Intelligent Child Monitoring System

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Abstract

In this paper, a child monitoring system is proposed to watch and track children while playing. In particular, the system detects the moving child using a background subtraction approach which relies on adaptive nonparametric Gaussian mixture modelling. Then, Kalman Filter is adopted for the tracking task. If the child oversteps the specified area or does something he is not supposed to do, the proposed system notifies the parents and convey a message to the child. The experimental results proved the effectiveness of the proposed system with an average F-score of 0.87 with a standard deviation of 0.07.

Keywords: Child Monitoring, Object Detection, Object Tracking, Gaussian Mixture, Kalman Filter.

1. INTRODUCTION

In their early years, children require continuous supervision from their parents and/or family members. Child supervision is a tedious task and requires a full-time dedication. In fact, children do not realize the danger they face and may put their own life in danger if no efficient monitoring is provided. According to recent studies, the most common causes of child accidents are distractions and inadequate supervision [1]. Usually, people think that these accidents relate only to outdoor activities or traffic accidents. However, the place that is supposed to be the safest, home is the place where accidents occur the most [2]. More specifically, they happen more frequently on the stairs and in the kitchen. Statistics show that in 2002 about 43,000 children have accidents in the kitchen, and around 58,000 children experience an accident on the stairs yearly [1]. Moreover, a disorganized house where the child has access to dangerous items increases the risk of accidents [3].

Lately, technology has witnessed a considerable development, and has become a major partner of our daily activities. In fact, it has affected most of people activity areas, such as communication, health service and education, through the deployment of intelligent solutions which aim to support humans and increase the effectiveness of their efforts. One of the areas where technology helped is child monitoring. Child monitoring systems would be helpful, if they allow the childcarer to do small tasks like washing the dishes, folding clothes, or preparing a meal while watching the children. This kind of systems has been reported in the literature [4]- [12]. Some of them, track the child either using sensors [4][5], radio receiver/transmitter [6]- [9], or GPS device [10]. They trigger an alerting message when the child goes far away. However, such systems are relatively expensive, need the child to wear a receiver which can be inconvenient for him, and use electromagnetic waves which may represent a danger for the child health. Other systems are based on camera devices [11] [12], and transmit only the scene of the child with no further processing to recognize the danger faced by the child. Besides, they do not track the child and do not alert the caregiver in case of problem. Therefore, the childcarer has to monitor the video continuously, which requires the same effort as watching the child directly.

In this paper, we propose a camera based child monitoring system which detects the child, tracks his movement and computes the distance from him to the different dangerous items and/or the boundaries of the safe area. Furthermore, the proposed system can communicate with the caregiver if the child approaches a dangerous item or adventures outside a pre-specified area. The design of the system involved the choice of several technical approaches related to object detection and object tracking.

As for object detection, the adaptive nonparametric Gaussian mixture [13] is chosen as solution for the child detection problem. In fact, although frame-differencing approach is a simple approach and can be adapted to different dynamic scenes, the moving object cannot be detected accurately [14]. Moreover, optical flow approach assumes that the brightness of the image to be constant, and the motion to be smooth [15]. On the other hand, background subtraction approaches [16] which consists in modeling the background and subtracting it from each current frame are reported to be simple to implement and give good results in case the background is well modeled [16]. However, it is sensitive to the changes of the scene background. In order to deal with the latter problem, adaptive background modeling based approaches have been proposed. More specifically, an adaptive parametric mixture model using three Gaussian is suggested in [17]. But, although this approach can deal with illumination changes, it cannot cope with new object introduction or object removal from the scene. An alternative solution is proposed in [13]. It is based on an adaptive nonparametric Gaussian mixture model. It aims at discarding repetitive motions that are small such as moving tree leafs. We will use this approach in the design of the proposed system. Concerning object tracking, we propose to use Kalman filter technique [18]. In fact, it is the most widely used approach for object tracking because it gives efficient results [19]. Most popular applications for Kalman filter [18] are the aircraft control application [20], spacecraft monitoring [21], and autonomous navigation [22]. In fact, since Kalman filter is iteratively predicting and estimating the prediction error, it gives optimal results by reducing the tracking error. Besides, due to its recursive characteristic the Kalman filter does not require all previous locations of the object to be stored and reprocessed at each frame. This makes it appropriate for online processing and easy to use and implement.

