{m_1} \cdot a_2^{m_2^2}}{(a_1+a_2)^{m_1+m_2+2}}\left(1+\frac{x_i}{a_1}\right)^{m_1}\left(1-\frac{x_i}{a_2}\right)^{m_2} +$$

$$\alpha_2 \frac{2}{a \cdot B\left(\mu_1+1, \frac{3}{2}\right)}\left(1-\frac{x_i^2}{a^2}\right)^{\mu_1} + \frac{\alpha_3 (a_k)^{a_{k+1}}}{a. \cdot e^{ak}\Pi(ak+1)} e^{-kx}\left(1+\frac{x_i}{a}\right)^{a_k}$$

$$+\alpha_4 \frac{1}{k^{1-p}\Pi(p-1)} e^{-\frac{K}{x_i}} * x^{-p} + \alpha_5 \frac{1(x_i-a)^{q_2}\,(x_i)^{-q_1}}{a^{q_2-q_1+1}\,.\,B(q_1-q_2-1, q_2+1} + \Bigg)$$

$$\alpha_6 \cdot \frac{2}{aB^{\left(\mu_1-\frac{1}{2}, \frac{1}{2}\right)}}\left(1+\frac{xi^2}{a^2}\right)^{-m}.$$

Type-1 updated equations

Type 1 density function is

$$f(x)=\frac{a_1^{m_1} \cdot a_2^{m_2^2}}{(a_1+a_2)^{m_1+m_2+2}}\left(1+\frac{x_i}{a_1}\right)^{m_1}\left(1-\frac{x_i}{a_2}\right)^{m_2} \sum_{l=1}^{M} \sum_{i=1}^{N} \log(P_l(x_i, \theta^g))\, P(\frac{l}{x_i}, \theta^g)$$

$$\sum_{l=1}^{M}\sum_{i=1}^{N}\left[-\log\ B(\mu_1+1,\mu_2+2)+\mu_1\log\ a_1+\mu_2\log\ a_2\right.$$
$$\left.-(\mu_1+\mu_2+2)\log\left(a_1+a_2\right)+\mu_1\log\left(1+\frac{x_i}{a_1}\right)+\mu_2\log\left(1-\frac{x_i}{a_2}\right)\right]$$
$$P(\mu/x_i,\theta^g).$$
$$\sum_{i=1}^{N}\left[\begin{array}{c}\log a_1-\log(a_1+a_2)+\log\left(1+\frac{x_i}{a_1}\right)\\ -\frac{\int_0^1 \log_z\cdot z^{4_1}(1-z)^{\frac{4}{2}}dz}{\int z^{\mu_1}(1-z)^{\mu_2}dz}\end{array}\right]$$
$$P(\frac{l}{x_i},\theta^g)\ =\ 0$$

$$\sum_{i=1}^{N}\left[\begin{array}{c}\log a_2-\log(a_1+a_2)+\log\left(1+\frac{x_i}{a}\right)\\ -\frac{\int_0^1 z^{\mu_1}\log\left(1-z\right)^{\mu_2}dz}{B(\mu_1+1,\mu_2+1)}\end{array}\right.$$

$$P\left(\frac{l}{x_i},\theta^g\right)=\ 0$$

2.3 Estimation Of Model Parameter Based On Expectation-Maximation

2.3.1 Updated Equations for Type-II

The density of Type-II is

f(x) = $\frac{2}{aB\left(\mu_1+1,\frac{3}{2}\right)}\ (1-\frac{x^2}{a^2})^{\mu_1}$ -a < x < ∞$\sum_{l=1}^{M}\ \sum_{i=1}^{N}\ \log\left(P_l(x_i,\theta^g)\right)P\left(\frac{l}{x_i},\theta^9\right)\sum_{l=1}^{M}\ \sum_{i=1}^{N}\ \left[\log_2-\log_a-\log B\left(\mu+1,\frac{3}{2}\right)+\right.$

$$\left.\mu\log\left(1-\frac{x_i^2}{a^2}\right)\right]P\left(\frac{l}{x_i},\theta^9\right)$$

Differential with respect to 'μ' and equating to zero

$$\sum_{i=1}^{N}\left[\log\left(1-\frac{x_i^2}{a^2}\right)-\frac{\int_0^1\ \log\ z\cdot z^{\mu}(1-z)^{-1/2}dz}{\int_0^1\ z^{\mu}(1-z)^{-1/2}dz}\right]P\left(\frac{l}{x_i},\theta^9\right)=0$$

$$\sum^{N}\left[\log\left(1-\frac{x_i^2}{a^2}\right)-\frac{\int_0^1\ \log\ z\cdot z^{4}(1-z)^{-1/2}dz}{\int_0^1\ z^{4}(1-z)^{-1/2}dz}\right]\frac{\cancel{c}\left(1+\frac{x_i}{a}\right)^{\mu_1}\left(1-\frac{x_i}{a_2}\right)^{\mu_2}}{\sum_{k=1}^{M}\ \alpha_k f_k(x_i,\theta^g)}=0$$

