Editing Sample

1 Developmental Editing

Note: This is the given content and needs to be rewritten to enhance the meaning and presentation.

Feature
Data Loss Prevention (DLP) Integration with TechShu-INT (the product)
Goal
• Data that is going outside TechShu-INT, should not disclosed sensitive content for an organization

Value Proposition
• TechShu-INT is a digital backbone that can connect to multiple peripheral systems (e.g. Teamcenter and SAP) to exchange data. Also, during exchange of data, TechShu-INT ensures that no accidental exchange of sensitive data within or outside organization boundaries.
• Data Loss Prevention (DLP) is a security solution that identifies and helps prevent unsafe or inappropriate sharing, transfer or use of sensitive data.
• TechShu-INT will be integrated with DLP solutions that accepts the text or file data as an input and responds if there is any sensitive content present. Based on DLP applications response, TechShu-INT will take action and abort ongoing operation if required.
• e.g. There is a process that transfers engine information from Teamcenter to SAP but there are patented engine designs which are not to be shared across any public platforms such as SAP. TechShu-INT will send all the engine information fetched from Teamcenter to DLP solution to find if there is any sensitive information is included. Based on DLP policy not to share patented engine designs, the DLP solution responds with sensitive data disclosure information. Based on the tool’s response TechShu-INT will abort the transaction and will raise an alert for sensitive data disclosure.

Edited Content

Data Loss Prevention Integration with TechShu-INT

Data Loss Prevention (DLP) is an intelligent tool that analyzes data and its criticality. DLP prevents data loss from an application, thwarts exchange of unwanted information between applications, and takes an action to stop an operation if it suspects data breach.

TechShu-INT has been integrated with DLP. With this enhancement TechShu-INT ensures peace of mind for our customers. Here is a list of the advantages of DLP.

Features & Advantages

Features	Advantages
Prevents data slippage	TechShu-INT is a digital backbone that allows connecting to multiple peripheral systems such as Teamcenter and SAP to exchange data. During exchange of data, TechShu-INT ensures that no accidental exchange of sensitive data happens within or outside organizational boundaries.
Fortifies sensitive data	DLP is a security solution that identifies and helps prevent unsafe or inappropriate sharing, transfer, or use of sensitive data.
Identifies sensitive data and takes an action	DLP is an intelligent tool that analyzes the text or file for data sensitivity based on configured data detection rules. For example, if data is being exchanged between applications, DLP detects whether the information is sensitive, patented, or copyrighted. Based on this DLP's analysis, TechShu-INT takes an appropriate action. TechShu-INT can even abort the ongoing operation if required.

2 Copy Editing

Table of Contents

DNS Analytics

The Analytics page displays different statistics related to DNS service and provides insights ~~of~~ into DNS service health, clients behavior, top queries, ongoing attacks, and so on, thus enabling quick overview of DNS operations.

DNS is a~~n~~ ~~important~~ key component of the Internet system that ~~translates~~ maps domain names ~~in~~to IP addresses.

Organizations utilize different rules and filters based on blacklists to block known malicious domain names. Comprehensive monitoring of DNS traffic is required to protect against ~~as a component of~~ cyber attacks ~~security~~.

~~The f~~Four types of Advanced DNS Analytics are as follows:

- **Threat intelligence** - Identification of malicious domains such as ~~(for example,~~ command-and-control, compromised name, and so on~~)~~. This method uses DNS analytics to generate new threat intelligence ~~that can be used~~ to block domain names, preventing future access to malicious domains.
- **Threat detection** - Detection of affected endpoints such as ~~(for example,~~ suspicious behavior patterns that ~~) is about to~~ detect ~~find~~ ~~ing~~ compromised systems quickly based on suspicious DNS behavior.
- **Domain categorization** - Automatic categorization of domain names ~~(for example,~~such as most queried domains vs most queried NXDOMAIN domains~~)~~.
- **Forensic markers** ~~-~~– Provides ~~ing~~ actionable information for forensics ~~(~~for ~~example,~~ top DNS clients and~~,~~ malformed DNS query trends~~)~~.

ADC App content and information analysis is based on ~~the~~ fast streaming of DNS queries. ADC App provides advanced analytics of the context, rate of queries, including the history of lookups, content~~s~~ of the response, and correlation with additional data sources.

