MULTICAST: MULTI CONFIRMATION-LEVEL ALARM SYSTEM BASED ON CNN AND LSTM TO MITIGATE FALSE ALARMS FOR HANDGUN DETECTION IN VIDEO-SURVEILLANCE

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ABSTRACT

Despite the constant advances in computer vision, integrating modern single-image detectors in real-time handgun alarm systems in video-surveillance is still debatable. Using such detectors still implies a high number of false alarms and false negatives. In this context, most existent studies select one of the latest single-image detectors and train it on a better dataset or use some pre-processing, post-processing or data-fusion approach to further reduce false alarms. However, none of these works tried to exploit the temporal information present in the videos to mitigate false detections. This paper presents a new system, called MULTI Confirmation-level Alarm SysTem based on Convolutional Neural Networks (CNN) and Long Short Term Memory networks (LSTM) (MULTICAST), that leverages not only the spacial information but also the temporal information existent in the videos for a more reliable handgun detection. MULTICAST consists of three stages, i) a handgun detection stage, ii) a CNN-based spacial confirmation stage and iii) LSTM-based temporal confirmation stage. The temporal confirmation stage uses the positions of the detected handgun in previous instants to predict its trajectory in the next frame. Our experiments show that MULTICAST reduces by 80% the number of false alarms with respect to Faster R-CNN based-single-image detector, which makes it more useful in providing more effective and rapid security responses.

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1 Introduction

The awareness of potential dangers is crucial for an effective and rapid security response. In most public places, for example in jewelries, banks or train stations, the simple presence of a weapon, such as a handgun, generates a situation of danger. If a handgun is detected within these areas, a security response should be given as soon as possible. The automatic detection of this kind of objects in video-surveillance can surely help reducing the amount of harm a delinquent can inflict.

The detection of handguns in video-surveillance is still an open issue as handguns are small, usually occluded with hands and can be made of reflective metallic materials. The complexity of the detection increases considerably in situations of danger due to sudden and violent movements which together with the large variability in light conditions decreases the quality of the frames. The later frequently produces false positives and the mitigation of these false positives is in fact a challenge in these scenarios [28].

All the works on weapon detection in videos apply one of the most influential single-image object detection models such as Faster R-CNN [22], SSD [14], YOLO [21], Efficientdet [24] or NAS-FPN [9]. The first studies in this context improved the detection in videos by building new datasets [17, 10, 27, 12, 11]. The most recent studies applied pre- or post-processing techniques to further reducing the errors [16, 26, 4, 19]. While other studies used data fusion to improve the overall performance [25, 2, 18, 1, 23]. However, none of these works tried to leverage the temporal information existent in the videos in order to mitigate the detection of false positives and hence reduce false alarms in handgun detection.

This paper presents MULTICAST, MULTI Confirmation-level Alarm SysTem based on Convolutional Neural Networks (CNN) and Long Short Term Memory networks (LSTM) (MULTICAST), that leverages not only the spacial information but also the temporal information existent in the videos in order to provide a more reliable handgun alarm system. MULTICAST consists of three stages:

- A handgun detection stage. This stage analyses the entire input frame searching for a potential handgun.
- A CNN-based spacial confirmation stage. When the first stage finds a possible handgun, the spacial confirmation stage double checks whether this detection is an actual true positive.
- An LSTM-based temporal confirmation stage. When activated, the third stage uses the positions of the detection from previous instants to predict its trajectory in the next frame. This stage is essential for recovering possible false negatives produced by the first stage.

Each stage updates an index that we name Confirmation Level (CL) to indicate how confident it is about the presence of a handgun in the frame (for stage 1) or in a region of the frame (for stage 2 and 3).

The main contributions of this paper can be summarized as follows:

- To present MULTICAST (MULTI Confirmation-level Alarm SysTem based on CNN and LSTM), a reliable handgun detection that reduces substantially the number of false alarms.
- To provide HandgunTrajector[2], a new training dataset for the prediction of handguns trajectory in videos. This dataset is used to train the temporal confirmation LSTM-based network.

Our experimental results on fifteen test-videos shows that MULTICAST based on Faster R-CNN for handgun detection, EfficientDet for the spacial confirmation and LSTM for the handgun trajectory prediction, reduces the number of false alarms by 80% with respect to Faster R-CNN based-single-image detector.

The rest of the paper is organized as follows. Section 2 reviews related works on handgun detection in videos. Section 3 presents the details of MULTICAST. Section 4 experimentally analyzes the capability of MULTICAST as single-image handgun detector and as alarm system and compares it with the most accurate single-image detector in handgun detection. Finally, Section 5 provides conclusions.

2 Related works

Most related works on visible weapon detection in RGB videos select one of the state-of-art single-image detectors and trains it on a new weapon dataset. The most recent studies in this context intend to further reduce the number of false positives (FP) and false negatives (FN) using either pre-processing, post-processing or data-fusion. As far as we

[2] HandgunTrajectory database can be found in `https://github.com/ari-dasci/OD-MULTICAST`

know, there does not exist any study on leveraging the temporal information existent in the videos with the objective to improve the detection of handguns in video-surveillance.

