Proceedings of 10th International Conference on Precision, Meso, Micro and Nano Engineering (COPEN 10)
December 07 – 09, 2017, Indian Institute of Technology Madras, Chennai – 600 036 INDIA

# Feature Extraction of Moving Object over a Belt Conveyor Using Background Subtraction Technique

**Pramod Kumar Thotapalli* CH. R. Vikram Kumar** B.ChandraMohana Reddy*****

* Research Scholar, JNTUA Research Centre, N.B.K.R.I.S.T, Vidyanagar,yudham.pramod@gmail.com
** Professor, Dept. of Mechanical, N.B.K.R.I.S.T, Vidyanagar, cvikramkumar@gmail.com
***Asst Professor, Dept. of Mechanical, JNTUACE, Anantapuramu, cmr_b@yahoo.com

## Abstract

Many Industrial Robots are becoming an autonomous system with the help of vision based Artificial Intelligence. Computer vision predominantly played a vital role in developing an autonomous robot, which provides more reliable information about the dynamic environment. The Industrial robots are widely used for objects pick and place operations. The capability of extracting moving object features in the video sequence is a fundamental and crucial problem in many vision systems. The objective of the present work is to extract the features of moving objects such as location, color and centroid over the belt conveyor using image subtraction technique and color based segmentation. The image subtraction methodology is developed based on Gaussian Mixture Model (GMM) which separates the moving objects from its background based on the intensity difference of respective pixel in the reference frame to current frame. The subtracted frame is further processed using RGB color based segmentation to separate the objects based on color. The centroid of the separated color objects is extracted using region properties. Feature extraction routine is developed using digital Image processing techniques in MATLAB.

Keywords: Industrial Robot, computer vision, feature extraction, Gaussian Mixture Model, belt conveyor

## 1. INTRODUCTION

Industrial automation is changing the scenario of product development in manufacturing systems. To ramp up the production, as per the demands of diversified needs of the customers, requires sophisticated technological development. Industrial robots with artificial intelligence play vital role in technological development which are commonly used for pick and place operations. Features like the location, shape, color and size of the object are very important for the robot controller to pick the desired object. Vision based artificial intelligence uses the stored statistical information of each pixel in the image frame. By deploying mathematical functions in the image processing algorithms, are used for feature extraction [1, 2].

In most of the automated systems, belt conveyor is used for transferring the objects from one workstation to another workstation. The vision system is used for identification and position recognition of an object over a conveyor belt. The vision algorithm extracts various features like colour, centre coordinates, orientation and the geometric parameter of the object in 2D image frame. The image frame provides information about the pixel positions of required distinct features of the object. The pixel location is mapped to work object coordinate system which intern useful for the robot controller to guide the robot arm to pick the required object in moving belt conveyor [5].

In the field of image and video processing analysis, background subtraction techniques are commonly used to track the foreground objects. Foreground detection pays attention to analyse new objects. Foreground object detection is the primary task for applying further image processing techniques to extract the distinct features of the objects coming into the scene. The features such as colour, size, shape, position are extracted from the subtracted image from the background.

A lot of background modelling methods had been developed and they are categorized into parametric and non-parametric methods. Various parametric approaches for background modelling [10, 11] are developed based on each pixel attributes. They are Gaussian mixture model (GMM) which models every pixel with a mixture of K Gaussian functions, Bayesian method, which models the background based on the prior knowledge and evidence from the data, and threshold decision method, based on threshold value it separate the foreground objects.

Unlike parametric background modelling methods, artificial neural networks based nonparametric algorithms was developed for self-organization background subtraction [13]. Kim et all [16] developed a codebook method to model the background which initializes code words of codebooks to store background states. Similarly various region based modelling approaches are developed based on Kernel density estimation (KDE) to separate the background [16]. Among all, Gaussian model is one of the most famous pixel- based parametric method due to its ability in handling multi-model backgrounds, and robustness to gradual illumination changes [10, 12].