2.3.2 Updated Equations for Type-III

The type-III density function is

$$\frac{\alpha_3(a_k)^{a_{k+1}}}{a.\cdot e^{ak}\Pi(ak+1)}e^{-kx}\left(1+\frac{x_i}{a}\right)^{a_k}\quad,-a<x<\infty$$

The Updated equations are

$$\sum_{l=1}^{M}\sum_{i=1}^{N}\ \log(\ P_l(x_i,\theta^g))P\left(\frac{l}{x_i},\theta^9\right)$$

$$\sum_{t=1}^{M}\sum_{i=1}^{N}\ \left[(a_k+1)\log a_k-\log a-a_k-\log\Pi(a_k+1)-kx+\text{kalog}\left(1+\frac{z}{a}\right)\right]\cdot p\left(\frac{l}{x_i},\theta^9\right)$$

Differentiating with respect to the parameter K

$$\sum_{i=1}^{N}\left[a\log_{ak}+\left(\frac{a_{k+1}}{a_k}\right)\cdot a-a-x_i+\text{a}.\log\left(1+\frac{x_i}{a}\right)\frac{-\int_0^\infty e^{-z}\log z\ z^{ak}\cdot a\,.dz}{\int_0^\infty e^{-z}z^{ak}\cdot dz}\right]P(l/a_i,\theta^g)=0$$

$$\sum_{i=1}^{N}\left[a\log_{ak}+\left(\frac{a_{k+1}}{a_k}\right)-(a+x_i+\text{a}.\log\left(1+\frac{x_i}{a}\right)\frac{-\int_0^\infty e^{-z}\log z\quad z^{ak}\cdot dz}{\int_0^\infty e^{-z}z^{ak}\cdot dz}\right]$$

$$\frac{¢\left(1+\frac{x_i}{a}\right)^{\mu_1}\left(1-\frac{x_i}{a_2}\right)^{\mu_2}}{\sum_{k=1}^{M}\alpha_k f_k(x_i,\theta^g)}=0$$

2.3.3 Updated Equations for Type-IV

The density function of type -IV is given by

$$\alpha_4\frac{1}{k^{1-p}\Pi(p-1)}e^{-\frac{K}{x_i}}*x^{-p},\ 0<\text{x}<\infty$$

The Updated equations are

$$\sum_{l=1}^{M}\sum_{i=1}^{N}\log(P_l(x_i,\theta^g))P\left(\frac{l}{x_i},\theta^9\right)$$

$$\sum_{t=1}^{M}\sum_{i=1}^{N}\left[(a_k+1)\log a_k-\log a-a_k-\log\begin{matrix}\Pi(a_k+1)\\ -kx+\text{kalog}\left(1+\frac{z}{a}\right)]\\ \cdot p\left(\frac{l}{x_i},\theta^9\right)\end{matrix}\right.$$

$$\sum_{i=1}^{N}\left[a\log_{ak}+\left(\frac{a_{k+1}}{a_k}\right)\cdot a-a-x_i+\text{alog}\left(1+\frac{x_i}{a}\right)\frac{-\int_0^\infty e^{-z}z^{ak}\cdot adz}{\int_0^\infty e^{-z}z^{ak}\cdot dz}\right]$$

$$P\left(\frac{l}{a_i},\theta^g\right)=0$$

$$\sum_{i=1}^{m}\sum_{i=1}^{N}\left[-(1-P)\log_k-\log\ \Gamma(P-i)-\frac{k}{x_i}-P\log\ x_i\right]P(\mu/x_i,\theta^9).$$

Differentiating ort the parameter $K\ and\ P\ respectively\ we\ have$

$$\sum_{i=1}^{N}\left[(p-1)\cdot\frac{1}{k}-\frac{1}{x_i}\right]p(-/x_i,\theta^9)=0$$

$$\sum_{i=1}^{N}\left[\log_k-\log_{x_i}-\frac{\int_0^\infty\log z\cdot z^{p-2}e^{-z}dz}{\int_0^\infty z^{p-z}e^{-z}dz}\right]P(l\mid x_i,\theta^g)=0$$

