# Automatic Visual Gun Detection Carried by A Moving Person

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***Abstract*—Few works are reported in firearm detection, even though, it has an important application in both the field of video forensic analysis and surveillance. Security of different crowded areas such as around airport, marketplace, places of worships, shopping mall, ceremonies events such as marriage, parties etc. always have a requirement of automatic detection of moving person carrying illegal weapon. In the present scope of the work, we propose a gun detection technique based on template matching which is invariant to scale & rotation. Template matching is a simple and traditional method used for object recognition with a disadvantage of high time complexity. We propose a innovative yet simple way to reduce the time complexity by employing a background subtraction methodology. Background subtraction algorithm handles other challenges too, such as sudden change of illumination. Experimental results illustrate that the proposed method outperforms efficiently in gun detection in video sequences with lesser number of True negatives in comparison with state-of-the-art template matching algorithms.**

***Index Terms*—Object Detection, Gun Detection, Database Creation, Crime Scene Analysis, Security & Surveillance.**

## I. INTRODUCTION

Automatic weapon detection recently gaining popularity to strengthening security system in sensitive areas [1], [2]. Therefore, several years CCTV cameras has been used for security purposes and it evolved to automatic surveillance system [3]–[5]. Recent automatic CCTV based surveillance system has the ability to detect suspicious intruder automatically. The automatic implementation of surveillance system could not reduce the manual intervention completely. In automatic implementation of surveillance system operators are required to confirm the suspicious intruder by observing activities of the object. one of the activity would be search for any weapons [5]. Concentrate on many monitoring screens is a challenging task for operators [6] [8] and often operators suffers from video blindness [7]. Hence, the implementation of automatic weapon detection has several applications.

Unlike object detection [9]–[12], weapon detection have several other challenges, such as:

- **High intra-class variability** is the most important challenge in detection of weapon. There are different types of weapons considering knife, firearms and they highly differ from each other regarding color, shape, size, etc., Whereas, if only one class of weapon is considered than also a number of variants can be found. This high intra-class variability restricts the selection of key features from these weapons for automatic identification.
- **Illumination challenge** highly occurs in outdoor scenarios able to change the color of weapon, which in short increase difficulty in recognition of weapons based on color property.
- **Occlusion** is more important in weapon detection than the object detection because of its size. As the size of the weapons are small compared to the human handling the weapon, therefore, detection of fully occluded weapon is next to impossible. It is difficult but possible to detect partially occluded weapon by considering its key components.

Considering the sensitivity of automatic weapon detection several research works has been published, that proposed methodologies for automatic detection of weapons as shown in Table-I. Template matching based methods are mostly employed for weapon detection, such as [5], [14], [17]. Prime disadvantage of template based methods are high time complexity and template based methods are not scaling & rotation invariant. [13], [16] used classifier based methods to overcome the disadvantages of template based methods. In classifier based methods one important step is the segmentation of gun from the input images. Features from the segmented gun images are used to train the classifiers. Therefore, classifiers based methods are dependent on the correct segmentation of the gun from the input image. Template based methods are also employed k-means clustering for extraction of blob from the input image to be matched with saved templates. K-means clustering used color information for segmentation of gun, but guns are presented with various color. Therefore, color based methods would not be reliable. To handle these challenges, [13] used sliding window for feature learning. Using of small sized sliding windows and training procedure make the detection of weapon possible correctly.