*Pramod Kumar Thotapalli, Research Scholar
JNTUA Research Center,
NBKR Institute of Science & Technology, Vidyanagar 524413
Email:yudham.pramod@gmail.com

ISBN: 978-93-80689-28-9

In subtracted image, the objects are also segregated based on their color. Color images provide more information than grayscale image, it is an array of blended R-G-B Intensities Color is defined as a perceptual result of light in the visible region of the spectrum as the incident on the retina. There are many color spaces such as RGB, HSV, YCbCr and L*a*b are available to identify the distinct color threshold value of individual histograms [1,2]. Color segmentation technique based R-G-B intensities is very easy to sort the objects. The sample color information of objects is stored in the database used as segmenting parameter for interest color distinctions.

Object properties are extracted using region properties to obtain the area, centroid, major and minor axis etc., of segmented regions in the image [14, 15]. Centroid is used to locate the position of objects. The centroid of an object can be determined based on arithmetic mean of all (x, y) coordinates of objects in the region of interest [9].

In this paper, an attempt is made to develop an algorithm to extract the various features of moving objects over the belt conveyor using image subtraction technique. The objective of work is to pick the object of interest using an industrial robot from a moving belt conveyor. To perform pick operation, robot controller requires definite object location on a conveyor belt that is within a work volume. This paper aims to extract features of the object moving over a conveyor using simple vision system. The extracted information of the object features is helpful to track the object location, color, size, etc., for an industrial robot to pick a specified color object. The program is developed in MATLAB software. The complete methodology adopted along with results and discussions are presented in this paper.

## 2. METHODOLOGY

The schematic arrangement of robotic work cell is shown in the Fig.1. A stationary camera is placed above the conveyer to take continuous images of the objects moving on the conveyor belt. Each image frame is processed with background subtraction, color segmentation and region properties techniques. The location of the object on the conveyor with reference to robot is defined based on work object coordinate system. First, the work object coordinates of the robot are defined on conveyor as shown in Fig.1. The robot work object coordinates is a reference point or a “Zero Point”, with this reference point, the coordinates of the object are determined from the subtracted image. Zero point is defined by positioning by the robot arm Tool Centre Point to required location of user interest. The subtracted image is useful to find the coordinate distances of each object with reference to zero point. Both the objects and zero point are on the same surface of the conveyor and have same vertical height from the ground, hence same Z –axis values. The zero point is robot initial point, from this point the coordinate distance along X-axis and Y-axis of the object from Zero Point are calculated using subtracted image is very helpful to move the robot arm of particular distance along X and Y axes.

The work object coordinate location in a work volume is marked by a point. The same mark in an image is considered as reference pixel or Zero Point. The distance between the reference pixel and object centre coordinates is calculated by mapping actual distance to pixel distance in image similar way the coordinates of the object along X and Y axis from Zero point is also determined.

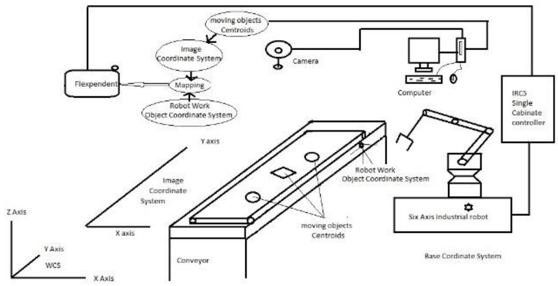



**Fig.1.Schematic arrangement of work cell**

Let the coordinates of zero point pixel are ($X_0$, $Y_0$) (robot work object) in an image frame, the coordinates of the object are ($X_1$, $Y_1$), where $X_1$ and $Y_1$ indicates the number of pixels in X direction and in Y direction respectively. The distance along X and Y are calculated by multiplying the number of pixels with actual length covered by each pixel in that direction. It is only possible by placing a camera fixed location at known height.

The methodology adopted in this work is shown in Fig.2, which represents a step by step image processing stages to extract the features of the objects. In this process capturing the continuous images is involved. Each input image is processed with respect to initial reference image by applying Gaussian Mixture Model used for foreground object detection in an image frame. Color segmentation is performed on output foreground object image frame to extract the features based on color. The segmented color frame is further processed to find the centroid using region properties. The complete algorithm is developed in MATLAB software.