That is

$$\sum_{i=1}^{N}\left\lfloor\frac{(p-1)}{k}-\frac{1}{k}\right\rfloor\frac{¢\left(1+\frac{x_i}{a}\right)^{\mu_1}\left(1-\frac{x_i}{a_2}\right)^{\mu_2}}{\sum_{k=1}^{N}\alpha_k f_k(x_i,\theta^g)}=0$$

$$\sum_{i=1}^{N}\left[\log_k-\log_{x_i}-\frac{\int_0^\infty\log z\cdot z^{p-2}e^{-z}dz}{\int_0^\infty z^{p-z}e^{-z}dz}\right]\frac{c\ .\ e^{\frac{-k}{xi}}.xi^{-p}}{\sum_{k=1}^{M}\alpha_k f_k(x_i,\theta^g)}=0$$

2.4 Kmeans Algorithm for Intialization Of Parameter

In order to initialize the parameter, the initial estimates of mean, variants are to be identified, in order to have initial estimates about the parameter, the kmeans algorithm is more significantly used. However in K means algorithm the value of K should be initialized properly so that the problem of under clustering and over clustering can be minimized, for this issue we consider the number of peaks of the image and basing on these peaks a rough estimate of values of K is considered. Basing this value of K number of clusterings are approximated. Once the clusters are identified each cluster has initial parameter μ (mu) and σ (sigma). However these values are to be optimized to have better estimate of the parameters which can be achieved by the usage of expectation maximization algorithm presented in the above section . The algorithm for K means is given below.

Algorithm:

1. Choose the number of groups you want to divide your data into.

2. Randomly pick a data point for each group and call it the "center" of that group.

3. Assign each data point to the nearest group center based on how close it is to each center.

4. Recalculate the center of each group based on the data points that belong to it.

5. Keep repeating steps 3-4 until the group centers stop moving around too much.

6. Look at a graph of the data and calculate a number called the "within-cluster sum of squares" for each number of groups.

7. Look for the point on the graph where adding more groups doesn't make the "within-cluster sum of squares" go down much more. This is called the "elbow point."

8. Choose the number of groups that corresponds to the "elbow point" on the graph.

2.5 Data Set Considered

In order to propose the current development methodology, we have considered a P.F.D. The initial numbers of regions are estimated using the K-means algorithms and E.M. algorithm is considered in the identification of the final values of the initial parameters within the image.

The methodology applied on a data base CDnet 2014 which contains two data sets, namely 2012 data sets and 2014 data set. For the experimentation purpose, we have considered 2014 data set. Both these data sets are camera capture, videos and comprising of both outdoor videos and indoor videos. It contains 11 categories of videos ranging from weather data acquired during the night, no resolution data and turbulence data. The span of the videos ranges from 1000 to 80000 frames captured no end cameras also it contain in video sequence from other cameras with different huge .The sample set of images of these data sets is presented below Figure 1.

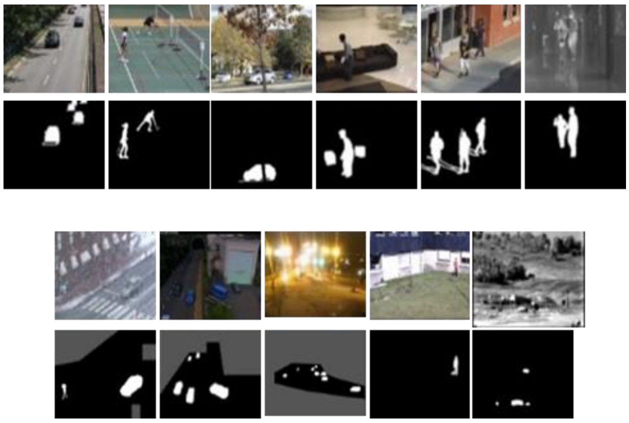

Fig. 1 video frames from each of the 11 categories in the new data set available at www.changedetection.net.

2.6.1 Ground Truth

To have an accurate comparison between the algorithms, all the videos in the above data set are considered to be possing ground truth and are capable of identifying the annotations during the motion of the video frame. However, there are certain limitations such as movement of trees, flags, etc., man made objects, air turbulence bundle along with each of the videos in the above mentioned data set.

2.6 Background Processing Techniques

In order to effectively identify the background, the more outstandingly, the following steps are to be taken care of

2.6.1 Post Processing

To have a well-defined background image, it is essential to initially process the input objects such that the deviation among the objects is low. These pixels with low disparity are considered to be background pixels else are considered as a foreground. However, certain limitations may take over and similar deviations may be accorded to both foreground and background information. So, to have a clear distinguish illumination correction need to be verified and the proper illumination helps to interpret the background image more apparently.