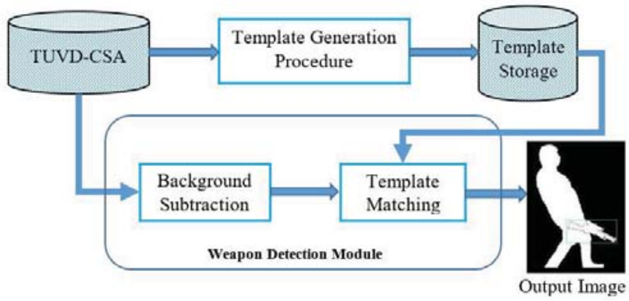


Fig. 1. Overall System Flow

TABLE I
REVIEW WORK ON FIREARM DETECTION

| Publications | Overview | Positive Aspects | Limitations |
|---|---|---|---|
| M. Grega et. al [13] | Use neural network to detect firearm from a video. First objects are detected using background subtraction and canny edge detection. Then used PCS features for firearm detection. | Detect object with firearm from video, then identify the firearm using classification. | Need to train the system. No features included to deal with illumination, occlusion, and rotation problems. |
| R. K. Tiwari et. al [14] | Used SURF features to detect firearm from images. K-means clustering is used for object detection from image. | Methods is immune to occlusion, rotation, scaling. | Works on images not on video frame, Only firearm is located not the object carrying it. |
| R. K. Tiwari et. al [5] | Describe challenges of illumination in detection of firearm. Used Harris point detector for firearm detection from images. | Methods is rotation, scaling and shape invariant. | Works on images not on video frame. |
| A. Glowacz et. al [15] | Describe knives detection from images using active appearance models. | Detect knives efficiently. | Only detect the knives from the image. |
| R Vajhala et. al [16] | Implement HOG feature and Neural Network based classifier for detection of both the firearm and knives. | Detect both knives and firearms efficiently. | Cannot deal with the shadow, illumination, occlusion problem. |
| N.Nandhini et. al [17] | Proposed a template based methods. Harris Point detector with the FREAK descriptors used for matching purposes | Provide promising results. | Cannot deal with the shadow, illumination problem, and Complex as need to train the system with positive and negative images. |

From the review of these methodologies we may noticed another difficulty which required serious attention, which is non-availability of dataset. As per our knowledge, excluding the dataset proposed in [13], there are no real time dataset till now designed for weapon detection. [16], [17] finds a way of this challenge is collection of videos or images from the web, movies, youtubes, etc.

In this scope of the work, we proposed a method that can handle the challenges regarding the automatic detection of weapon. In addition, we implement gun detection method along with the state-of-the-art methods on a newly designed real time dataset. We described briefly about the design of the proposed real time dataset.

Rest of the paper is organized as follows: Section II describes a brief introduction of proposed dataset and Ground Truth generation procedure; The proposed procedure for detection of weapon is describes in Section III; In Section IV an extensive evaluation of existing background subtraction methods and proposed gun detection method is presented, followed by qualitative & quantitative analysis of those approaches and finally, in Section V we concludes the paper.

## II. DATABASE DESCRIPTION

We have implement the proposed method on newly created dataset, **Tripura University Video Dataset for Crime Scene Analysis (TUVD-CSA)**, which is available in (http://www.mkbhowmik.in). There are total of 150 nos. of video clips out of which 65 videos are captured in indoor condition and 60 videos are captured in outdoor condition. The indoor video clips are captured in class room, laboratories and outdoor videos are in parking places, building premises, corridors, garden, open fields, different crossings (3 way, 4 way) etc.. of Tripura University campus. As earlier mentioned, [16], [17] implement methods on data collected from web.Therefore for fair comparison we also downloaded 25 video clips from different we sources. More than 5 Lacs frames can be extracted from the 150 nos. video clips. The capturing setup includes a Nikkon D5100 camera with 30 fps(frame per second) positioned at an angle of $60^0$ on a tripod stand of height 9 ft. The resolution of each frame of the video clips is 1920X1080 and captured with Nikkor 18-55mm lens with Shutter speed 1/125 - 1/200 and Aparture of f/5.6 - f/8. Few samples of the dataset along with different features has shown in Fig. 2.