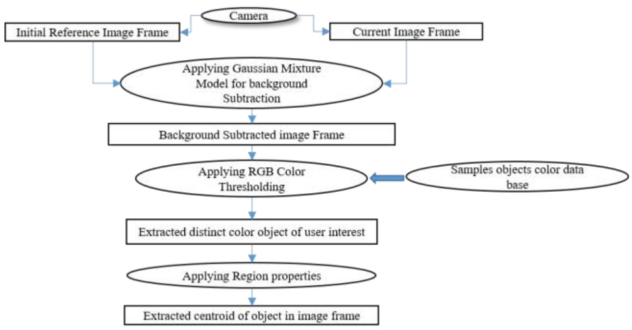



**Fig.2.Flow Chart involved in Feature extracting**

## 3. FEATURE EXTRACTION

### 3.1. Gaussian Mixture model

Gaussian Mixture Model is an algorithm deals with moving foreground object in the scene. It separates the foreground and background using probability density function. Each pixel is combination of different intensities of RGB. The probability density function is a mixture of individual intensities of RGB is called Gaussian component density. First the Gaussian component density of each pixel is determined for a reference frame. When the new objects enter into the frame causes variation in intensities of the pixel in the region of the objects. This frame is considered as a current frame and the again the Gaussian component density current frame is also determined. The Gaussian component density of each pixel of current frame is compared with Gaussian component density of reference frame pixel. At particular pixel the Gaussian component density of the current frame and reference frame is same, then it indicates to background otherwise it indicates to foreground. Based on comparison between each pixel, the object is separated from the background, which intern helps in determining the features of the objects appeared in the foreground image frame [7].

A Gaussian Mixture Model (GMM) is the classical pixel-based parametric method is a parametric probability density function represented with a mixture of K Gaussian component densities. The number of Gaussian component density is predefined and suggested to set K= 3 or 4 or 5. It does not need to store a set of input data in the running process and it uses the mean value and covariance to measure the pixel. GMM deals with the dynamic background by assuming that the intensity values of a pixel are modelled by multimodal distributions. It is used to calculate probability distribution of input pixel value x from current frame at time t being a background pixel. The foreground is sensitive to illumination changes. It defines a pixel value within 2.5 standard deviations of a distribution. This threshold can ensure that performance of the algorithm is only slightly disturbed by illumination changes, which is extremely useful when different regions have different lighting. An excellent background modelling method should effectively identify periodical or irregular movement of objects.

*3.1.1 Background Modelling (Reference frame)*

Background subtraction (BS) techniques share a common framework: they make the hypothesis that the observed video sequence I is made of a fixed background in front of which moving objects are observed. With the assumption that a moving object at time t has a color(or a color distribution) different from the one observed in B background , the principle of BS methods can be summarized by the following formula:

$$\chi_t(x) = \begin{cases} 1 & if \quad d(X_{x,t}\ , B_x) > \tau \\ 0 & otherwise, \end{cases} \tag{1}$$

Where $\chi_t$ is the motion label field at time t (also called motion mask), d is a distance between $X_{x,t}$ the video frame at time t at pixel x and $B_x$ the background at pixel x; τ is a threshold. The main difference between most BS methods is how B is modelled and which distance metric d is being used.to model the background is with a color image B [17]. This image can be a picture taken in absence of moving objects and/or estimated via a temporal median filter [10].In order to keep the background up to date, it can be iteratively updated as follows

$$B_{x,t+1} = (1-\alpha)B_{x,t} + \alpha.X_{x,t} \tag{2}$$

Where α is an updating constant whose value ranges between 0 and 1.forground pixels can be detected by thresholding distance matrices as:

$$d = \max\left\{ | X^R_{x,t} - B^R_{x,t} |, | X^G_{x,t} - B^G_{x,t} |, | X^B_{x,t} - B^B_{x,t} | \right\} \tag{3}$$

Where exponents R, G and B stands for the Red, Green and Blue channels. Each background pixel with probability density function learned from reference frames. In this case, the Background Subtraction problem often becomes a probability density function-thresholding problem. For instance, to account for noise, model every background pixel with a Gaussian distribution $\eta(\mu_{x,t},\Sigma_{x,t})$where $\mu_{x,t}$ and $\Sigma_{x,t}$ stand for the average background color and covariance matrix over pixel x at time t. In this context, the Mahalanobis distance metric can be the likelihood [17]:

$$Mahalanobis = \sqrt{| X_{x,t} - \mu_{x,t} |^T * \Sigma_{x,t}^{-1} * | X_{x,t} - \mu_{x,t} |} \tag{4}$$