The seminal paper in handgun detection in videos is [17], where the authors trained Faster R-CNN on a new handgun database[3]. The obtained model achieves good results on high quality YouTube videos but produces an important number of FP and FN on lower quality videos. Similarly, the authors in [10] built a dataset using images from a Closed-Circuit TeleVision (CCTV) installed at the University of Seville and synthetic data generated by Unity game engine[4]. They showed that Faster R-CNN based on Feature Pyramid Network and ResNet-50 can be used as weapon detector in quasi real-time CCTV.

Several works addressed reducing the number of FP and FN in handgun detection in realistic video surveillance environments using pre-processing [16, 4] and post-processing approaches [26, 19]. For example, the authors in [4] presented a pre-processing technique that help improving the quality of the videos in changing illumination environments. They showed that this technique improves the detection of knives in videos. The experimental results in [26] showed that analyzing the detected handguns using an auto-encoder improves the overall precision of the detection in videos. In [19], the authors showed that the use of binarization techniques such as OVO and OVA improves the overall performance of handguns and knives detection. However, this solution implies a high computational cost that makes real time execution impossible.

Some other works proposed using information fusion to improve the detection of handguns in videos [18, 25, 2, 1]. For example, the authors in [18] fused the binocular information to eliminate an important number of possible FP from the background in the frames. This approach showed a high potential in reducing the number of FP. However, the required setup is not available in regular video surveillance environments, i.e., two synchronized symmetric cameras set at a specific distance and orientation angles. In [1], the authors used the persons skeletal pose estimate to detect the threat in an image. They designed a multi-stage classification model. Namely, a first CNN determines whether a person and a handgun are present in an image. If so, a second CNN estimates the pose of the person and finally a feed-forward neural network assesses the threat level based on the joint positions of the persons skeletal pose estimate from the previous stage. The main drawback of this approach is that it does not perform a detection task, it only classifies individual frames. Similarly, in [23], the authors first use the person pose estimate to locate the areas of the hands in the image then analyze the presence of the handgun in those regions. The main limitation of this approach lies the strong dependence between pose estimation and handgun detection, if the pose estimation fails, the detection of the handgun also fails.

Nevertheless, there does not exist any work on using the temporal information available in videos with the objective to improve the detection of handgun in video-surveillance. The few existing works try to leverage such information to improve object detection in general [3]. For example, to achieve a faster object-detection in mobile CPUs, the authors in [13] combined a fast single-image object detection with convolutional LSTM layers to create an interweaved recurrent-convolutional architecture. The authors in [15] used the LSTM network to improve the association between objects of different frames and hence improve the detection of objects in videos in general. They feed the LSTM with the visual features resulting from the SSD detector, the information of locations and predicted classes. This approach allows recovering lost detections and correcting the predicted class in case it changes radically.

Differently to the aforementioned works, the present work leverage the temporal information independently on the CNN visual features. We use an LSTM network to predict the trajectory of the handgun based only on its historical positions, bounding box coordinates.

[3] https://github.com/ari-dasci/OD-WeaponDetection/tree/master/Pistol%20detection