2.6.2 Algorithm For Background Elimination

In order to have the background information, we have considered the differences between n^{th} and $n-1^{th}$ frame such that the static video content acquired. If the difference between n^{th} frame is greater than $n-1^{th}$ frame, then it is considered as a background as it is considered as a foreground.

2.6.3 Difference Between the Frames

The difference between any two frames in a video sequence is sometimes considered 't' and't-1', and if the subsequent difference is more than a threshold, it will be treated as another introductory background. The decision of the identify the threshold is presented in the following subsections.

2.6.4 Adaptive Background Difference

Here, we have considered two frames within the video sequence, namely at a period 't ' and 't-1'.One of the frame considered has current frame and another one is assumed to be the reference. Now with this consideration frame is represented as H (a, b) =Z(a, b)-K(a, b) if the value of H(a,b) >t it is assumed to be the background information else this difference is considered as the foreground information.

2.7 Algorithm For Background Subtraction

Step 1: Get pixel density for the image.

Step2: Applying thresholding methods like adaptive background difference then the background objects of the video sequences are identified

Step 3: Each of the video sequences are post processed

Step4: The intensities of the foreground are given as input to the proposed model P.F.D.

Step5: Basing on the Compound likelihood of the probabilities, every pixel has classified either a background or foreground.

Step6: From the step 5 obtains the image assessment metrics

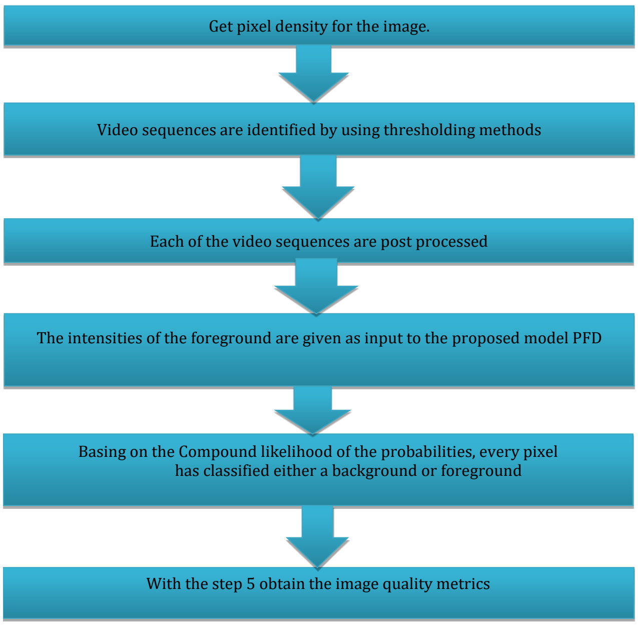

Fig.2 Proposed Model Architecture

2.8 Experimentation

In order to exhibit the proposed model, we have considered the methodology based on the P.F.D Each of the images are considered and the static frames are obtained. Based on the adaptive thresholding methods proposed, the background objects of these video sequences are identified and each of the videos is post processed .

The intensity of the foreground is given as input to the model and is based on the probability of composite probability; each pixel is classified either to background or foreground.

The complete experimentation is carried out in the mat laboratory environment on the data set considered.

The experimentation is conducted and the results assessed using performance assessment methods as practical.

2.9 Assessment Methods

To determine the effectiveness of the developed method, the following Metrics are taken into account.

The performance metrics are expressed as

$$P.R = TP/\,(TP + FP) \tag{1}$$

$$R.C = TP/\,(TP + FN) \tag{2}$$

$$A.C = TP + TN/\,(TP + TN + FP + FN) \tag{3}$$

$$F.S = (2 * P.R * R.C)/(P.R\ + R.C) \tag{4}$$

$$M.S.E = FP + FN/M * N \tag{5}$$

$$R.M.S.E = M.S.E \tag{6}$$

$$F.N.R = FN/\,(TP + FN) \tag{7}$$

$$F.P.R = FP/\,(FP + TN) \tag{8}$$

$$P.S.N.R = 10log10\ (R2/M.S.E) \tag{9}$$

$$P.W.C = 100 *\ (FN + FP)/(FN + TN + FP + TP) \tag{10}$$

Where

TP- The amount of Foreground pixels categorized as foreground,

FN-The amount of Foreground pixels categorized as Background.

FP-The amount of pixels of background pixels categorized as foreground.

TN-The amount of background pixels categorized as background

3. Results

The results are attributed by considering proposed method and different description about each condition baseline, thermal, Dynamic background, shadows, camera jitter, and Bad weather.