Where $X_{x,t}$ and $\mu_{x,t}$ are RGB vectors and $\Sigma_{x,t}$ is a covariance matrix. To account for illumination variations, the mean and covariance of each pixel can be iteratively updated as follows:

$$\mu_{x,t+1} = (1 - \alpha).\mu_{x,t} + \alpha.X_{x,t} \tag{5}$$

$$\Sigma_{x,t+1} = (1 - \alpha).\Sigma_{x,t} + \alpha.(X_{x,t} - \mu_{x,t})(X_{x,t} - \mu_{s,t})^T \tag{6}$$

Note that the covariance matrix can be a 3 × 3 matrix or can be assumed to be diagonal to reduce processing costs. Model every pixel with a mixture of K Gaussians. Thus, the probability of occurrence of a color at a given pixel by x. The probability of input pixel value P $(X_{x,t})$ from current frame at time t being a background pixel is represented by the

$$P(X_{x,t}) = \sum_{i=1}^{K} w_{i,x,t} * \eta(X_{x,t}, \mu_{i,x,t}, \Sigma_{i,x,t}) \tag{7}$$

Where,

$P(X_{x,t})$ is the probability density function of $X_{x,t}$ in a parametric form and composed of a sum of Gaussians of each pixel x at time t.

K is the number of Gaussian distributions.

$\eta(X_{x,t}, \mu_{i,x,t}, \Sigma_{i,x,t})$ is the $i^{th}$ Gaussian probability density function.

$W_{i,x,t}$ is the estimate of the weight of the $i^{th}$ Gaussian at time t,

$\mu_{i,x,t}$ is the mean value of the $i^{th}$ Gaussian at time t,

$\sum_{i,x,t}$ , is the covariance matrix of the $i^{th}$ Gaussian probability density function,

At time t there are K distributions of Gaussian for each pixel from ($x_1$ …….$x_n$) determined by the available memory and computational power (Currently K= 3 is used). A new pixel x, is checked against the exiting K Gaussian distributions, until a match is found. A match is defined as a pixel value within 2.5 standard deviations of a distribution. If none of K distributions match the current pixel value, the least probable distribution is replaced with a distribution with the current value as its mean value, an initially high variance, and low prior weight. The prior weights of the K distributions at time t, $W_{i,t}$ are updated as,

$$W_{i,t} = (1-\alpha)W_{i,t} + \alpha.M_{k,t} \tag{8}$$

Where α is a learning rate and $M_{k,t}$is 1 for the matched, otherwise, $M_{k,t}$ is 0.

The parameters $\mu_{i,t}$ and standard deviation $\sigma_{i,t}$ for unmatched distributions remain the same. When they match the new observation, they are updated as follows

$$\mu_{i,t} = (1-\rho)\mu_{i,t} + \rho.x_{i,t} \quad .... (9)$$

$$\sigma_t^2 = (1-\rho)\sigma_{t-1}^2 + \rho(x_t - \mu_t)^T (x_t - \mu_t) \quad .... (10)$$

Where $\rho$ is the second learning rate defined as $\rho = \alpha\eta(x_t \mid \mu_k, \sigma_k)$.

To recognize a pixel in a frame as a foreground or background pixel [6]. The following way to estimate the background model, first the K Gaussians distribution are ordered by a value of W/then only the first B distribution are chosen as background model, distribution should satisfy

$$B=\arg\min_b\left(\sum_{k=1}^{b} W_k > T\right) \tag{11}$$

Where T is as assigned threshold. If pixel value cannot match the background model distribution. They will be labelled in motion.

### 3.2 Colour Threshold

RGB colour space is widely used throughout computer graphics. Red, Green and Blue are three primary colors (individual components are added together to form desired color) and are represented by a three dimensional, Cartesian coordinate system the indicated diagonal of the cube as shown in Fig.3.