[4] https://unity.com/

3 MULTICAST: MULTI Confirmation-level Alarm SysTem based on CNN and LSTM

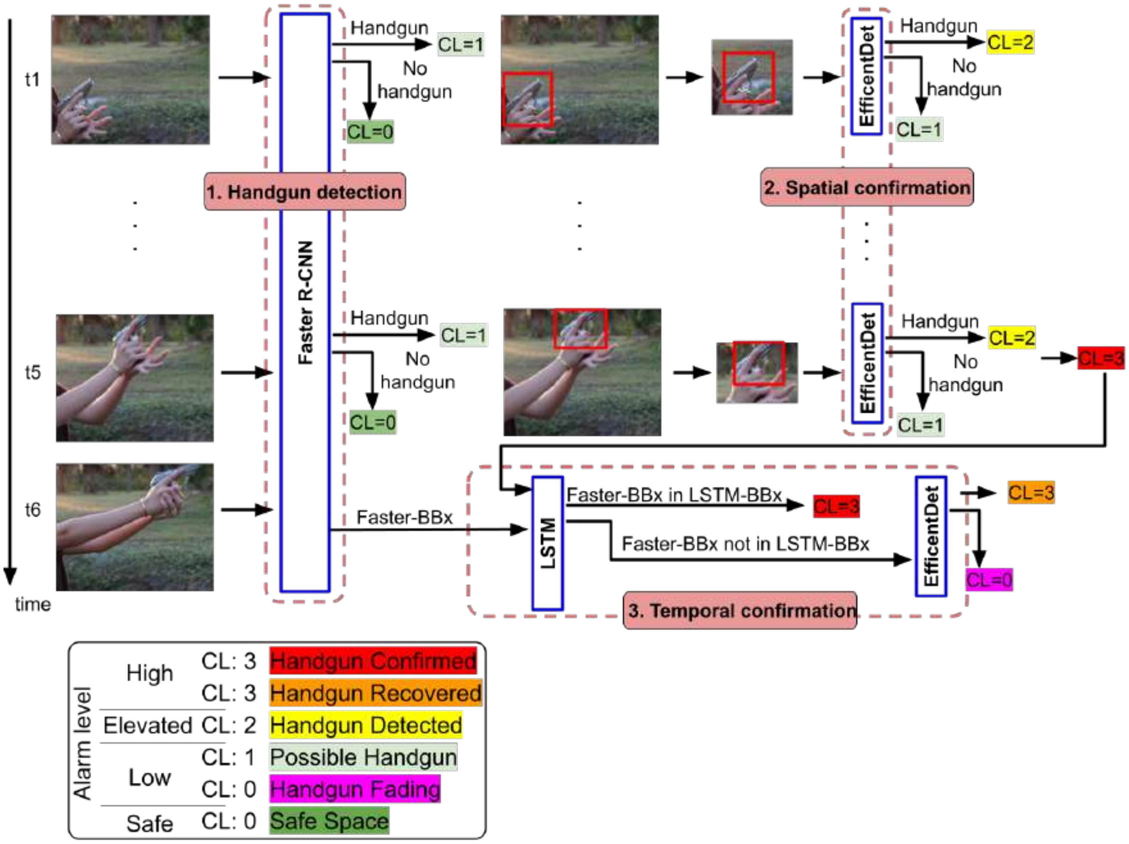


Figure 1: Overview of the proposed MULTI Confirmation-level Alarm SysTem based on CNN and LSTM. MULTICAST includes three stages, handgun detection, spatial confirmation and temporal confirmation.

The proposed system is composed of three stages, i) handgun detection, ii) spatial confirmation and iii) temporal confirmation, as shown in Figure 1. Each stage includes all the necessary mechanisms to guarantee the correct functioning of the whole alarm system in all the situations, as described in the following subsections. Each stage updates an index that we name Confirmation Level (CL) to indicate how confident it is about the presence of a handgun in the frame (for stage 1) or in a region of the frame (for stage 2 and 3).

For a simple communication with the end-user, the CL value is translated into global alarm level about the presence of danger in the whole frame. We define four alarm levels, safe, low, elevated and high. The correspondence between each CL value and alarm level is shown in Table 1. For a more accurate feedback to the end-user, an extra useful information about the state of the handgun detection, i.e., plotted in right lower corner of the frame(s).

Table 1: Definition of the the alarm levels and corresponding Confirmation Level (CL) values.

Alarm level	CL	Meaning	Shown message in the frame
Safe	0	No handgun is present in the scene.	*Safe Space*
Low	0,1	CL is set to 1, when the first stage has detected a possible handgun in at least one frame. CL is decreased to 0 when the temporal confirmation has not recovered a detection [i].	*Handgun Fading for CL=0 Possible Handgun for CL=1*
Elevated	2	A detected handgun is confirmed by the spacial confirmation stage in at least one frame. This is considered as a critical situation that requires human verification.	*Handgun Detected*
High	3	A detected handgun is confirmed by the spacial confirmation in five frames and/or by the temporal confirmation. This value is kept as 3 when a handgun detection is recovered in at least one of the subsequent five frames after a false negative by stage 1. This is considered as highly critical situation that requires immediate attention.	*Handgun Confirmed*

[i] Notice that the value of CL depends on what happened in the current frame and also on what happened in the previous instants

3.1 Stage 1: Handgun detection

This is the main stage for the detection of handguns in individual frames. This stage analyzes globally the whole input frame using Faster R-CNN and searches for a possible handgun. If a possible handgun is detected in a frame, its associated CL is increased to 1 and the area around the detected handgun with an extra padding is cropped and sent for its further analysis to the spacial confirmation stage. When multiple handguns are present in the frame, the same procedure is applied for each detected handgun. The next stages, stage 2 and 3, are activated for each individual handgun detection.

3.2 Stage 2: Spatial confirmation

The spacial confirmation stage is based on a CNN-based detection model such as EffiecientDet. This stage is activated when a handgun is found by the main stage. In particular, the cropped region of each detected handgun by Faster R-CNN is analyzed by this stage using a different type of detectors, in this study we used EffiecientDet. If the detection is confirmed in at least one frame, CL is increased to level 2. If the detected handgun is confirmed in five consecutive frames, CL is set to 3, the overall alarm level is set to high and the temporal confirmation analysis is activated.

Notice that this stage analyzes each detected handgun individually.

3.3 Stage 3: Temporal confirmation

The temporal confirmation stage is based on an LSTM-network to predict the trajectory, of the confirmed handgun by stage 2, in the next frame. The predicted trajectory actually refers to the bonding box of the area where the handgun could possibly move to in the next frame. Each bounding box is determined by the X and Y coordinates of the left bottom corner and right top corner.

