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Comparative Analysis of Motion Detection Methods or Video Surveillance Systems

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Abstract: In this paper, a motion detection module is proposed for real time dynamic video frames by comparing the three major classes of methods for motion detection namely Background Subtraction, Temporal differencing and Optical Flow method .A hierarchical background model is proposed based on segmenting the background images. The region model is extracted from the histogram of a specific region which is similar to the kind of a Gaussian mixture model. The pixel model is described by histograms of oriented gradients of pixels in each region based on the co-occurrence of image variations. Silhouette detection algorithm is proposed. The experimental results are carried out with a video database to demonstrate the effectiveness, which is applied to both static and dynamic scenes by comparing it with some well-known motion detection methods namely Temporal differencing and Optical Flow method and based on the results a motion detection module for dynamic video frames can be developed which is cost effective, shows high rate of accuracy, low rate of complexity, and well adapt to different kinds of shadow distribution.

Keywords: Background subtraction, hierarchical background model (HBM), pixel model, and region segmentation.…

Introduction

Background subtraction is a powerful and useful mechanism for detecting many changes in a sequence of images. There are many approaches for performing the background subtraction method. The main method involves the segmentation technique. [1]Background images are segmented into many regions and this segmentation is done by Mean-shift algorithm. From the segmented regions, we construct a hierarchical model that consists of region model and pixel model. The region model is mainly extracted from the histogram of a specific region which is similar to the Gaussian mixture model. The pixel model is based on the image of variation that occurs at the same time. These variations are described by the histogram of each region in pixels. As the images change frequently, the locations of background objects are not fixed, so each pixel of the segmented regions is assigned a weight to denote the probability that this pixel belongs to one region. The main disadvantage is that they usually neglect the fact that the background images consist of different objects whose conditions may change frequently.

The most widely used background subtraction methods are non-parametric and mixture-of-Gaussian models. The main task for designing a background subtraction algorithm which is fast is the way of selection done in a detection threshold. The thresholds of varying video frames are selected by means of two models [2].There is usually a non-parametric model defined and in addition to it, a foreground model is introduced. There are two processes involved in Background subtraction that work in a loop: background modelling and foreground detection. In background modelling, the model in the view of a camera of the background is created and is periodically updated to handle the changes in illumination. In foreground detection, there involves two decision, first is made as to whether a new intensity fits the background model; second is the resulting label field which is fed back into background modelling to see that no foreground intensities is contaminating the background model. The inclusion of a foreground model tends to grow the detected regions rather than shrinking them. The main disadvantage of this paper is that the inclusion may lead to few false positives at the initial label field.

According to the functional characteristics of real-time image processing systems there were many existing digital image processing algorithms, but the most important Feature to have a reasonable hardware and software division for the realization of the functions existed [3]. With the basis of software and hardware division, a FPGA-based image processing system structure is built and respectively designs the structure of image acquisition and storage, image processing, real-time display and other functional modules. FPGA consists of four parts that involves lOB (input and output module), routing resources, logic unit, Block Ram Their main functions are:

1. Input and output module: It is defined as the interface of the chip with the outside and is used to complete both the input and output of different electrical characteristics.

2. Logic unit: It is the main core used to complete all the logic functions.

3. Routing resource: It is used to connect the logic unit, lOB and Block Ram, mainly to achieve the good signal transmission.

4. Block Ram: It is used to achieve data storage.

Finally, the pre-processing circuit that is designed is experimentally verified, and the results show that the realization of the hardware design can meet the system functions and their time requiring for processing, which have certain practical value.