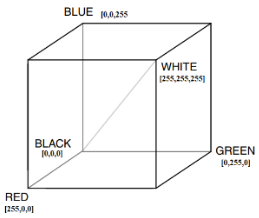



**Fig.3 RGB color Space**

For color segmentation, first the colors of the various moving objects are stored in color database. The stored color data base is used for creating the color mask for a particular colour object. The color mask is used as filter to extract blend characteristic feature of particular colour in an image [8]. In colour mask each colour has minimum and maximum values of RGB, to indicate a particular co0lour. Based on maximum and minimum values the threshold values individual components are put together to filter the particular color. The general equation for creating a color mask is shown below

$$I(i,j)=\begin{cases} 0, P(i,j) < T_{\min} \\ 1, T_{\min} \le P(i,j) \le T_{\max} \\ 0, P(i,j) > T_{\max} \end{cases} \tag{12}$$

The above function is used as filter mask to extract the object based on color. Different color objects are moving on belt conveyor. Color segmentation technique is used to sort individual color objects in an image.

For particular colour mask if the threshold value lies between the minimum and the maximum value, then the objects belongs to that colour will appear in the image and other colours are shown as 0(dark). The procedure is adapted for each pixel.

### 3.3 Centroid of the Object

The centroid of the object is very important parameter to find the location of the object. Image is a statistically distributed intensities levels. By using region properties the centroid, major and minor axis of the moving object on a conveyer are extracted [5].

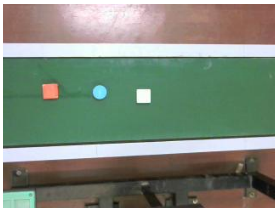
The centroid of the object where $(x_i, y_i)$,i=(1,2,…………n) are the boundary points of the object[9]. Then centroid ( $\bar{x}, \bar{y}$ ) of object is calculated by

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{13}$$

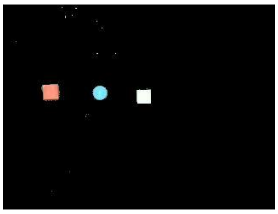
## 4. RESULTS AND DISCUSSION

The continuous video of moving belt conveyer is captured through a stationary camera. The belt conveyer is operating at constant speed. Various steps involved in obtaining the centroid of a particular color object using GMM, color segmentation and region properties are given in Fig.4.(a) to (f).

**(a) Initial Reference Image Frame**



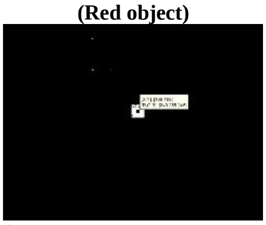
**(b)Current Image Frame (Objects moving in Conveyers)**



**(c)Background Subtracted output Image Frame**

**(d)User selection object Based on color and its centroid (Red object)**

**(e)User selection object Based on color and its centroid (Blue object)**



**(f) User selection object Based on color and its centroid (White object)**

**Fig.4. Processed input & output Images using image processing technique**

Fig.4 (a) shows an initial reference image frame which is used as a reference statistical database Fig.4 (b) current image frame where the objects are moving on a conveyer. The objects in the foreground are subtracted from background using GMM technique, the subtracted image with only objects is shown in Fig.4(c). In the subtracted image frame small spots other than objects are found due to illumination changes in workspace. The conveyer is movement will also create dynamic illumination changes. For obtaining better results constant illumination to be maintain in workspace. The background subtracted output image is further processed for adopting colour threshold and region properties to extract the specific colour and its centroid of the objects in moving belt conveyer as shown in consequent output images in Fig. 4 (d),(e), and (f). Fig.4 (d) shows the subtracted image with red color object along with centroid. Fig.4 (e) shows the blue color object along with centroid, Fig. (f) Shows white color object along with centroid.

The Table1 reveals the size of object in terms of number of pixels. The dimension of object in terms of pixel is extracted and it can be used in determining the actual size of the object by mapping image coordinates to object coordinates. The extracted centroid of the object in an image frame is mapped to the robot centre coordinates which intern helps for developing an autonomous robot for pick and place operation. In this work the Z-axis is taken as constant. The camera is placed at top of the objects, with a single camera it is not possible to find the height of the object. If the objects of different heights moved conveyor the present algorithm may not work. It requires second camera to identify the heights of the object.