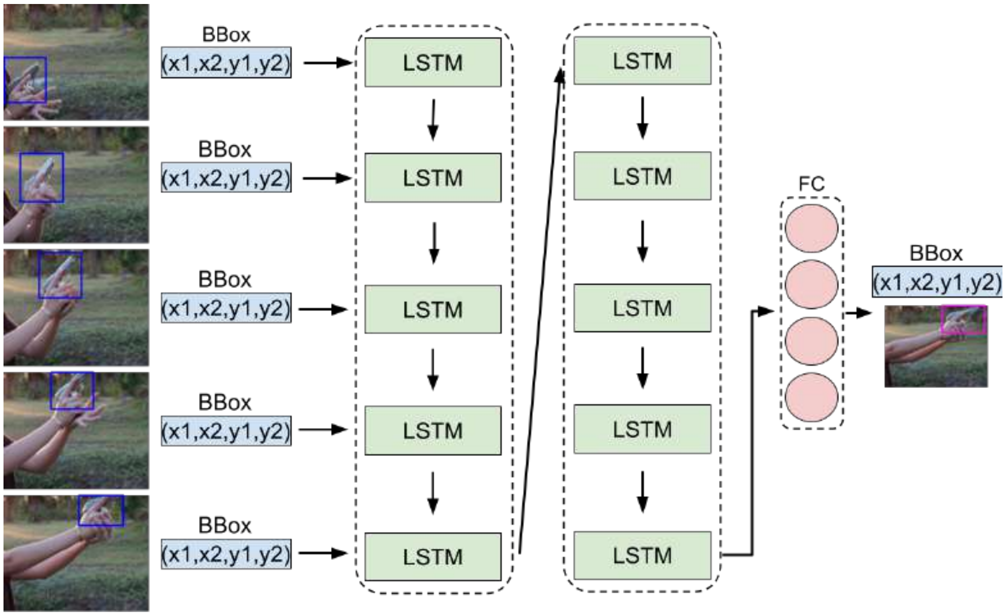


Figure 2: Architecture of the used LSTM-based network used in the temporal confirmation stage.

The LSTM-based network used in this stage contains two LSTM layers, as it is shown in Figure 2. Each LSTM cell has 200 units. This architecture has been selected over other architectures due to its simplicity, low computational cost and robustness.

For training this network to predict the trajectory of a detected handgun in the next frame, we built a dataset named HandgunTrajectory[5]. This dataset includes five files obtained from the analysis of five different videos. Each file contains a list of predicted bounding boxes obtained from Faster R-CNN. Each line of the list represents, the id of the frame, the X,Y coordinates of the left bottom corner and right top corner of the bounding box and the name of the object class.

When activated, the LSTM-network receives from the first stage a list of bounding box coordinates of the detected handgun in the last five frames. Then, it predicts the bounding box in the next frame. The predicted bounding box is compared with the obtained bounding box from Faster R-CNN after analyzing the sixth frame. If both bounding boxes match, CL value is kept as 3 and this detection will be tagged as *Handgun confirmed*. If the bounding boxes do not match, because probably Faster R-CNN has produced a false positive, a recovering process is performed. Namely, the predicted area by LSTM-net is cropped and analysed by EfficientDet in up to five instants or frames. If EfficientDet finds a handgun in that region of the frame, CL value is kept as 3 and the detection will be tagged as *Handgun Recovered*. On the contrary, if EfficientDet does not confirm the presence of handgun in five consecutive instants, CL value is decreased to 0 and the detection is tagged as *Handgun Fading*.

Notice that this stage analyzes each detection individually.

4 Experimental analysis

In this section, we analyze, compare and evaluate MULTICAST in two different tasks, i) as a single-image handgun detector applied to videos (section 4.1) and ii) as an automatic alarm system (section 4.2). Therefore, we performed two different experiments with different experimental setups. Afterwards, we analyse in more details the false alarms and false negatives mitigation in section 4.3 and section 4.4 respectively.

The common considerations for both experiments are as follows. To select the detection model to be included in stage-1 of MULTICAST and also to be used as baseline for comparison purposes, we performed an exhaustive experimental analysis of different single-image detectors and feature extractors, e.g., SSD, EfficienDet and Faster R-CNN. We found that R-CNN based on ResNet 101 provides the best results in handgun detection and hence, we used Faster R-CNN (ResNet 101) in all the experiments described bellow.

[5] HandgunTrajectory database can be found in `https://github.com/ari-dasci/OD-MULTICAST`

We also used the dataset[6] provided by [17] for training the detectors included in stage 1 and stage 2 of MULTICAST.

To better differentiate between the predictions of the different stages in MULTICAST in the frames of the videos, the bounding boxes produced by stage 1 are highlighted in blue color, the bounding boxes produced by stage 2 are highlighted in green color and the predicted bonding boxes by the LSTM stage are highlighted using the purple color.

4.1 MULTICAST vs. Faster R-CNN in the task of single-image handgun detection

In this analysis, we evaluate and compare MULTICAST with Faster R-CNN as single-image handgun detectors on five test videos. To ease the comparison, only the correctly detected handguns by MULTICAST with CL=2 and CL=3 are considered as True Positives.

Test set videos: To check the behaviour of MULTICAST as handgun detector at the frame level, we selected five videos fragments from different YouTube videos showing guns in different situations. Each video presents different detection challenges as described below:

- Vid1 [7]: This video shows a person shooting quickly in very different angles in an outdoor environment.
- Vid2 [20]: This video shows an actual robbery with handgun in a restaurant indoor. Although the illumination is good, the quality of the video is low.
- Vid3 [5]: This video shows at least three persons in each scene. It is an outdoor video with good quality but with deficient illumination.
- Vid4 [8]: This video shows an actual jewelry robbery with handgun. The illumination of this video is not uniform and there are four persons in the scene.
- Vid5 [6]: This video shows a fake robbery with three persons, poor illumination and with multiple camera angles. The main challenge of this video is that the camera angles change constantly in the video, which constantly interrupts the temporal continuity of the video. This is clearly an unsuitable video for MULTICAST.