There is usually need of synchronization between the image acquisition and external trigger events. Hardware and software triggering are widely used although they have several limitations.[4] Soft synchronization is investigated in this paper to operate by time tagging both the trigger events and images in a video stream and thus by selecting the image corresponding to each trigger event. For the soft synchronization a stochastic model is developed and, based on the model, the uncertainty interval and confidence for correct image selection are determined, and an efficient and perfect calibration method is derived. For this method, the images are streamed from the camera to the image processing computer. This is where the images are time tagged, and then the image is selected which corresponds to the timing of an external trigger event. This method provides several advantages that include post-triggering capability and natural support for rapidly arriving trigger events, and increased flexibility with respect to how the trigger event is sensed and communicated, and reduced cost through the opportunity to use a data-network interface. The main disadvantage of soft synchronization is the timing resolution that is limited by the frame rate.

First, the background images which are given as a input are segmented by mean shift segmentation [6]. This technique is based on the mean shift algorithm. For estimating the density gradients, a simple nonparametric procedure is used here. Thus, this program can produce a high quality edge image, or provide, by extracting all the significant colors, and a pre-processor for content-based query systems. Gray level images are handled as color images having only the lightness coordinate.

In Intelligent Transportation Systems, the moving shadows were also been wrongly detected as foreground object. This causes bad effect on the latter targets tracking and identify. To minimize the shadows that lie in different regions, there has been implemented a method of moving shadow detection which uses Susan algorithm [5] based on Image edge detection. Video highway data is taken with avi format. Then the edge is detected from Susan method and also from the mixed Gaussian method. Background is obtained by distribution. According to the experiments, susan method is easy to operate and possesses high rate of accuracy, low rate of complexity, and well adapt to different kinds of shadow distribution.

Related Work

Background Subtraction is a process to detect a movement or significant differences inside of the video frame, when compared to a reference, and to remove all the non-significant components. A Hierarchical model is developed from the segmented regions of background using Mean-shift algorithm.

General body of the manuscript

This Hierarchical model consists of two models, region model and pixel model. The region model is mainly similar to that of the mixture of Gaussian and is mainly extracted from the histogram of regions which are specific. The pixel model is mainly made up of images that can take place at the same time and are connected to each other. The method proposed in this paper involves two processing levels. These are the steps taking place in existing system.

1. The frames of the video are segmented into regions by mean shift and are taken as the input.
2. Next, according to their position to form uniform segments for a scene region different frames are merged. When this procedure takes place, a dynamic strategy of representing region borders is also developed, which leads to a more robust performance for dynamic background.
3. Then the gray value histograms of these regions are computed to build the region models, and pixel models are computed by the pixel cooccurrence within each region.
4. The region models are always built as Gaussian mixture models describing the number of components that are determined by a cluster algorithm.
5. For detecting foreground objects, we first usually segment an input frame according to the uniform segments determined.
6. Next, each region is detected whether it contains foreground objects by a corresponding region model.
7. If the detected result shows that a region contains foreground objects, first we will detect the pixel belonging to the foreground with the help of pixel models .Secondly after detecting each frame, parameters of region models and pixel models will be updated.

Advantages:

❖ It's not necessary that each model must be set constant parameters because assigning different parameters according to the region also leads to a more accurate description;

❖ The weighted pixels in each region makes both the descriptor of region and pixels more precise; and

❖ The hierarchical models reduces the time cost by just deciding which region contains the foreground and can avoiding other regions that doesn't contain

Because in some dynamic scenes, the locations of background objects are not fixed, each pixel of the segmented regions is assigned a weight to denote the probability that this pixel belongs to one region.

Disadvantages:

❖ The main disadvantage is Noise. Mean-shift algorithm does not remove the complete noise in the background subtraction.

❖ The second is the shadows. Even the shadows are detected as moving object in the existing system.

Proposed Solution

To overcome the problems faced in existing system, we use a advanced technique called Support-Vector Machine for segmenting the background images. The segmented images are meant to form a hierarchical model. This hierarchical model contains region model and pixel model.