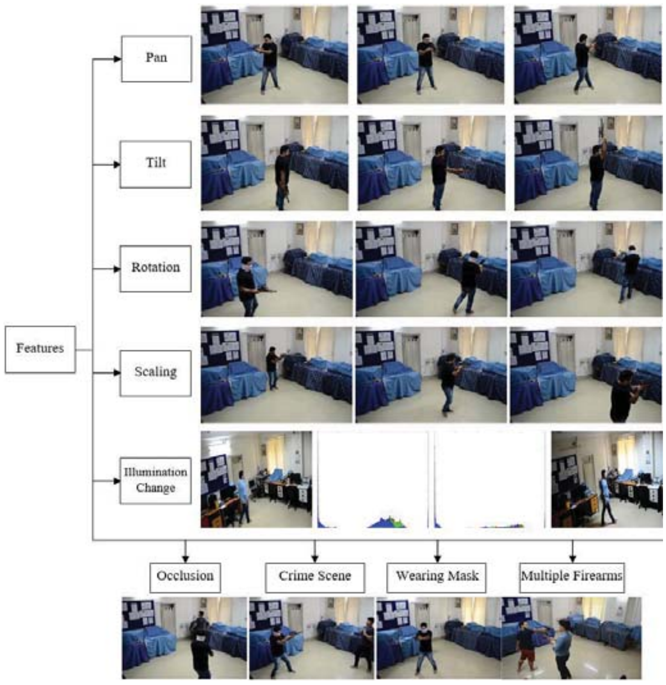


Fig. 2. Few dataset samples along with different features; **First** and **Second** row represents panning and tilting of gun respectively; **Third** row represents rotation of gun along with object; **Fourth** row represents the scaling of gun; **Fifth** row represents the Illumination change effect, and it is shown through the histogram plot; **Sixth** and final row represents occlusion of gun, mimic crime scene, person with mask on the face, and a scenario where multiple gun appears.

Different real time features are incorporated in this dataset such as, effects of different illumination condition. In addition occlusion, rotation, scaling, panning, tilting of gun are successfully captured in this dataset. To analyze the performance of detection methods prior ground truth information is necessary. For the same reason, the dataset is annotated manually with the TSLAB [21] application tool. Few example of ground truths are shown in Fig. 3.

Fig. 3. Samples of few Ground Truth along With Original Frame

## III. Methodology

From the review it can be identified that template matching methods are more reliable for detection of weapons from the video frames. But it is bit consuming as, the templates are searched for the whole image to match. To reduce this time complexity, few works [14] used color based segmentation for detection of most probable area of weapon. Color based segmentation are dependent on the color information of the weapons. As firearms are present with different colors, color based segmentation will produce a large number of false positives and false negatives in real time applications. The proposed methodology overcome these difficulties efficiently.

The proposed is based on edge based template matching. Shape of the gun is reliable than the color of the gun. Therefore, shape dependent templates are generated for different type of guns, which intern reduce the space complexity of the template storing memory. Afterwards, during detection of the weapon from the input image we employed a background subtraction method. Background subtraction generate images with moving objects. Gun handled by moving person is dangerous than a weapon present in the image idle. Due to background subtraction, templates will be searched for a sub region instead of the whole image. The overall block diagrm of the proposed method has shown in Fig 1.

### A. *Object detection*

First step of our proposed method is to detect moving persons carrying firearms in hand from the video sequences. Our primary concern is to handle change of illumination problem properly. Change of illumination is an well known problem of object detection but it has adverse problem in firearm detection. Firearms are prone to change its color and texture in illumination. Prior works reported change of illumination as a major problem in detection of firearm. So, we concentrate on the problem of change in illumination during the video. If the object detction algorithm miss the firearm due to illumination then template matching cannot detect the firearm. There are different algorithms in literature that can handle illumination properly such as Multiple Temporal Difference (MTD) [10], Gaussian Mixture Model (GMM) [9], ViBe [11] and Illumination Sensitive Background Subtraction (ISBS) [12]. We use the ISBS algorithm for object detection. Comparison between the existing methods are showed in result section.

### B. *Template Generation*

The template generation method comprises four step are shown in Fig. 4. input of the template generate method is the RGB image of the gun. First step of the algorithm is to convert it to gray image. We required the boundary of the gun, so to process RGB image will increase the burden of the system. So, Gray image is used. Edge detection of the gray image is the second step. Any edge detection algorithm can be used such as canny edge detector, sobel operator etc. Edge detection algorithm produces the boundary of the gun. Then the other parts of the images are deducted. Using this algorithm, templates of any type of gun can be generated automatically. It will save the time and reduce manual interventions.

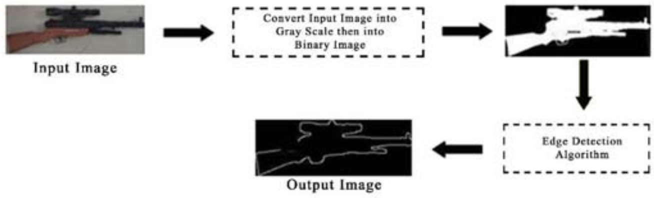


Fig. 4. Template Generation procedure

### C. *Proposed firearm Detection Method*

Simple template matching is employed here for firearm detection. Template matching is a well known approach in object detection. [18] first established the principle of template matching modified by hough transform. Template matching has different approaches such as, feature based matching and template based matching. Template matching approach should immune to rotation, scaling & detection problems. Working principle of template matching is to search for a given template in an image. Our aim is to identify firearm in the video frames. So, we search for the firearm template in the input frame. Template representing the firearm will also need to generate. Thus, in template matching there are three steps: edge image creation, search for a template and then calculate the similarity between the template and the input image.