Evaluation metrics: To evaluate the performance of MULTICAST as handgun detector at the frame level, we used four metrics, *accuracy*, *precision*, *recall* (also known as sensitivity), and *F1 measure*, which evaluates the balance between *precision* and *recall*. Where

$$accuracy = \frac{TP + TN}{Total\ images},$$

$$precision = \frac{TP}{TP + FP},$$

$$recall = \frac{TP}{TP + FN},$$

and

$$F1\ measure = 2 \times \frac{precision \times recall}{precision + recall}$$

Where, True Positives (TP) refers to the number of handguns correctly detected in the frames of the input video. In the case when a given frame has two visible pistols, the detection model must produce two bounding boxes that will be considered as two TP only if each bounding-box has an intersection over union larger than 70%. False Positives (FP) refer to the number of bounding boxes produced by the detection model in which there is no pistol or a tiny part of the pistol. If a pistol is detected more than once, the number of redundant bounding boxes will be considered as FP, since we have already applied the Non-maximum suppression method to unify redundant detection of the same object. True Negatives (TN) refers to the total number of frames where there is neither visible pistols nor false positives. False negatives (FN) refers to the number of visible pistols that are not detected by the object detection algorithm.

For this Setup, it was not possible to evaluate the mAP or the conventional object detection AP as MULTICAST relays on a lower confidence threshold, that is 0.1 for the first stage detector and 0.3 for the second stage detector. So a simple AP is calculated as the area of the rectangle caused by the fixed threshold of the experiment as:

$$AP = precision * recall$$

[6] https://github.com/ari-dasci/OD-WeaponDetection/tree/master/Pistol%20detection

Results and analysis: We evaluated two MULTICAST versions. The first, MULTICAST(FSL) is based on Faster R-CNN, as handgun detector, SSD as spacial confirmation stage and LSTM as temporal confirmation stage. The second MULTICAST(FEL) is based on Faster R-CNN, as handgun detector, EfficientDet as spacial confirmation stage and LSTM as temporal confirmation stage.

The analyzed videos with MULTICAST(FSL), MULTICAST(FEL) and Faster R-CMM are available through[7]. The performance of MULTICAST(FSL), MULTICAST(FEL) and Faster R-CNN(Resnet 101) on the test-videos are shown in Table 2.

Table 2: Performance comparison between MULTICAST(FSL) (Faster R-CNN, SSD, LSTM), MULTICAST(FEL) (Faster R-CNN, EfficientDet, LSTM) and Faster R-CNN (ResNet 101) used as single-image handgun detectors in five test videos.

		TP	FP	TN	FN	Accuracy	Recall	Precision	F1	AP
						(0-100%)	(0-100%)	(0-100%)	(0-1)	(0-1)
Vid1	Faster R-CNN	1665	77	378	246	87.76%	87.13%	**95.58%**	0.91	0.83
	MULTICAST(FSL)	1707	110	357	204	88.66%	89.32%	93.95%	0.92	0.84
	MULTICAST(FEL)	**1782**	124	350	129	**91.58%**	**93.25%**	93.49%	**0.93**	**0.87**
Vid2	Faster R-CNN	125	174	426	188	69.13%	39.94%	41.81%	0.41	0.17
	MULTICAST (FSL)	121	39	474	192	74.65%	38.66%	**75.63%**	0.51	**0.29**
	MULTICAST(FEL)	**154**	127	445	159	**75.16%**	**49.20%**	54.80%	**0.52**	0.27
Vid3	Faster R-CNN	1610	131	224	403	78.78%	79.98%	92.48%	0.86	0.74
	MULTICAST(FSL)	1703	62	286	310	85.44%	84.60%	**96.49%**	0.90	0.82
	MULTICAST(FEL)	**1813**	112	263	200	**89.18%**	**90.06%**	94.18%	**0.92**	**0.85**
Vid4	Faster R-CNN	20	130	2178	115	90.45%	14.81%	13.33%	0.14	0.02
	MULTICAST(FSL)	15	45	2250	120	93.21%	11.11%	25.00%	0.15	0.03
	MULICAS(FEL)	**26**	33	2274	109	**94.65%**	**19.26%**	**44.07%**	**0.27**	**0.08**
Vid5	Faster R-CNN	132	136	632	209	69.20%	38.71%	49.25%	0.43	0.19
	MULTICAST(FSL)	130	126	644	211	70.11%	38.12%	50.78%	0.44	0.19
	MULTICAST(FEL)	**147**	61	718	194	**78.35%**	**43.11%**	**70.67%**	**0.54**	**0.30**

As it can seen from Table 2, in general, MULTICAST(FEL) overcomes Faster R-CNN on all test videos obtaining higher values of TP, F1-measure and AP. Recall that MULTICAST triggers an alarm only after a spacial and temporal confirmation process. Although the number of FP is higher for MULTICAST(FEL) on some test videos, most of these false detections are filtered by the the spacial and temporal confirmation stages.

In addition, MULTICAST(FEL) based on EfficientDet as spacial confirmation stage achieves better results than using SSD.

4.2 MULTICAST vs. Faster R-CNN as handgun alarm system in video-surveillance

In this section, we analyze the potential of MULTICAST as handgun alarm system. MULTICAST triggers an alarm only when the CL value associated to a handgun detection reaches CL=3. Faster R-CNN triggers an alarm when a handgun is detected in a frame.