The support vector machine is mainly based on statistic learning. .They are defined as supervised learning models with associated learning algorithms that can analyze the data and recognize the patterns, and also used for classification and regression analysis. It is a new machine learning theory. The support vector machine has been widely applied to many applications like pattern recognition, function approximation and system identification as because support vector machine is able to deal with both the classification and clustering

Classification and Regression by SVM

Generally the model can be divided into Support Vector Regression and Support Vector Classification. The Training data set is given as $\{(c_i,d_i)\}^N_{i=1}$ where ci $\in R^n$ and corresponding binary class label b_i bi ε $\{-1,1\}$where a_i is the ith input vector with known binary target b_i , Let ϕ be a non-linear mapping from the data which are original to a high-dimensional feature space, and it is mainly used to replace sample points c_i , c_j and they have their mapping images as $\varphi(c_i)$ and $\varphi(c_j)$ respectively.

The weight and bias of hyper plane is defined as w and b, respectively. We define the hyper plane which may be ready to act as a decision surface in feature space , as such,

$$\Sigma^{i}_{i=1}\ w_i\ \phi_j\ (c)+b=0$$

First we need to separate the data linearly in the feature space and so the decision function must meet a constraint conditions. The optimization problems are

$$Minimize\ \phi(\omega,\varepsilon) = 1/2\,\|w\|^2 + c\ \Sigma^{l}_{i=1}\,\varepsilon_i$$
$$Subject\ to\ d_i[(w.c_i)+b\,]>=1-\varepsilon_i \qquad ($$

Where εi is defined as a stack variable mainly used to relax the margin constraints which are hard. The regular constant C > 0 is mainly used to implement the trade-off between the maximal margin of separation and the classification error.

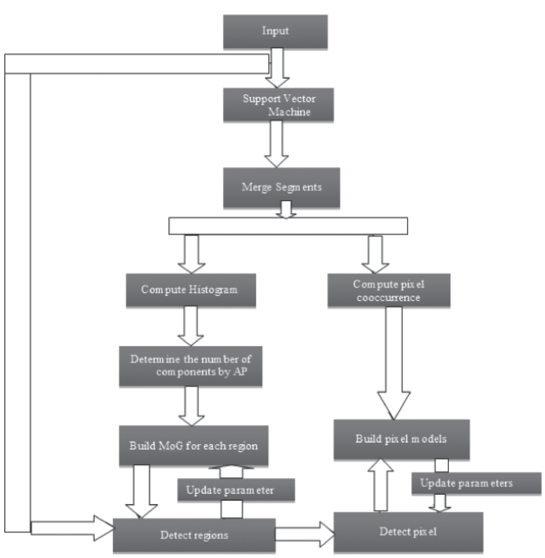

Figure : Hierarchial Model Using SVM

Normally there is a problem of which data cannot be linearly separated in classification. So to avoid this problem, the Support Vector Machine can map the data which are given as input into a feature space which are high dimensional. Usually the Support Vector Machine constructs an optimal hyper plane in the high dimensional space which is transferred into a non- linear decision frontier by first converting it into original space. The non-linear expression for the classification function is given as equation.(3)

$$t(x) = \Sigma^{l}_{i=1}\, a_i d_i\ K(c_i\,.\ c) + b \qquad (3)$$

The performance of SVM also includes the choice of this non-linear mapping function. The SVM applied uses the basis function to perform the operation of mapping. This function is expressed in (4).

$$K(c,d)= \exp(-s(c-d)^2) \qquad (4)$$

The s parameter in the above equation shows the reflection of the degree of generalization that is made to apply to the data used. Less generalization can be achieved in Support Vector Machine by obtaining more datas. When there is little s, it may reflect more generalization and a big one reflects less generalization. When the input data is not normalized, this parameter can perform a normalization task.

The classification scheme may be also defined with the case of the regression. In this case, the main idea for training the SVM by using d values different from +1 and -1. .Then, an approximation function is derived that fits approximately the known values only.

Silhouette Detection Algorithm

Silhouette detection Algorithm is mainly used to detect the angle point of the image that is moving. This Algorithm is mainly involved to do the geometry observation mainly on the basis of image's gray-scale. Then it divides the pixels into 3 main points. They are angle point, edge point and flat area. To satisfy a different value when measured in different directions we need to apply round template to image.