The following topics are covered:

DNS Analytics: KPI

~~The~~ **KPI Bar** for the **ADC Analytics** tab displays the following information:

Widget / Field	**Description**
QPS	Displays ~~N~~number of DNS queries received per second and is ~~.~~ ~~R~~refreshed every minute.
DNS Query Health	Displays ~~P~~percentage of processed DNS queries ~~among~~ from all incoming requests. Displays ~~A~~average over last 3 minutes of data and is r~~. R~~efreshed every minute. Dropped packets could be due to malformed query, non~~-~~-DNS packets, or configured deny policies.
DNS Response Health	Displays p~~P~~ercentage of good DNS Response (NO ERROR) ~~among~~ from all DNS responses. Displays ~~A~~average percentage over last 3 minutes of data and is ~~. R~~refreshed every minute.
Avg. Latency	Displays ~~L~~latency between DNS Query and Response. Displays ~~A~~average over last 3 minutes of data in ~~m~~milliseconds~~s~~ and is ~~.~~ ~~R~~refreshed every minute.
Avg. Query Size	Displays the ~~Q~~query size in bytes. Displays ~~A~~average over last 3 minutes of data and is ~~. R~~refreshed every minute.
Avg. Response Size	Displays ~~R~~response size in bytes. Displays ~~A~~average over last 3 minutes of data and is ~~. R~~refreshed every minute.
Unique IPs	Displays u~~U~~nique source IPs average for the last 3 minutes of data and is ~~. R~~refreshed every minute.

DNS Analytics: QPS

The **ADC App > Analytics** section displays the following QPS widgets for the **DNS service** selection:

Widget/Field	Description
QPS with Query Types	Displays ~~N~~number of DNS queries received per second grouped by query types such as A, AAAA, NS, and so on.
QPS with Response Codes	Displays ~~N~~number of DNS responses per second grouped by response codes.

DNS Analytics: Other Metrics

The **ADC App > Analytics** section displays the following DNS query health monitoring and Top sources widgets for **DNS service** selection:

Widget/Field	Description
DNS Health	Displays ~~T~~time series of DNS Query and Response health.
Avg. Latency	Displays ~~A~~average values of historical latency in a time series graph. By default, Area chart is displayed.
DNS Query Latency	Displays t~~T~~he fastest and slowest latency in response to DNS queries sent to the DNS server or recursive server until ADC gets a response from the DNS server or recursive. It consists of the following elemnts: • **Time**: The DNS latency data in milliseconds. The chart ~~data~~ represents the number of requests in each latency time range.

	• **Current**: Number of DNS queries in the last 2 minutes. • **Avg**: Average number of DNS queries for every 2 minutes in the selected time range. • **Maximum**: The maximum number of DNS queries for every 2 minutes in the selected time range.
Cache Hit Rate	The Cache Hit Rate and Cache Miss Rate charts. • DNS cache hit rate indicates the number of cache hits per second. • DNS cache miss rate indicates the number of cache misses per second.
Avg. Size	Displays ~~A~~average size of Query packets and response in bytes in a series graph.
Malformed DNS Query Rate	Displays ~~R~~rate of malformed queries received per second.
Request By Source Port	Displays ~~Q~~query distribution by source port in Tree map, donut, or table format.
Top DNS Queries	Displays ~~Q~~query distribution by • Top DNS Queries~~UERIES~~ • Top DNS Queries (NXDOMIAN)
Top Source IPs (v4 and v6)	Displays 2 widgets for IPv4 and IPv6 display chart based on dynamically sampled logs in the last 12 hours: • Client IP: Top clients that send the most DNS Queries. • Client IP (NXDOMAIN): Top clients that send the most DNS query results in the NXDOMAIN response. • Query Size: Top clients that send the highest DNS Query sizes. • Response Size: Top clients that result in the highest DNS

	response payload size.
Unique IPs	Displays ~~U~~unique source IPs over time.
Response Sources	Displays ~~P~~percentage of response from backend servers, A10 Cache, A10 GSLB, and so on.