Test videos: We recorded ten short videos using two conventional home security cameras. These test videos were named as VideoAlarm from VideoAlarm1 to VideoAlarm10[8]. The first five videos show a handgun. The other five videos do not contain handgun but show different situations than can cause a false alarm.

Evaluation metrics: For assessing and comparing the potential of MULTICAST as handgun alarm system, we only evaluate whether the system triggers an alarm or not in the presence or not of an actual handgun in the scene. That is, if an actual handgun present in the video, at least in one frame, and the model detects it, the overall evaluation of the video as a TP. Otherwise, the overall evaluation of the video is a FP. If there is no handgun in the video and the system detects one, then the overall evaluation of the video is FN. Otherwise, the overall evaluation of the video is TN.

[7] https://www.youtube.com/playlist?list=PLiMogcXRP-Fokc_FcZbXJnbGQLtAyKflh

[8] The resulting videos of this analysis can be found in https://drive.google.com/drive/folders/1qvvlP4gCjDKZhZJbGSXf3TIb1e1is_Ru?usp=sharing

Results and analysis: To evaluate the capacity of MULTICAST to be used as alarm system, we consider the presence of a handgun in the entire scene rather in the individual frames. In other words, we evaluate the capacity to produce an alarm when there is an actual handgun in the video.

The results of a comparison between MULTICAST and Faster R-CNN are shown in the Table 3. GT to refers to Ground Truth. We consider GT as a binary value to indicate the presence (GT=1) or not (GT=0) of handgun in the video. GT=1 indicates that at least one handgun detection alarm was triggered in a video. GT=0 indicates that even if sparse handgun detections have occurred, the alarm wasn't triggered for a video.

Table 3: A comparison between MULTICAST and Faster R-CNN as alarm system. GT is a global measure to indicate whether a handgun is present in the video. GT=1 indicated that an alarm must be triggered and GT=0 must not.

	GT	Faster R-CNN	MULTICAST (FSL)	MULTICAST (FEL)
VideoAlarm1	1	1	0	0
VideoAlarm2	1	1	1	1
VideoAlarm3	1	1	1	1
VideoAlarm4	1	1	1	1
VideoAlarm5	1	1	1	1
VideoAlarm6	0	1	1	0
VideoAlarm7	0	1	0	0
VideoAlarm8	0	1	0	0
VideoAlarm9	0	1	0	0
VideoAlarm10	0	0	0	0

As it can be seen from Table 3, MULTICAST(FEL) and MULTICAST(FSL) trigger respectively 80% and 60% less false alarms than Faster R-CNN. MULTICAST(FEL) fails only in one video, i.e., VideoAlarm1. This improvement can be explained by the fact that MULTICAST(FEL) spacial confirmation with EfficientDet eliminates a large number of occasional false positives as it checks the presence of a handgun in five consecutive frames.

The analyzed videos with MULTICAST(FSL), MULTICAST(FEL) and Faster R-CNN are available through[9].

For a more global analysis, we summarized the overall accuracy, precision, recall and F1 measure of MULTICAST(FEL), (FSL) and Faster R-CNN, on the ten test videos, in Table 4. Again, these results clearly show that MULTICAST(FEL) provides substantially better accuracy, precision and F1 over Faster R-CNN. Although, Faster R-CNN provides a higher recall over MULTICAST, it produces a larger number of false alarms, which makes its use impractical in video-surveillance environments.

Table 4: Overall performance of MULTICAST and Faster R-CNN as alarm systems on the ten test videos.

	Faster R-CNN	MULTICAST (FSL)	MULTICAST (FEL)
Accuracy	60.00%	80.00%	90.00%
Precision	55.56%	80.00%	100.00%
Recall	100.00%	80.00%	80.00%
F1	0.71	0.80	0.89

The results show that MULTICAST triggers much less false alarms than Faster R-CNN. In Table 5 the percentage of false alarms and true alarms, and how much improvement represents is shown.

