Object Tracking and Detection for Immovable Object Using Intuitionistic Fuzzy Logic for Video Processing

R. Revathi[1] and M. Hemalatha[2]

Research Scholar, Department of Computer Science, Karpagam University Coimbatore, India
** Prof & Head, Department of Computer Science, Karpagam University Coimbatore, India*

Abstract

The process of characterizing the instances of particular objects like face, Vehicles in a road and part of a place in the photographs or videos is termed object detection. Abandoned object discovery exploitation chase primarily based approaches are typically become unpredictable in complicated investigation videos owing to noise, occlusions, lighting changes, and alternative factors. This paper presents a novel structure to powerfully and proficiently observe abandoned objects supported background subtraction. In this proposed system, the background is sculptural by Gaussian mixture. So as to carry complicated things, varied enhancements are enforced for noise removal, fast lighting remodel adaptation, fragment reduction, and maintaining a stable update rate for video streams with completely different frame rates. So as to substantiate this new propose approach the object detection technique exploitation Intuitionistic logic based on block matching techniques has been used. The experimental results obtained were tested on benchmark video sequences. The obtained results are terribly promising in terms of robustness and effectiveness.

1. Introduction

The process of identifying the instances of objects such as faces, Vehicles and construction places of the images or videos is called object detection. Detection algorithms normally used to extract the features and learning algorithms to identify instances of an object. The applications is commonly used in the retrieval of image, security, surveillance, and vehicle parking systems.[1].

The identification of an object in an image or video is described in object detection. Computer Vision System Toolbox ropes various approaches to detect the object, template matching, blob analysis algorithm. Template matching is proposed by small image, or pattern, to indentify the region in bigger image. Blob analysis algorithm states that segmentation and blob properties to find the interest of the objects [2].

2. Application

- •Android Eyes - Object Recognition[3]
- •Image panoramas[4]
- •Image watermarking[5]
- •Global robot localization[6]
- •Face detection [7]
- •Optical Character Recognition [8]
- •Manufacturing Quality Control [9]
- •Content-Based Image Indexing [10]
- •Object Counting and Monitoring [11]
- •Automated vehicle parking systems [12]
- •Visual Positioning and tracking [13]
- •Video Stabilization [14][15].

3. Methodology

3.1 Pre-processing

An operation at the lowest level of abstraction is called image preprocessing. Such operations do not raise information content of image but reduce the information measure[41,42].The goal of pre-processing is an development of the image data that prevent the development of unwanted relation or increase some image features applicable for processing and analysis task. Pre- processing is being without a job in images. Neighboring pixels equivalent to one real object have the same or similar brightness value.[43]

In preprocessing the videos are converted into grey scale videos and then by applying various filtering techniques best filter is obtained. According to this for Gaussian Noise Winer filter, Salt and Pepper Noise Median filter and for Periodic Noise 2DFIR filter is best for the video. Depending upon the PSNR and MSE Value the best filters are identified. This is calculated by higher the PSNR value and lower the MSE values. This can be calculated; when the filter is best i.e. when the PSNR value is high and MSE value is low the filter is best for that video.

3.2 Segmentation

Segmentation refers to the process of partitioning a digital image into multiple regions (sets of pixels). The main aim of the segmentation is to find the boundaries and to locate the objects. Though there is various segmentation .in this paper Gaussian Mixture is used.

3.2.1 Gaussian Mixture Model:

A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities. GMMs are commonly used as a parametric model of the probability distribution of continuous measurements or features in a biometric system, such as vocal-tract related spectral features in a speaker recognition system. GMM parameters are estimated from training data using the iterative Expectation-Maximization (EM) algorithm or Maximum A Posterior (MAP) estimation from a well-trained prior model. Gaussian Mixture is based on Background subtraction.

Among the high-complexity methods, two methods overlook the literature review; Kalman filtering and Mixture of Gaussians (MoG).

Both have their advantages, but Kalman filtering gets forced in all the paper for deed object trails that can't be removed. Since it looks like a possible deal breaker for various applications, MoG performs well. MoG is more forceful, as this handles multi-modal distributions.