3 Line Editing

~~-~~Recognition of Vision~~-~~-based Activities of Daily ~~living recognition based on~~Living Using Linear Predictive ~~coding~~Coding of Histogram of Directional Derivative

~~sidharth B Bhorge~~

Sidharth B Bhorge

~~Ramchandra R. Manthalkar~~

Assistant Professor, Dept~~.~~. ~~*of electronics*~~. of Electronics, ~~Professor, Dept., of E*&TC*~~

Vishwakarma Institute of Technology, Pune, India. siddharth.bhorge@vit.edu

Ramchandra R. Manthalkar

Professor, Dept., of E & TC, Shri Guru Gobind Singhji Inst. ~~*Of*~~of Engg & Tech
~~*Pune, India*~~ Nanded, India
~~*Siddharth.bhorge@vit.edu*~~ rrmanthalkar@sggs.ac.in

Abstract

In this paper, we have introduced a novel approach for recognition of activities of daily living (ADL~~) which refers to the classification of~~). These activities ~~frequently performed~~are the ones that the human beings perform in daily life. At the object level, an innovative idea is proposed to segment and track a moving object from the background. The proposed object segmentation uses a cosine of angle between the expected color vector and current image color vector from computational color model. At feature level, we have presented a linear predictive coding of histogram of directional derivative as a spatio-temporal descriptor. Our proposed descriptor describes the local object shape and appearance within cuboids effectively and distinctively. A multiclass support vector machine ~~is then~~has been used to classify the human ~~activity~~activities. The proposed framework for recognition of indoor human activity ~~recognition is~~has been extensively validated on ~~a~~the benchmark of Activities of Daily Living (ADL) datasets, ~~where it was manifested~~with a focus that ~~our~~this methodology is robust and ~~attaining~~attains more precise human activity recognition rate as compared to ~~state of art~~current methodologies available.

Keywords: Human activity recognition, activities of daily living, Histogram of Directional derivative

1. Introduction

An activity of daily living (ADL) has become a most demanding ~~issue~~topic in pattern recognition and computer vision community. ~~It has~~ADL is equipped with numerous applications, such as automated surveillance (Ismail H. et. al. 2000), smart home (Mohsen and Asma 2015), health monitoring, and elderly care system (Zhao Z. et. al. 2008). Several studies show that it ~~becomes~~is necessary to provide solutions for ~~rising number of~~ the elderly people ~~to~~who live alone and independently~~.~~, whose number is rising at a faster rate because of viability of good healthcare facilities and reducing mortality rate. However, the data produced from ~~such~~ presently widely used sensors are huge and complex~~,~~ that make it ~~is impossible for human~~difficult to continuously monitor and analyze the data. Therefore, it is ~~necessity of~~important that we should opt automated sensor data analysis techniques ~~which~~that can provide accurate ~~classification and~~ recognition of human activities~~.~~ and their classification. Further, automatic human activity recognition has gained prominent interest for research ~~interest~~ in recent years due to an important role in these applications. ~~The human activity detection is used to study the making~~Recognition of human activity is studied

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to understand the lifestyle ~~and summarize the~~ of people ~~activities~~and their needs over a period of time.

Monitoring and classification of activities of daily living can be carried out by numerous sensors, such as wearable accelerometer (Zhang and Sawchuck 2013), audio sensors (Yale S. 2013), video cameras (Z. Zhou 2008~~)~~), and their various combinations (Medjahed et. al, 2011). These sensors have various advantages ~~like~~such as unconstrained real-life conditions and less computational cost. The main drawbacks, however, are they may be obstructive ~~and interfere with~~against carrying out the tasks in our daily ~~work, also~~life. Also they cannot provide a complete picture of ~~activity es taking place.~~the activities that encompass the entire life of a man over longer time span. On the other hand, ambient sensors provide limited information as they are specific to location. The other class of activity recognition based on visual sensors provides additional comprehensive and precise information as compared to wearable and environmental sensors. Therefore, it ~~provide~~provides high recognition rate and can be enhanced by combining with other sensor-based ~~techniques~~technologies (Jin et. al. 2012). Video-based techniques can be broadly classified into the techniques based on object-level feature and low-level ~~features~~feature. The object-level feature ~~based approaches~~ techniques use appearance, direct motion, silhouette, and shape ~~as features~~ (Bobick et. al 2001). However, object-level features tend to be weaker against change in illumination object deformation and variation in ~~view point~~viewpoint and changes in background. In this paper, we ~~chose~~selected recognition scheme that ~~make~~makes use of local feature such as spatio-temporal interest points ~~as~~because these features are more robust than ~~global~~commonly used features. ~~These~~Importantly, these features represent motional and structural information over space and time. Generally, these features are directly extracted from video sequence without applying pre-processing steps ~~on video sequence.~~. Also, they are more robust to noise and reduce the failure rate arising due to segmentation and tracking.