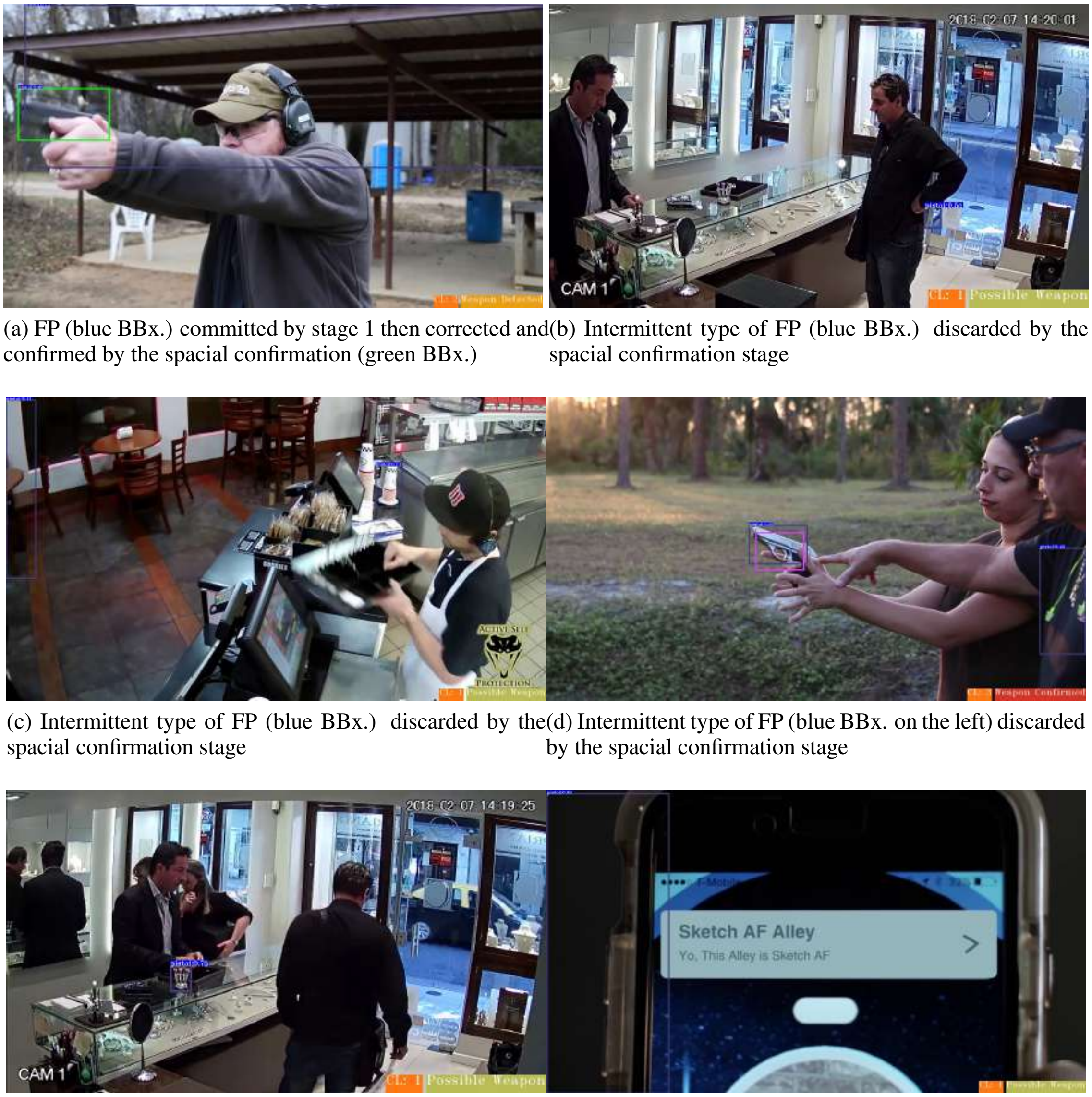
Table 5: Improvement (in %) of MULTICAST over Faster R-CNN as alarm system.

	#False Alarm	Improvement vs Faster R-CNN
Faster R-CNN	80%	-
MULTICAST(FSL)	20%	60%
MULTICAST(FEL)	0%	80%

[9] https://www.youtube.com/playlist?list=PLiMogcXRP-Fqom8EmM_Um4Z-h3XmEVhQs

4.3 Analysis of false positives eliminated by MULTICAST

After a careful analysis of the errors committed by Faster R-CNN in the first stage and then corrected by MULTICAST, we can distinguish between two types of FP. The first type occurs intermittently showing a varying confidence level, see examples in Figure 3(a), (b), (c) and (d), where the blue color bounding box indicates the false positive committed by Faster R-CNN. In spite of the blur in the handgun area in the frame, MULTICAST was able to correct that erroneous area (delimited by the blue box) by means of the spacial confirmation detector (delimited by the green box).



(a) FP (blue BBx.) committed by stage 1 then corrected and confirmed by the spacial confirmation (green BBx.)

(b) Intermittent type of FP (blue BBx.) discarded by the spacial confirmation stage

(c) Intermittent type of FP (blue BBx.) discarded by the spacial confirmation stage

(d) Intermittent type of FP (blue BBx. on the left) discarded by the spacial confirmation stage

(e) Persistent type of FP (blue BBx.) discarded by the spacial confirmation stage

(f) Persistent type of FP (blue BBx.) discarded by the spacial confirmation stage