*1) Template matching:* Providing the input image and template image, matching is performed by searching the template matching part in source image. There are two existing methods for searching the matching part: generalized Hough transform and searching based on cross correlation.

*a) Proposed Scaling and Rotation Invariant Template Matching*: Proposed Template Matching is the enhancement of existing Hough transform. Existing Hough transform is used to detect analytically defined shapes such as circles, ellipses etc. To detect arbitrary shapes proposed template matching is used. Existing Hough transform is unable to detect arbitrary shape and it requires the mathematical description of shapes. Whereas, proposed template matching is used to detect shapes that undergone some rotation and uniform scaling. First step is to calculate gradient direction of the template image. Suppose, $I_{x,y}$ is a gray scale template image. Using convolution gradient values $(G_x, G_y)$ are calculated. Given the values $(G_x, G_y)$ gradient directions can be calculated as follows:

$$\theta = tan^{-1}(G_y/G_x)$$

$\theta$ represents the gradient angle of the template image. Using this $\theta$ value a R-table is generated. The R-table is indexed by $\Delta\theta$. For each $\Delta\theta$, a tuple, $\left(\theta,\, \theta',\, \gamma,\, L,\, \alpha,\, r\right)$ is recorded. To calculate these values, a line is drawn from each edge point of the contour of the template to a reference point $(x_c, y_c)$. The reference point, $(x_c, y_c)$ is selected arbitrarily. The drawn line has been extended in y- direction until it reaches to another contour. Here, $L$ represent the line length, whereas, $r$ and $\alpha$ represent the length of the line and its angle with x-axis. This equation able to generate rotated template for matching.

There are may be one or more template objects present in the target image at any position. Gradient direction, $\theta$ is calculated for each edge element of target image using the same operator as in the template. Initialize the accumulator array $A\left(X_{c\min},\ X_{c\max},\ Y_{c\min},\ Y_{c\max}\right)$ to 0. $\theta_d$ gradient angle and $L_d$ the line length are identified for the each edge element in the target image. For each value in the R-table obtain the $(\theta,\ L,\ \alpha,\ r)$ from following equation:

$$\Delta\theta \approx \theta_d - \theta_d^{'}$$

And also use the following equation, for calculate updated $S$ and $\beta$

$$s = L_d/L$$
$$\beta = \theta_d - \theta$$

A reference point $(x_c, y_c)$ is then calculated using the following equation:

$$x_c = x + rs\cos(\alpha+\beta)$$
$$y_c = y = rs\sin(\alpha+\beta)$$

Algorithm 1: Proposed Template Matching

Input: An image $I$ of size $MxN$

Output: Coordinates of a box that surround the detected firearm, $(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4)$

1. $I_grad \leftarrow GradientImage$
2. Iterate $i$ till $i > M$
   1.1 Iterate $j$ till $j > N$
   1.2 Calculate the direction of each pixel
   1.3 $P \leftarrow I_grad(x_i, y_j)$
   1.4 Draw a line to $(x_i; y_j)$ with the length r and angle with x-axis $\alpha$
   1.5 compare the gradient and angle of $(x_i; y_j)$ with the corresponding pixel of template.
   1.6 Calculate the updated $S$ and $\beta$ using following equation

$$s = L_d/L\beta = \theta_d - \theta$$

   1.7 A reference point $(x_i; y_j)$ is then calculated using the following equation:

$$x_c = x + rs\cos(\alpha+\beta)$$
$$y_c = y = rs\sin(\alpha+\beta)$$

   1.8 Increment Local accumulator $A(x_i, y_j)$ 9. End For
10. each local peak in the array is reported as the detected object position
11. Output position $(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4)$
12. End

Accumulator array $A\left(x_c, y_c\right)$ is incremented and each local peak in the array is reported as the detected object position. The algorithmic steps are shown in Algorithm 1.