~~The state-of -art~~

Current methods ~~achieves~~achieve good results for recognizing human activity ~~recognition~~, but there is still a room for improvement for ~~in terms of recognition~~attaining accuracy in human activity recognition and lowering down the computational cost. ~~The current state~~Some of ~~art uses a~~the common methods are spatio-temporal interest point detection and their description using Histogram of Oriented Gradient (HOG) or Histogram of optical flow (HOF). A HOG descriptor is widely used to represent the local appearance and structural information. It works on the principal of orientation quantization of gradient vector, which is normal to edge. Therefore, it does not give structural or orientation information ~~apart from~~except normal direction. To extract the structural and appearance information not only in normal direction but also in other directions provided by unit vector~~. We proposed~~, we propose Histogram of directional derivative as local descriptor.

We ~~address~~have addressed these issues by proposing a novel approach ~~to~~for segmentation and tracking at object level and new local spatio-temporal interest point descriptor at feature level:

- At object level, we ~~develop~~developed an accurate and computationally efficient segmentation and tracking algorithm to handle dynamic background change in ~~an~~ indoor environment.
- At feature level, we proposed Histogram of Directional Derivative to represent the local appearance and structural information, which is more discriminative than HOG. ~~And hence~~Hence, we can achieve more recognition rate ~~as~~ compared to ~~state of art~~the current methods.

The rest of the paper is organized as follows. Section 2 describes the different ~~type~~types of descriptor in the literature. Section 3 gives the proposed methodology for foreground segmentation and feature extraction using linear predictive coding of Histogram of directional derivative descriptor. Section 4 demonstrates the experimental results of proposed method on URADL activities of daily living dataset ((Messing R et. al. 2009)), Grenobel smart home video (Anthony F. et al. 2010) dataset,

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benchmark KTH (Schuldt C et. al 2004) dataset, and Weizmann dataset (Gorelick et. al. 2007). Conclusions are presented in ~~section~~Section 5.

2. Related Work

In recent years, a number of techniques have been developed to monitor and analyze the human activities. These techniques can be broadly divided into two categories: global and local representation of human actions. The global representation ~~scheme~~technique makes use of motion history images, space-time volume, and trajectory-based descriptors. A global spatio-temporal (Bobick and Davis 2001) representation of motion is constructed by using an object motion history images. These types of motion templates are constructed by assigning a temporal history of motion at each pixel location. It can record the global motion information in a visual cue. Further, the combined motion and shape features (Ahmad M. and S.W. Lee 2008) are used for action recognition. The global shape and motion flow are extracted by applying combined local global optical flow and invariant moments respectively. The spatio-temporal features such as orientation, shape and action dynamic (Gorelick et al. 2007) are extracted by using the solution to the Poisson equation. It uses a three dimensional spatio-temporal pattern of silhouettes as action model. The motion history images and interest points are combined (Tian et al. 2012) by applying local and global motion filters. The temporal information is captured by motion history of image (MHI) and 2D Harris corner point detector is applied to record spatial information. Then ~~they applied~~ global smoothening filter and local motion filter are applied to remove the noise due to individual pixel motion. This ~~novel~~ approach is used to detect actions in crowded video sequences. A novel framework based on the principal called slow feature analysis (SFA) (Zhang Zhang and Dacheng Tao 2012) is introduced and a discriminate analysis technique is used to characterize the slowly varying features in action video sequences. ~~Recently~~Additionally, an evolutionary computation (Li Liu et al) method is used to automatically learn and extract the best set of features from input video sequences for action recognition. The motion history images are constructed (Du-Ming Tsai et. al. 2014) by assigning motion strength at each pixel based on the length of flow vector. However, these methods not only experience a spatial localization but also ~~they~~ are sensitive to change in illumination and noise. The local representation scheme overcomes these limitations by focusing on local region over space and time. Dollar (Dollar et al. 2005) used a set of linear filters to extract spatio-temporal interest points in a video sequence. The linear filter evokes the strong response for periodic as well as complex motion. Then ~~they applied~~ the local feature descriptor methods ~~to represent them~~ are applied in a compact form. However, these descriptors suffer from illumination change. The transform-based techniques (Ling Shao et. al. 2011) such as Fourier transform, discrete cosine transform, and wavelet transform are on extracted spatio-temporal interest points ~~to represent it into compact from~~A. They are compacted from a histogram of oriented rectangles (N. Ikizler and P. Duygulu 2009) ~~is~~ constructed by extracting small region from segmented silhouette. The major shortcoming of this approach is that the construction of ~~(~~HOR~~)~~ depends on extracted human silhouettes. P Banerjee and R. Nevatia (P Banerjee and R. Nevatia 2011) developed a model~~, which learn~~ that analyses the spatio-temporal neighborhood structure in terms of pair wise co-occurrence statistics of ~~codeword~~code word. These approaches model a complex dynamics of human activity and ~~led~~lead to a substantial increase in parameter estimation and computation time. Histogram of oriented gradient (Dalal and Triggs 2005) and scale-invariant feature transform (SIFT) (Lowe 2004) descriptors build histogram by quantizing 2D gradient orientation in a support region. ~~Since the~~The gradient of orientation is not a function of magnitude and is also unaffected by illumination change and image noise. It has been proven to be more robust and powerful approach for spatio-temporal feature description (Ghamadi et. al. 2010, Derpanis et. al. 2013). Recently, a number of methods ~~are~~have been developed to recognize human action based on 3D spatio-temporal features. The orientation of 3D spatio-temporal feature is usually described by using spherical coordinate system. These descriptors experience a singularity problem at poles due to quantization and have less discrimination capability due to less number of polyhedron. The proposed framework uses the spatial temporal interest points as local features~~, these features~~ that are considered to be more robust