The centre pixel of the template is always called as nucleus. While detecting the edge, we need to move the template which is in round to the image, and then compare every gray value of the pixel in the template along with the nucleus. If the D-value is smaller than the threshold value, mark that this point has similar gray-scale to the nucleus.

$$q(w,w_0)= \begin{cases} 1, & |O(r)-O(r0)|<= d \\ 0, & \text{else} \end{cases} \qquad (5)$$

The parameter d is defined as the threshold value. If the d value is smaller than the threshold value, then that point is marked as to that similar gray-scale to the nucleus. q(w,w0) is defined as the pixel function. O(r0) is the gray-scale value of the nucleus that is in the center of template. O(r) is defined as the gray-scale value of other pixels in the templates. D is defined as the threshold value.

Therefore, for any image area the template goes through, the area which is formed by all the pixels to satisfy the formula (1) called as similar nucleus value area (USAN)[6]. The size of USAN area is as follows,

$$n(r_0)= \Sigma q(w , w_0) \qquad (6)$$

There are two main aspects to consider by using Silhouette detection Algorithm for detecting image edge:

1) The template selection
2) To determine the value for d & g's threshold value.

The two elements used here are used to determine the efficiency of edges that are detected.

The template selection:

As the image is digitalized, the template found cannot be the real round .Hence to overcome this we use rectangle template (2m+1) * (2m+1) instead.

To determine the value for d & g's threshold value:

Threshold value D is used to determine the contrast ratio of the object and background that are recognizable. Area with smaller contrast ratio, D should be smaller. Area

Implementation and Experimental Results

This solution was implemented using MATLAB. It is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, you can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable you to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages.[11]

Performance Evaluation

It is important that after the application by the proposed model, has good results over existing techniques. The proposed method's performance is compared with many several available methods. The performance has been observed by calculating noise in the background subtraction

Conclusion and Future Extensions

The objective is to develop a motion detection Technique just to extract foreground objects in a wide range of environmental conditions. Our new technique was designed to handle the problems typically associated with the background subtraction done by hierarchical model. To overcome the problem of noise and shadows an advanced technique called support vector machine for segmenting the background images can be used .The segmented images are meant to form a hierarchial model contains region and pixel model. The support vector machine is based on statistic learning . The background subtraction using support vector machine can be used to overcome the problem of shadows and noise and can provide complete feature data.

Acknowledgments

In the Acknowledgments section, appearing just before the References, the authors may credit others for their guidance or help. Also, funding sources may be stated. The Acknowledgments section does have a section heading at level 1, as in this example. Following this section the References section begins for which

authors must use the style “Reference” (Font Calibri, font size 9, first row left indented 0.4 cm) and use reference citation rules as per the journal Landslides. Please follow the rules of the same journal also for citations within the text body.

In the following section we present some example of formatting for references related to edited books, conference proceedings, periodic journal papers, scientific reports and web sites. References must be, firstly, in alphabetical order and then in date order, descending.

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Extreme Value Analysis of Daily Rainfall in Trincomalee,Sri Lanka

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Abstract: In Sri Lanka, flooding due to heavy rainfall is one of the main natural hazards that generate disasters, which has caused loss of life, and enormous damage and destruction to property. It is important to model the extreme rainfall to protect the natural resources from the impact of climate change. The main objectives of this study is to fit the best distribution to the extreme daily rainfall measured over the Trincomalee region for the years 1950-2007 with the Maximum Likelihood parameter estimation method. This study also predicts the extreme rainfall, the return periods and their confidence band. Based on two general approaches (1) Block Maxima approach considering annual maximum rainfall and (2) Point Process approach considering rainfall which exceeds some specific threshold value. The Generalized Extreme Value distribution and the Generalized Pareto distribution are the classical distributions corresponding to the methods 1 and 2 to describe the extremes of rainfall and to predict its future behaviour. It was found that Gumbel distribution fits well with the annual maximum rainfall and Exponential distribution fits well the rainfall over the specified threshold value of 105 mm. The return levels of 2, 5,10,20,50,100 and 200years and their confidence band were also estimated.