## IV. Experimental Results and Discussion

### A. Performance Analysis

We have compared the performance of the proposed method with the state-of-the-art methods mentioned in Table-I. However, quantitative measurement of moving object detection is not an easy task. Performance of detection algorithm are evaluated by pixel-wise comparing the resultant binary image with the corresponding ground truth (GT). Few performance metrics are adopted by the research community for this pixel-wise comparison. In this scope of the work, accuracy, recall, precision and F1 score are used for the analysis of performances of the detection methods. The matrices are tabulated in Table II [19].

The results shown in Table III showed that the proposed method performed well compared to the others. Quantitatively, proposed method acquires best precision and recall value which implied high accuracy value. and also take minimum time for processing. Classifier based methods are also shown competitive results but fails in scaled guns and rotated guns. Which overall decrease the average values of the matrices. Whereas, proposed method performed well in these situation too. Generalized Hough transform of the proposed method make possible the detection of rotated and scaled guns. In the later section, we also evaluate performance of proposed method with different background subtraction algorithm and with different matching procedure.

TABLE II
Metrics that are Used for Quantify the performance of Object Detection Method

| Name | Acronym | Computed as | Better if |
|---|---|---|---|
| Recall | Rec | TP/(TP+FN) | ↑ |
| Precision | Prec | TP/(TP+FP) | ↑ |
| F-measure | F1 | (2×Prec×Rec)/(Prec+Rec) | ↑ |
| Accuracy | Acc | (TP+TN)/(TP+FP+FN+TN) | ↑ |

The computational complexity of GHT can be represented by $(n_p/R_q)n_tS_q\theta_q$ and memory requirement is $N^2S_q\theta_q$. Where, $n_p$ is the number of edge pixels in the prototype object, $R_q$ is the resolution of the R-table index, $n_t$ is the number of edge pixels in the test image, $S_q$ is the resolution of the scale parameter, $\theta_q$ is the resolution of the rotation parameter. And $N^2$ is the size of the accumulator array.

TABLE III
Comparison of the performances of proposed methods with existing methods

| Algorithms | Rec | Prec | F1 | Acc | Time |
|---|---|---|---|---|---|
| M.Grega et.al. [13] | 0.9207 | 0.9334 | 0.9270 | 92% | 3 sec |
| R.K. Tiwari et.al. [14] | 0.8362 | 0.8868 | 0.8531 | 85% | 3.2 sec |
| R.K. Tiwari et.al. [5] | 0.7519 | 0.7157 | 0.7334 | 75% | 2.5 sec |
| A.Glowacz et. al. [15] | 0.7829 | 0.7625 | 0.7726 | 78% | 2 sec |
| R.Vajhala et.al. [16] | 0.9027 | 0.9123 | 0.9075 | 90% | 2.3 sec |
| N.Nadhini et.al. [17] | 0.8831 | 0.8972 | 0.8901 | 90% | 3.3 sec |
| **Proposed Method** | 0.9537 | 0.9421 | 0.9512 | 95% | 1.5 sec |

### B. Comparison of state-of-the-art Background Subtraction Methods

In this section, we present the comparison of performances of proposed algorithm with different object detection methods. In particular, we implement proposed method with GMM [9], MTD [10], ViBE [11]. For qualitative comparison Four object detection approaches are compared using a selection of scenes featuring different illumination change.

In this scope of the work, ISBS background subtraction algorithm used as the first step of the proposed method. Background subtraction algorithm reduce the time complexity and matching search space. Besides background subtraction algorithm should be able to handle illumination problem. Keeping this in mind we compare few milestone background subtraction methods with ISBS algorithm. Table IV reported the average accuracy of detection masks generated by GMM [9], MTD [10], ViBE [11], and the ISBS [12] approach for each tested videos respectively. This observation demonstrates that the ISBS [12] approach attains the highest accuracy among all the detection approaches. Fig. 5. shows some frames of a video sequence, ground truths, and binary mask of moving objects obtained by the GMM [9], MTD [10], ViBE [11], and ISBS [12] approaches respectively. Since weapon detection is our first target, we apply weapon detection using our proposed template matching method for above methods and report the detection results in Table IV.