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than the global features in different scenarios such as changing lighting conditions, zoom-in ~~zoom-out and object deformation. In our proposed methodology, we build a sub-region codebook of extracted feature by using k-means clustering, which groups the similar features. Centroids of the clusters are called codeword of the codebook and named as video words~~and zoom-out, and object deformation.

In our proposed methodology, we built a sub-region codebook of extracted feature by using k-means clustering that combine similar features. Centroids of the clusters are called code word of the codebook and named as video words.

3. Indoor ~~human activity recognition framework~~Human Activity Recognition Framework

This section describes the complete flowchart of the proposed human action recognition system as shown in ~~figure1~~Figure 1. In training phase, first, we ~~extract~~extracted the foreground by using our proposed object segmentation method and then ~~the~~ Dollar's (Dollar's et. al. 2005) interest point detector ~~is~~was applied to extract interest points and corresponding cuboids from training video sequences. The spatial information (Z. Zhang and D. Tao 2012~~) is~~) was introduced by dividing the foreground bounding box into six regions. ~~We then represent~~Then, we represented each cuboid by using ~~our~~the proposed Linear Predictive Coding (LPC) of Histogram of Directional Derivative (HODD) descriptor. The codebook of each region of the training video sequences ~~is~~was then constructed by applying k-means clustering on all descriptors. Each descriptor ~~is~~was uniquely represented by cluster centers (video words) based on metric used as Euclidean distance. So, all training video sequences ~~are~~were represented as membership of codebook. At the time of the testing phase, we ~~follow~~followed the same steps as training session and ~~represent~~represented each testing video sequence using a membership of codebook formed in testing session. Then the testing video sequences ~~are~~were classified by using a support vector machine (SVM) model build during the training phase. The following subsections describe the complete human activity recognition framework.

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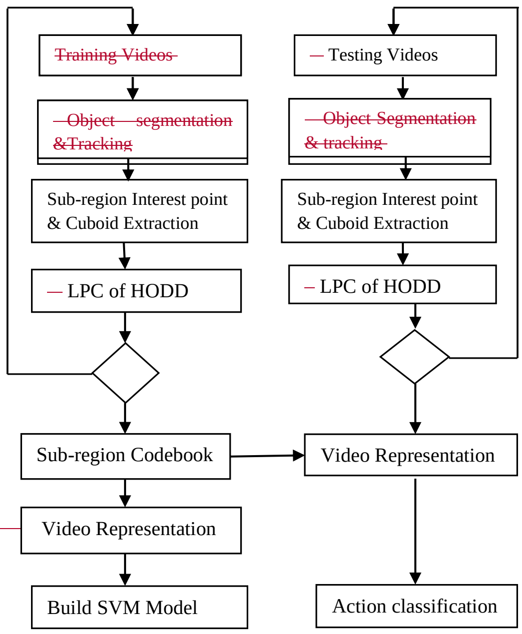

~~Figure1.~~Figure 1. Flowchart of human activity recognition system.