Keywords: Generalized Extreme Value distribution, Point Process, Pareto distribution, Maximum Likelihood estimation, Threshold value,Stability Plot.

Introduction

Heavy rainfall is one of the most severe weather hazards affect Sri Lanka. Extreme rainfall events leading to the severe flooding and landslide, which can threaten human life, damage to agriculture, buildings and infrastructure, and disrupt transport and communications. Trincomalee district is one of the 25 administrative districts of Sri Lanka situated in the Northern most part of the Eastern Province, where the local economy is largely based on agriculture and fisheries.

A number of scientific studies have been done on extreme rainfall in different locations all over the world. In Sri Lanka, Varathan et al. (2010) have analysed the extreme rainfall in Colombo using Annual Maxima method and Peak over Threshold method. They have used 110 years data and found that Gumbel distribution fits well the annual maximum data and exponential distribution fits well the peak over threshold data. In Malasiya Zalina et al.(2002) found that the GEV distribution is the most appropriate distribution for describing the annual maximum rainfall series in Malaysia. They did a comparative assessment of eight candidate distributions such as Gamma, Generalized Normal, Generalized Pareto, Generalized Extreme Value, Gumbel, Log Pearson Type III, Pearson Type III and Wake by in providing accurate and reliable maximum rainfall estimates using L-moment parameter estimation method for Malaysia.

In this study, we analysed 57 years daily rainfall from 1950 to 2007 in Trincomalee district. We used two techniques, one is by considering annual maximum rainfall for which we used the Generalized Extreme Value distribution (GEV) and the other one is by considering exceedance over the specified threshold value for which we used the Generalized

Pareto Distribution (GPD).For both of these techniques maximum likelihood method was used to estimate the parameters.

Extreme Value Theory

The Generalized Extreme Value Distributions

Three classes of distributions are named as Extreme Value Distributions, with types I, II and III, and also known as Gumbel, Fréchet and Weibull families, respectively. A better analysis can be done combining the three models into one single family of models named the generalized extreme value distribution (GEV):

$H(x) = \exp\{-(1+\xi(x-\mu)/\psi)^{-1/\xi}\}$;where $\psi > 0$ –scale, ξ - shape and μ - location parameter.

According to the value of ξ, H(x) can be divided into following three standard types of distributions:

Type I: If $\xi \to 0$ (Gumbel Distribution, exponential-tail decay)

$H(x) = \exp(-e^{-x})$, all x

Type II: If $\xi > 0$ (Frechet Distribution with $\alpha = 1/\xi$, power-tail decay)

$$H(x) = \begin{cases} 0 & ; x < 0 \\ \exp(-x^{-\alpha}) & ; x > 0 \end{cases}$$

Type III: If $\xi < 0$ (Weibull Distribution $\alpha = -1/\xi$, finite upper endpoint)

$$H(x) = \begin{cases} \exp(-|x|^{\alpha}) & ; x < 0 \\ 1 & ; x > 0 \end{cases}$$

The Exceedances over Threshold

An alternative approach is the Peak over Threshold (POT) method which is one of the special cases of point process representation. Maximum Likelihood estimation is relatively easiest method to estimate the parameters of the POT model. With an assumption of the daily data to be independent with common distribution function F, given a high threshold value u and looking at all exceedance of u, the distribution of excess value is given by,

$$F_u(y) = \Pr\{X \le u + y | X > u\} = \frac{F(u+y)-F(u)}{1-F(u)}, y > 0$$

According to the Balkema and de Hann (1974), Pickands(1975) thearom, for the sufficiently large threshold the distribution of Exceedances may be approximated by GPD, which means that, letting $u \to \infty$ leads to an approximate family of distributions given by,

$$G(y) = 1 - (1 + \frac{\xi(y-u)}{\sigma})^{-1/\xi}$$

is the Generalized Pareto family and which is converges to an Exponential family when $\xi \to 0$.