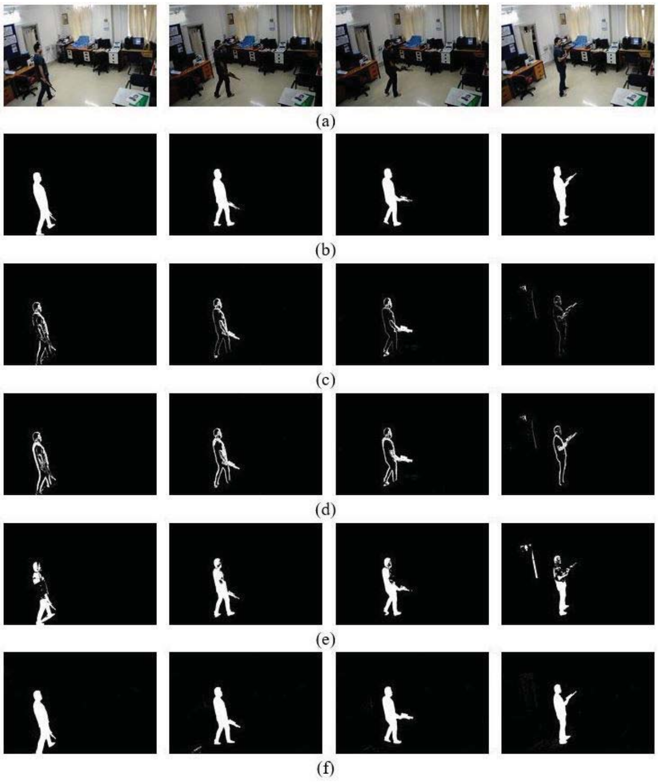

Fig. 5. (a) Original Video frames and (b) ground truths. The remaining four sub-pictures present the binary mask of moving objects generated by the (c) GMM [9], (d) MTD [10], (e) ViBE [11], (f), and ISBS [12] approaches.

TABLE IV
QUANTITATIVE MEASUREMENT OF THE EXISTING STATE-OF-THE ART BACKGROUND SUBTRACTION METHODS

| Algorithms | Rec | Prec | F1 | Acc |
|---|---|---|---|---|
| GMM [9] | 0.8000 | 0.8888 | 0.8380 | **85%** |
| MTD [10] | 0.6363 | 0.7000 | 0.6660 | **65%** |
| ViBE [11] | 0.8412 | 0.8548 | **0.8479** | 86% |
| ISBS [12] | **0.9642** | 0.9473 | 0.9550 | 96% |
| **Proposed Method + BG Algo** | | | | |
| Proposed Method + GMM | 0.6363 | 0.5833 | 0.6086 | **55%** |
| Proposed Method + MTD | 0.6739 | 0.4696 | 0.5534 | **40%** |
| Proposed Method + ViBE | 0.7962 | 0.7049 | 0.7477 | **72%** |
| Proposed Method + ISBS | 0.8596 | 0.83.5 | 0.8477 | **82%** |

## C. Template Matching

Aim of the Proposed algorithm is the detection of the objects with firearm. So, after the detection of the objects from the video the firearm detection algorithm is execute on the obtained results. In this work, three template matching methods [20], namely, Normalized squared difference (NSD), Normalized correlation coefficient (NCC) and Cross correlation (CrossCorr) that can be used in detection of firearm from video frames are compared with the proposed methods. Proposed Template generation method able to generate the templates of firearm with different scaling and rotation. So, during the comparison of the templates to the input frame, all the rotated and scaled templates are used. Therefore, it can detect firearm with different scaling and rotation. Here, the input frame refers to the output of the object detection algorithm, that contains only the objects. The comparison of the proposed method with the mentioned method the generated templates are used. Fig.6 demonstrate some examples of detected firearm that are rotated in different angle and scaled position. The box outlined by red color represent the detected firearms in Fig. 6. First row of Fig.6. shows the example of firearm rotation, such as (a) represent the firearm rotation at an angle of $-45^0$, (b) represent the rotation at an angle of $0^0$, (c) depict the rotation of firearm at an angle of $45^0$. Proposed method able to detect firearm in all the rotation due to its template generation procedure. The next six rows represents the results generated by the other methods. Whereas, the last row of Fig.6. shows the results of proposed method in detecting scaled firearms in videos and it shows its effectiveness properly. Therefore the results proved the efficiency of template matching algorithm in detection of firearm with less time complexity. Our proposed method reduces the time to detect firearm from the whole image using moving object detection algorithm. Moving object detection algorithms detect the moving object first and then we employed the simple template matching algorithm for detection of template. So, the time to compare the template with the whole image is reduced as we compare the templates with the detected moving object.