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3.1 Moving Object Segmentation and Tracking

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A number of algorithms ~~are~~have been developed in literature to model the background. ~~In (R. We Cucchiara et. al. 2003)~~ proposed a ~~novel~~ background subtraction method (R. Cucchiara et. al. ~~it~~2003) that statistically ~~model~~models the adaptive background image. ~~In (C. We Wren et al. 1997)~~ developed a real-time tracking system (C. Wren et al. ~~it~~1997) that utilizes a Gaussian mixture model for illumination distribution analysis ~~and then it estimate~~that estimates the parameters using Maximum A Posteriori Probability (MAP). Eigen-backgrounds and illumination distribution analysis have been presented ~~in~~ (C. Stauffer et. al. 2000, L. Wang et. al 2003.) A detailed review of the background modeling techniques is given ~~by~~ (M. Piccardi 2004). It describes simple as well as complex background modeling techniques. A computational color model ~~proposed by~~ (T. Horprasert et. al. 1999) is used to segment a moving object from the background. It utilizes brightness distortion and chromaticity distortion to differentiate foreground objects from the background. The brightness distortion is invariant under brightness ~~a change is shown by~~ (C. Wren et. al. 1997). An adaptive background image is modeled by computing the average values of its RGB component over past M frames. The expected RGB color at i[th] pixel in background image is represented by $E_i= [E_R(i), E_G(i), E_B(i)]$ and pixel in the current frame is denoted by $I_i=[I_R(i), I_G(i), I_B(i)]$. As shown in figure 2(b) by projecting a vector I_i on to E_i and using the property of orthogonal vectors the brightness distortion α_i is given as

$$(I_i - \alpha_i E_i).E_i = 0 \qquad (1)$$

$$\alpha_i = \frac{I_i \cdot E_i}{E_i \cdot E_i} = \frac{\left(\frac{I_R(i)\mu_R(i)}{\sigma_R^2(i)}\right)+\left(\frac{I_G(i)\mu_G(i)}{\sigma_G^2(i)}\right)+\left(\frac{I_B(i)\mu_B(i)}{\sigma_B^2(i)}\right)}{\left(\frac{\mu_R(i)}{\sigma_R(i)}\right)^2+\left(\frac{\mu_G(i)}{\sigma_G(i)}\right)^2+\left(\frac{\mu_B(i)}{\sigma_B(i)}\right)^2} \qquad (2)$$

and chromaticity distortion CD_i is given by (3)

$$CD_i = \|I_i - \alpha_i E_i\| = \sqrt{\left(\frac{I_R(i)-\alpha_i\mu_R(i)}{\sigma_R(i)}\right)^2+\left(\frac{I_G(i)-\alpha_i\mu_G(i)}{\sigma_G(i)}\right)^2+\left(\frac{I_B(i)-\alpha_i\mu_B}{\sigma_B(i)}\right)^2} \qquad (3)$$

The values of brightness distortion α_i and chromaticity distortion are used to separate the foreground pixels from the background. If CD_i is greater than threshold (T_1) or α_i less than threshold (T_2), it is classified as foreground pixel. These values are used to learn the resemblance of the chromaticity distortion and brightness distortion between modeled background frame and the current frame. The threshold values (T_1 and T_2) are automatically determined by using a statistical learning procedure. The probability distribution of α_i and CD_i are computed and the thresholds are calculated by deciding an acceptable detection rate. This method is more robust than the typical Gaussian distribution algorithm (Z. Zhou 2008~~); in~~). In fact authors (T. Horprasert et. al. 1999) have shown that α_i and CD_i distributions are not Gaussian. ~~In this paper, we proposed to use~~We used a cosine of angle between the vector E_i and I_i to dispense with the issue of threshold selection. It has been found that the cosine of angle between the two vectors is much more discriminating than the values of α_i and CD_i.