**Table.1 Pixel coordinates of various coloured object.**

| Name of the object | Centroid of object in image coordinate (Pixel) | | Size of the object in image coordinates (Pixel) | |
|---|---|---|---|---|
| | X | Y | Major axis | Minor axis |
| Red square | 56.657 | 102.67 | 20.655 | 20.069 |
| Blue circle | 114.59 | 104.02 | 17.358 | 16.685 |
| White square | 166.08 | 108.42 | 19.533 | 18.455 |

## 5. CONCLUSIONS

The features of objects on a moving belt conveyer based on color, size and centroid is extracted by adapting Gaussian mixture model, color segmentation and region properties using digital image processing techniques. The extracted features are useful for developing autonomous robots for identifying the position and size for handling operations.

## ACKNOWLEDGEMENTS

The project is funded by AICTE, New Delhi, Government of India under Research Promotion Scheme.

## References

[1] Digital Image Processing Using MATLAB 2nd Ed.by Gonzalez, Woods, and Eddins 2009

[2] Digital Image Processing 3rd Ed. (DIP/3e) by Gonzalez and Woods © 2008

[3] Rahul Kumar, et al Object Detection and Recognition for a Pick and Place Robot, *IEEE Asia-Pacific World Congress on Computer Science and Engineering* 2014,

[4] R. De Maesschalck, D. Jouan-Rimbaud, D.L. Massart, The Mahalanobis distance *Chemometrics and Intelligent Laboratory Systems* 50 2000 1–18

[5] Pramod Kumar Thotapalli, CH. R. Vikram kumar, B.Chandra Mohana Reddy, Trace the centroid of coloured object on a conveyor using Digital Image *Processing Proceedings of ICMTS-2017*, IIT Madras 33-37

[6] P. Wayne PowerJohann A. Schoonees, Understanding Background Mixture Models for Foreground Segmentation, Proceedings Image and Vision Computing New Zealand 2002, 267-271

[7] Chris Stauffer W.E.L Grimson Adaptive background mixture models for real-time tracking, Computer Vision and Pattern Recognition, IEEE, 1999, 246-252

[8] P.B.Vijayalaxmi, Rohan Putta, Gayatri Shinde, Punit Lohani, Object Detection Using Image Processing For An Industrial Robot, *International Journal of Advanced Computational Engineering and Networking*, Volume- 1, Issue- 7, Sept-2013,21-26

[9] D. Chaudhuria, A. Samalb, A simple method for fitting of bounding rectangle to closed regions,*Pattern Recognition 40 (2007) 1981 – 1989*

[10] Yong Xu[a,b],*, Jixiang Dong [a], Bob Zhang [c], Daoyun Xu[d] Background modelling methods in video analysis: A review and comparative evaluation *CAAI Transactions on Intelligence Technology* 1 (2016) 43-60

[11] C. Stauffer, E. Grimson, IEEE Trans. Pattern Anal. Mach. Intell. 22 (8) (Aug. 2000) 747-757.

[12] Munir Shah Jeremiah D. Deng, Brendon J.Woodford Video background modelling: recent approaches, issues and our proposed techniques *Machine Vision and Applications* (2014) 25:1105–1119

[13] Lucia Maddalena and Alfredo Petrosino A Self-Organizing Approach to Background Subtraction for Visual Surveillance Applications *IEEE Transactions ON Image Processing*, VOL. 17, NO. 7, JULY 2008 1168-1177

[14] P. Kapsalas, K. Rapantzikos, A. Sofou, Y. Avrithis Regions of Interest for Accurate Object Detection *International Workshop on Content-Based Multimedia Indexing*, CBMI 2008. 147-154

[15] Ejofodomi OA, Ofualagba O, Ovoradua VO, Oviri JO, Ettoh GO, et al Object Detection and Tracking for Wireless Motion Control using MATLAB and *I robot Create. Adv Robot Autom* 4. (2015): 136

[16] K. Kim, T. Chalidabhongse, D. Harwood, L. Davis, Background modelling and subtraction by codebook construction, in: *Int. Conf. on Image Processing*, 2004, pp. 3061-3064.

[17] Yannick Benezeth, Pierre-Marc Jodoin, Bruno Emile, Hélène Laurent, Christophe Rosenberger. Comparative study of background subtraction algorithms. *Journal of Electronic Imaging, Society of Photo optical Instrumentation Engineers*, 2010,