By an example this can be more effective like, a leaf shaking against a blue sky has two modes—leaf and sky. MoG filters out both. Kalman filters effectively track a single Gaussian, and these are therefore uni modal: they can filter out only leaf or sky, but not both typically.

In MoG, the frame is not the background values. But the background model is Constant. Each pixel location is represented by a number (or mixture) of Gaussian functions that sum together to form a probability distribution function F,

The mean u of each Gaussian function (or component), can be thought of as an knowledgeable estimation of the pixel value in the next frame—pixels are usually background is assumed. The weight and standard deviations of each component are measures of assertion in that approximation (higher weight & lower σ = higher confidence). There are usually 3-5 Gaussian components per pixel—the number normally depends on memory limits.

To verify if a pixel is part of the background, then the comparison to the Gaussian works and tracking it. If the pixel value is within the scaling factor of a background component's standard deviation σ, it is considered as a part of the background. Else it is foreground.

3.3 Feature Extraction

Feature Extraction is used to determine the moving object in the sequence of frames. Feature extraction is the quality of source to specify the dataset correctly.

3.3.1 Detecting Abandoned Objects

The goal of such detection algorithms is the notification of a human operator about potentially critical events such as unobserved objects placed in public areas. The operator will then decide how to proceed based on the information provided by the system. This contribution focuses on the automatic detection of abandoned objects, such as suit cases or bags, in areas accessible to the public.

Whether an object is classified as abandoned or not depends on several factors: First of all, it has to be recognized as an object, i.e. it has to have a minimal extent and a sufficiently large probability of being foreground. In order to be considered as potentially abandoned, such an object has to be still and no humans must be close by. If all these requirements are fulfilled over a certain period of time, the candidate object can be regarded as abandoned and thus a potential security issue. The system should thus trigger a notification. The proposed abandoned object detection algorithm is implemented as a four stage system: People tracking, candidate region extraction, direct verification, and alerting.

3.3.2 Immovable object:

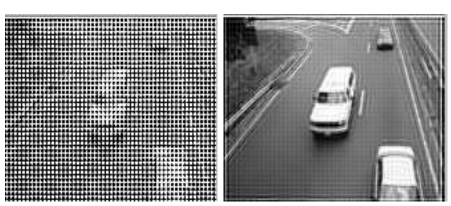
Proposed Abandoned object detection

The present system which is modular in nature and consists of five different modules and each module as follows:
1. Capture the video
2. Data extraction and conversion unit
3. Back ground subtraction using Gaussian mixture
4. Object tracking
5. Alarm rising and display of detected Abandoned Object

IV. Results And Discussion

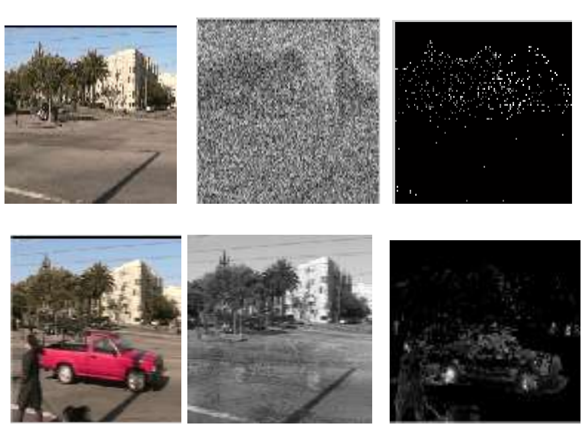
4.1 Pre-processing

In this Pre-processing stage the video with Gaussian noise, salt and pepper noise and Periodic Noise are taken under consideration. The test was conducted on these videos by applying different noise filters. The result shows for Gaussian noise the wiener filter best suits, Salt and Pepper noise is effectively removed by Median filter and for the periodic noise 2D FIR filter performs better than other filters.