We compare the proposed method with the NSD, NCC and

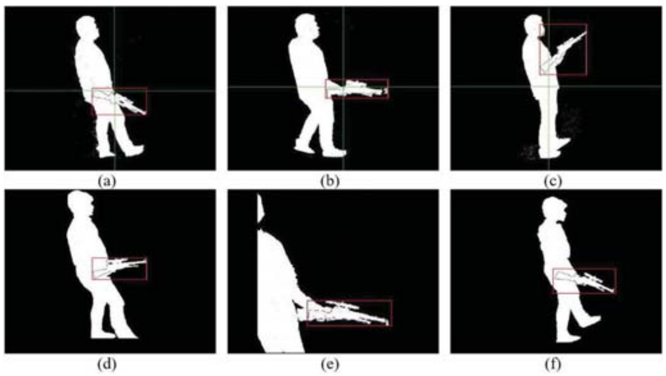

Fig. 6. Results of rotated and scaled firearm. (a) firearm is rotated with $-45^0$ angle. (b) firearm is in $0^0$ position. (c) firearm rotated with $45^0$ angle. (d),(e) & (f) firearm scaled in far & near from the camera.

CrossCorr. An object was detected by $20\%$ IoU (Intersection of union) criterion described in [21]. Under this condition, the detection is counted as positive if the object bounding box overlapped more than $20\%$ with the ground truth; otherwise, it is identified as a False Positive. Fig.7 shows the plots of the detection rate against the number of false positives y varying the IoU. Detection rates in $0.3$ and $0.4$ False Positives per Image (FPPI) represent the performances of methods. As the

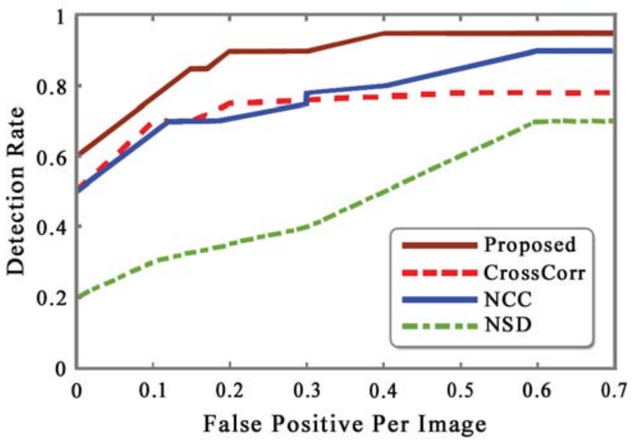


Fig. 7. Comparison of weapon detection results. Magenta curve show performance of our method. Green curves, dotted red curves and blue dotted curves show performances of methods in NSD, NCC and CrossCorr respectively

plots show, the results of our method are better than the others according to the detection rate in 0.3 and 0.4 FPPI.

## V. Conclusion

This paper presents a effective firearm detection algorithm which features low time complexity and high performance. Simple template matching algorithm performs efficiently along with a object detection algorithm. Object detection algorithm reduce the search space for the template matching algorithm. So, the procedure employed here has low time complexity. Used Objection detection algorithm is compared with the other and provide more accurate results qualitatively & quantitatively in different illumination condition. Change in illumination is a challenge in detection of firearm as they changed the color along with the illumination. The object detection algorithm that can effectively manage the change in illumination is used here. After detecting the object the proposed template matching algorithm is performed for detection firearm. The template matching algorithm is able to detect firearm with different rotation and scaling. the experiment results also indicate the effectiveness of proposed algorithm. Theoretically, the method also requires less time then the conventional template matching algorithm as it compares the template with the detected object part of the image. The proposed method has a shortcoming in detection of firearm that are partially occluded by object. The proposed method cannot performed efficiently in moving background where the background keep changing per seconds. The future work will concentrate on the detection of firearm that are partially occluded by the object.

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