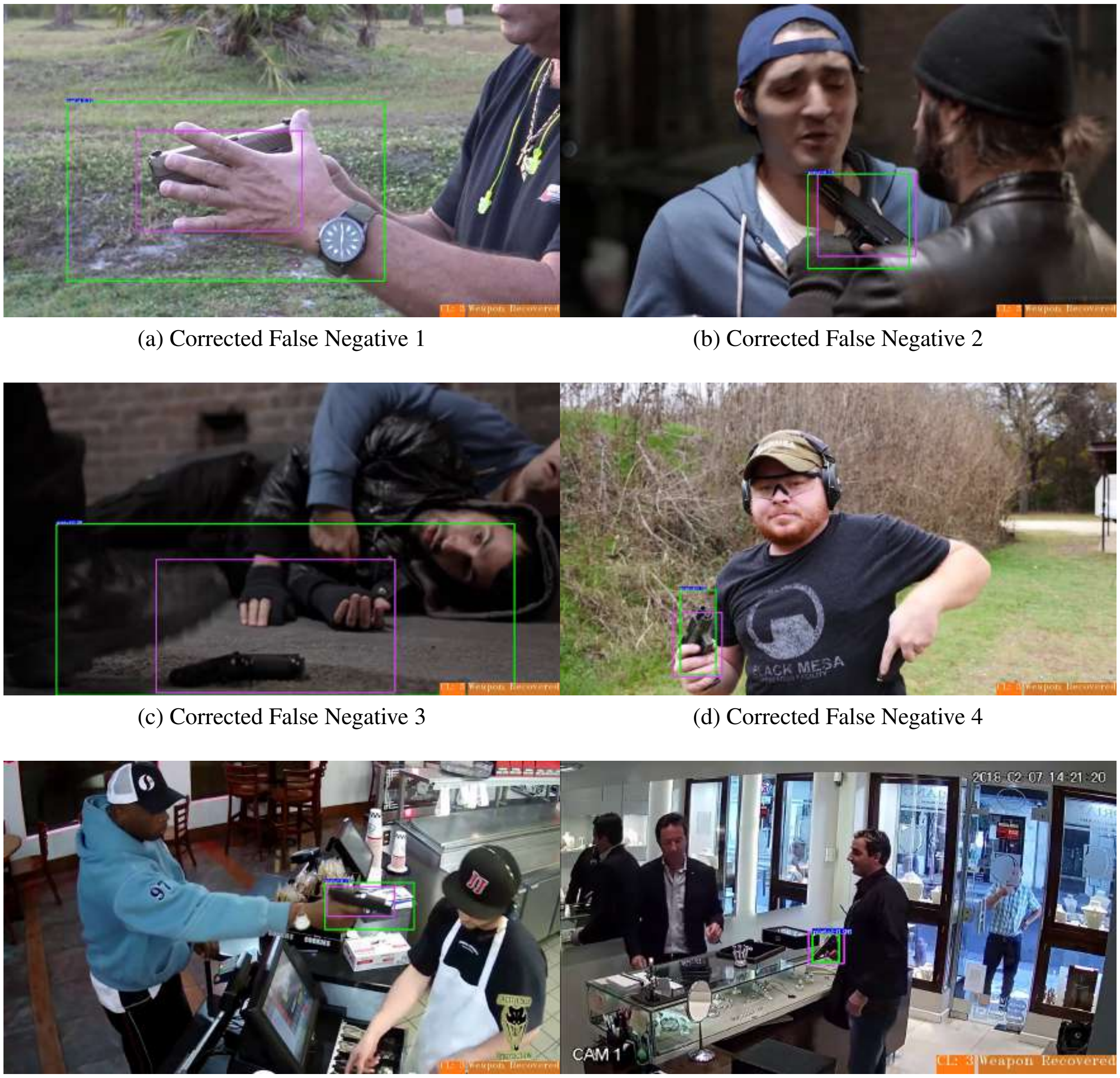
Figure 3: Examples of FP corrected/discarded by MULTICAST. Frames extracted from Videos [5], [8], [20], [7] and [6].

The second type of FP are persistent FP detections on a particular object such as the glass shown in Figure 3(e) and the cellphone in Figure 3(f). Although the first stage detect these objects as possible handgun, the confirmation stage of MULTICAST confirmed that these detections do not correspond to actual handguns.

In summary, MULTICAST has been able to eliminate most of both types of FP. It has eliminated most of the intermittent FP and reduced substantially persistent ones thanks to its confirmation mechanisms.

4.4 Analysis of false negatives recovered by MULTICAST

Faster R-CNN usually produces an important number of FN with a low confidence. Among these FN, we can distinguish between two types. The first type of FN occurs when the detection is difficult because the handgun is far from the camera or due to poor image quality. The second type of FN occurs when the detector temporally loses the handgun due to sudden changes in the light conditions, position or due to partial occlusion. In these situations MULTICAST is able to recover the detections thanks to the temporal confirmation mechanism as shown in Figure 4. The handgun omitted by Faster R-CNN due to partial occlusion in Figure 4(a) is recovered by MULTICAST thanks first to the temporal confirmation (purple BBx.) then confirmed by the spacial confirmation stage (green BBx.). The FN in Figure 4(b) and (d) were caused by a sudden change of the position. The FP in Figure 4(c) was caused by a slight change in illumination and position. The FP in Figure 4(e) and (f) were due to the bad quality and blur in the frame.



(a) Corrected False Negative 1

(b) Corrected False Negative 2

(c) Corrected False Negative 3

(d) Corrected False Negative 4

(e) Corrected False Negative 5

(f) Corrected False Negative 6

Figure 4: Examples of False Negatives recovered by MULTICAST. The frames come from videos[5], [8], [20], [7] and [6].

5 Conclusions

This work presented MULTICAST, MULTI Confirmation-level Alarm SysTem based on CNN and LSTM, that leverages not only the spacial information but also the temporal information existent in the videos for a more reliable handgun detection. MULTICAST allows mitigating the false positives produced by single-image detection models. Our experimental results showed that thanks to the spacial and temporal confirmation mechanisms, MULTICAST is able to eliminate a large number of FP and FN and hence reduces the false alarms to 80% with respect to Faster R-CNN.

MULTICAST can help improving the response time and effectiveness in detecting threats in different places by transforming the participation of a human in surveillance into high level supervision.

As future work, we are working on adapting MULTICAST to Closed-Circuit TeleVision (CCTV) and edge computing devices.

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