The above methods are presented in following Figure 3

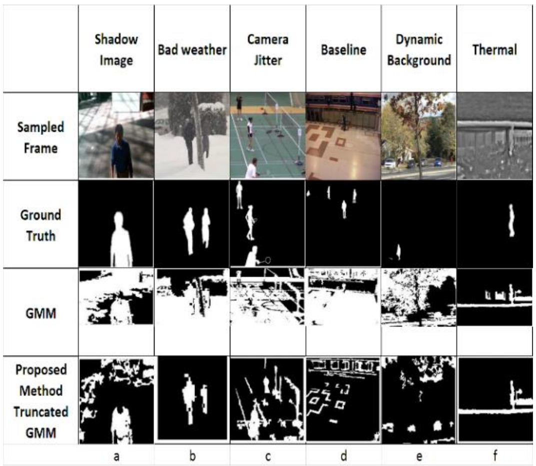

Fig. 3 Foreground object detection of shadow, bad weather, camera jitter, Dynamic Background, baseline, thermal from the CD net 2014 Dataset.

After evaluating the metrics proposed , the result derived against the consider date is presented in tables 1 to 6

Table 1. Assessment Metrics of different models on SHADOW video from CD net DATASET

Metrics\Model	***GMM***	***TRUNCATED GMM***
P.R	0.0129	0.0167
R.C	0.123	0.0437
A.C	0.9374	0.9731
F.S	0.0182	0.0385
M.S.E	0.0144	0.02
R.M.S.E	0.1202	0.1415
F.P.R	0.0626	0.0269
F.N.R	0.723	0.942
P.S.N.R	66.5661	75.917
P.W.C	6.2635	2.6926

Table 2. Assessment Metrics of different models on BADWEATHER video from CD net DATASET

Metrics\Models	***GMM***	***PFD***
P.R	0.0327	0.0709
R.C	0.0694	0.0561
A.C	0.9513	0.9642
F.S	0.0486	0.0593
M.S.E	0.0114	0.0203
R.M.S.E	0.1067	0.1424
F.P.R	0.0487	0.0348
F.N.R	0.806	0.9219
P.S.N.R	65.0952	69.6053
P.W.C	4.8731	3.8665

Table 3. Assessment Metrics of different models on CAMERA JITTER video from CD net DATASET

Metrics\Models	***GMM***	***PFD***
P.R	0.023	0.0409
R.C	0.042	0.0381
A.C	0.9364	0.9743
F.S	0.037	0.0643
M.S.E	0.0141	0.0898
R.M.S.E	0.1186	0.2997
F.P.R	0.0636	0.1904
F.N.R	0.065	0.9819
P.S.N.R	64.683	72.6308
P.W.C	6.3566	4.0348

Table. 4 Assessment Metrics of different models on BASELINE video from CD net DATASET

Metrics\Models	***GMM***	***PFD***
P.R	0.0081	0.0127
R.C	0.0342	0.0876
A.C	0.9633	0.9764
F.S	0.0181	0.0169
M.S.E	0.0046	0.0162
R.M.S.E	0.068	0.1273
F.P.R	0.0367	0.0236
F.N.R	0.8358	0.9914
P.S.N.R	66.0696	71.5137
P.W.C	3.6736	2.361

Table. 5 Assessment Metrics of different models on DYNAMIC BACK GROUND video from CD net DATASET

Metrics\Models	***GMM***	***PFD***
P.R	0.0031	0.0162
R.C	0.0248	0.0626

A.C	0.9577	0.9745
F.S	0.0121	0.0189
M.S.E	0.0125	0.0192
R.M.S.E	0.1117	0.1384
F.P.R	0.0423	0.0255
F.N.R	0.7246	0.8614
P.S.N.R	67.2044	65.3431
P.W.C	4.2342	2.5476

Table 6. Assessment Metrics of different models on THERMAL video from CD net DATASET

Metrics\Models	***GMM***	***PFD***
P.R	0.0021	0.0152
R.C	0.0452	0.0926
A.C	0.9881	0.9989
F.S	0.0121	0.0149
M.S.E	0.0095	0.0079
R.M.S.E	0.0975	0.089
F.P.R	0.0118	0.0101
F.N.R	0.6958	0.8924
P.S.N.R	68.3876	69.1748
P.W.C	2.1862	1.014

4. Conclusion

In this paper, the methodologies proposed for the effective background subtraction based on P.F.D is presented. The method is subject to CD Net 2014 data set and the results derived are valued against assessment metrics. The results are tabulated in the tables 1 to 6 . The methodologies are compared with those of the G.M.M-based model and the obtained result A.C was best presented against all measures considered. This highlights the effect of the proposed method.

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Author contributions

All authors are equally contributed.

Conflicts of interest

The authors declare no conflicts of interest.

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