Return Periods

The return period represents the average recurrence interval over an extended period of time. Theoretically return period is the inverse of the probability that the event will be exceeded in any one year, that is, T =1/P, where T is the return period in number of time intervals, and P is the probability of the next event's occurrence in a given time interval.

Data and Methodology

Daily rainfall data for the periods from 1950 to 2007 for the Trincomalee District were considered. The data was collected from the Department of Meteorology, Trincomalee and the statistical software R was used for the analysis. To fit the distribution and estimate the return levels the Univariate extreme value theory was applied for the data set. Initially the GEV distribution was considered for the annual maximum rainfalls and then by testing the hypothesis on shape parameter, the best fitting distribution was identified. Secondly the GPD to the rainfall over specified threshold value was considered, and then by testing the shape parameter the best fitting distribution was identified. To identify the threshold value the mean residual life plot and stability plots were used. With the identified model 95% confidence band and return levels were estimated.

Results and Discussion

Fitting Generalized Extreme value (GEV) Distribution for the annual maximum rain fall.

Table 1 shows the estimated value of the parameters of the GEV distribution using maximum likelihood estimation method. Even though, it can be concluded that the data fits the Weibull distribution well, since ξ <0, the null hypothesis that the data fits the Gumbel distribution (ξ = 0) cannot be rejected at 5% of significance level (p-value = 0.22 > 0.05).

Table 1: Maximum Likelihood parameter estimates

Parameter	Estimate	Standard Error
μ	108.46	5.541
ψ	38.35	3.843
ξ	-0.10	0.077

(Likelihood ratio statistic: 1.50, p-value: 0.22)

Table 2 gives the return levels of the annual maximum rainfall and their 95% confidence band for some return periods. The 100 year return period is 248.6 mm, means that in any given year we can expect 248.6 mm or more rainfall with the probability 0.01.

Table 2: Return levels and their confidence band

Probability	Return Period	Return Level	Lower	Upper
0.5	2	122.3	110.89	134.38
0.2	5	161.7	147.67	178.86
0.1	10	185.4	168.86	210.06
0.05	20	206.4	186.86	242.39
0.02	50	231.4	206.95	282.16
0.01	100	248.6	219.83	312.71
0.005	200	264.5	230.98	343.70

Figure 1 reveals the confidence bands of return periods using Annual Maxima method and in which all the data points fall within the confidence band except one rainfall (273.4 mm) occurred on 2007.

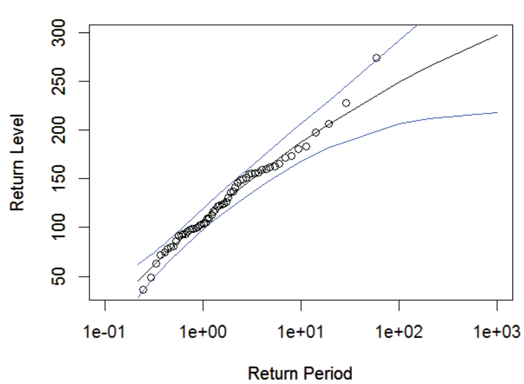

Figure 1 : Return level plot of Annual maximum rainfall

Fitting Generalized Pareto Distribution (GPD) for the Peak over threshold rain fall.

Identification of threshold value.

The mean Exceedances above u (threshold value) should be linear, so the idea is to looking for linearity in a plot of the empirical mean residual life plot (Stuart coles, 2001, Matthew J.Pocernich, 2002). According to the Figure 2, the threshold greater than 90 looks reasonable.