Periodic Noise 2D FIR Filter

4.2 Segmentation

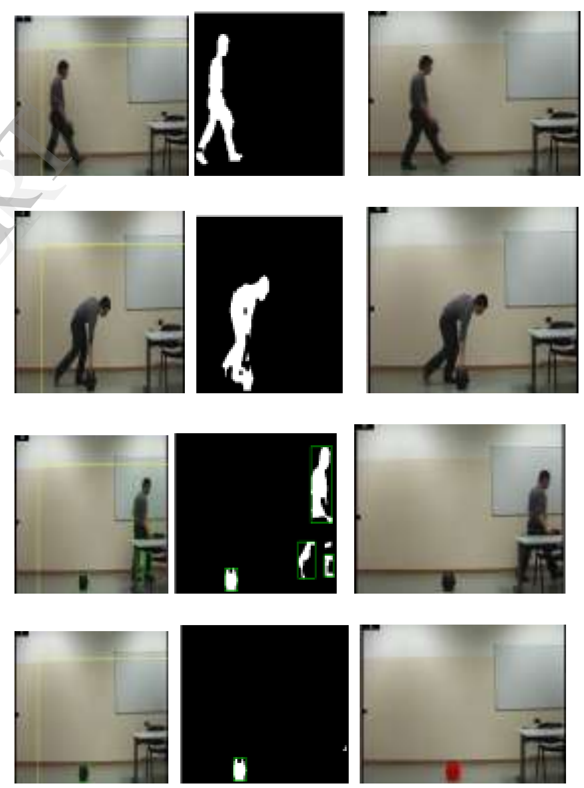


(a) Original Image (b) Gaussian Mixture (c) Segmented Image

The segmentation technique is used to cluster the related objects by performing background subtraction using Average Median. This technique best suited for moving objects segmentation. The result shows the input image and the previous frame and after applying the Average Median and subtracting the background objects the foreground displayed the result in the figures. The result shows that the Moving Object Segmentation can be done best using the average median compared to the frame difference it is revealed that the accuracy of average median is high.

4.3 Immovable object:

Input FramesThreshold Abandoned object detection



Detail procedure of abandoned object detection (our own video sequence in outdoor environment).

In the above figure the result shows the tracking of objects and identifying the abandoned object. The frame in the left end shows the region of interest and identifies the object of interest. The middle column frames shows the foreground objects movement. The last column identifies the abandoned object by displaying the discovered object in red color. The object identified is normally bounded in the green color boxes.

4.4 Object Identification and Object Tracking

Intuitionistic fuzzy degree is defined as the greater the degree of membership function than the degree of non membership and the degree of hesitation of current block in the present frame.

Intuitionistic fuzzy membership value $\mu A(x)$, Non membership value $\nu A(x)$ and hesitation value $\pi A(x)$ for every macro block of the reference frame and current frame.

Intuitionistic fuzzy membership value of the macro block of the previous frame is greater than Non membership value $\nu A(x)$ and hesitation value $\pi A(x)$ of the macro block of the current frame. Through this we calculate the cost function of IFD till the location for eight. When we obtain the ninth location we attain the origin.

i. Distance:

We are considering the two fuzzy sets of membership degree m, non-membership degree n and the hesitation degree p in as

X = {x1, x2. . . xn}.
Let A = {< x, µA(x), nA(x) > | x Î X}
And
B = {< x, µB(x), nB(x) > | x Î X}

As the next step we consider the hesitation degree with the interval or range of membership. The interval is due to the hesitation or the lack of membership assigning values. The distance measure is taken into account for hesitation degrees.

Object tracking in video is performed by applying the Block Matching using three step approach of Intuitionistic Fuzzy to set the motion vector of the moving objects then finding the threshold of each object and detecting and tracking the objects which exceeds the threshold value as moving objects.

V. Conclusion

In this paper we have presented a new framework to robustly and efficiently perceive abandoned objects in complex environments for real-time video surveillance. The mixture of Gaussians background subtraction method is used to identify both background and static foregrounds by using the same Gaussian mixture model. Our method can handle occlusions in complex environments with crowds.

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