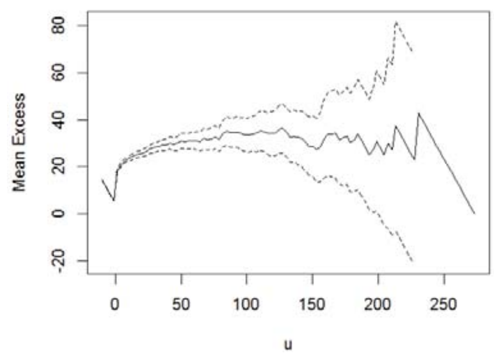

Figure 2 : Mean Residual Life plot of daily rainfall

Selecting the threshold value is a Bias-variance trade-off. If the threshold is too low which is bias because of the model asymptotic being invalid, if the threshold too high, which is also bias because of large variance due to few data points. An alternative approach is to fit the Poisson process model at many thresholds and look for parameter stability. According to the Figure 3 the threshold 105 looks high.

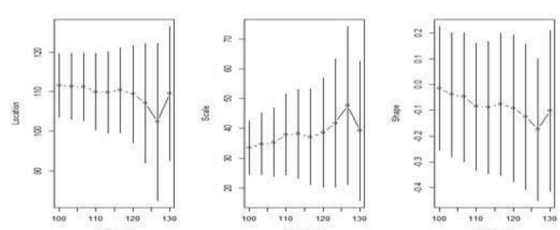

Figure 3 : Poisson process model for the threshold between 100 and 130

According to the Table 3 it shows that the estimated value of the parameters of the GPD using maximum likelihood estimation method.The null hypothesis that the data fits the Exponantial destribution (ξ = 0) can not be rejected at 5% of sifnificance level (p-value = 0.61 > 0.05).

Table 3: Maximum Likelihood parameter estimates

(Likelihood ratio statistic: 0.26, p-value: 0.61)

Parameter	Estimate	Standard Error
μ	36.87	6.287
ψ	-0.06	0.120

The return levels and their 95% confidence band for the return periods were estimated based on the identified distribution which is shown in Table 4.From this table it can be interpreted that the return level of the 100 year return period is 256.03 ,which means in any given year we can expect 256.03 mm or more rainfall with the probability 0.01.

Table 4: Return levels and their confidence band

Probability	Return Period	Return Level	Lower	Upper
0.5	2	135.6	128.20	144.79
0.2	5	166.6	154.08	182.81
0.1	10	188.7	172.80	215.33
0.05	20	210.2	190.06	254.75
0.02	50	236.9	210.02	302.96
0.01	100	256.0	223.03	331.74
0.005	200	274.5	234.31	359.25

Figure 4 shows the return periods and their confidence band using the peak over threshold method. In which all the data points fall inside the confidence band.

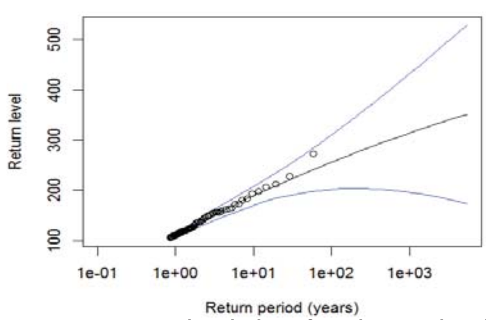

Figure 4 : Return level plot of peak over threshold rainfall

Conclusions

The rainfall data was obtained for a period of fifty seven years (1950 - 2007) for the Trincomalee District, Sri Lanka. In this study the extreme value analysis was carried out using two methods such as Annual Maxima method and Peak Over Threshold method. The annual maximum data fits the Gumbel distribution well. The rainfall of 248.6 mm occurred in 2007 falls outside of the confidence band in the return level plot of the annual maximum rainfall. For the peak over threshold method, the threshold value was determined using the graphical approaches such as the mean residual life plot and the stability plot, and the data fits well the Exponential distribution. But, in peak over threshold method all the data points exceed the specified threshold (105 mm) fall inside the confidence band of the return level plot. More else, both Annual maxima and Peak over Threshold models give similar or comparable predictions of return periods and confidence band. The estimated return periods and their confidence band could be useful to minimize the damages due to heavy rainfall for some extant.

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