2. BACKGROUND

Videos are used in many applications such as video surveillance, video storing and retrieval, traffic monitoring, human-computer interaction, etc. For these applications, object tracking can be an essential task [23]. It is the process of searching in a frame for an object of interest usually the moving object in order to estimate its trajectory in the video. It is a challenging problem due to the moving camera, to occlusion occurrence, and to the brusque change of the scene or the moving object appearance. Nevertheless, most of object tracking approaches assume a fixed camera in order to make the problem less challenging [24].

For object tracking, the frame is segmented into foreground and background. The foreground part is the set of pixels that correspond to the moving object while the background part is the set of remaining pixels. That is why the identification of the moving object is the first step of any object tracking system. However, there is no general approach for it since moving objects present different characteristics regarding color, texture, and shape depending on the considered application.

In this following, we present an overview of the two main components of the proposed system. Namely, we outline the object detection approach based on the adaptive nonparametric Gaussian mixture model [13], and the object tracking using Kalman filter [18].

2.1 Adaptive Nonparametric Gaussian Mixture Model Approach

The adaptive nonparametric Gaussian mixture model approach [13] models each pixel by a weighted mixture of Gaussian distributions. The number of Gaussian, K, is constrained to be between 3 and 5. Using the K Gaussian distributions, the probability of a pixel x_t at time t is defined as

$$p(x_t) = \sum_{j=1}^{K} w_j \, \eta\left(x_t, \theta_j\right) \tag{1}$$

In (1), w_j is the weight of the j^{th} Gaussian, and $\eta\left(x_t, \theta_j\right)$ is the normal distribution defined as

$$\eta(x_t; \mathbf{\theta}_K) = \eta(x_t; \mathbf{\mu}_k; \textstyle\sum_k) = \frac{1}{(2\pi)^{\frac{1}{2}} \mid \sum_k \mid^{\frac{1}{2}}} e^{-\frac{1}{2}(x_t - \mathbf{\mu}_k)^T \sum_k^{-1} (x_t - \mathbf{\mu}_k)} \tag{2}$$

where $\mathbf{\mu}_k$ and $\sum_k$ are the mean and covariance of the k^{th}Gaussian function. These Gaussian distributions are related to the color distributions in the scene and their respective weights are related to the time that a given color proportion remains in the scene. The background is then defined by the colors that have the largest weights (probabilities) since they stay longer in the scene.

The adaptive nonparametric Gaussian mixture model approach [13] uses also the notion of fitness. It is defined as

$$fitness = \frac{w_k}{\sigma_k} \tag{3}$$

It is a measure of how compact a color is in the color space. In fact, background colors tend to small variance whereas the moving object colors tend to have large variance because of the change in the surfaces during movement. A selective updating scheme is adopted. It consists in comparing each new pixel to the other models in terms of fitness. If the match is found, then the corresponding model is updated. Otherwise, a new Gaussian model is added.

The first Gaussian component that matches the considered pixel is updated using (4), (5), (6), (7), and (8).

$$w_k^{t+1} = (1-\alpha)w_k^t + \alpha p(w_k|x_{t-1}) \tag{4}$$

$$\mu_k^{t+1} = (1-\alpha)\mu_k^t + \rho x_{t-1} \tag{5}$$

$$\textstyle\sum_k^{t+1} = (1-\alpha)\sum_k^t + \rho\,(x_{t+1} - \mu_k^{t+1})(x_{t+1} - \mu_k^{t+1})^T \tag{6}$$

$$\rho = \alpha\,\eta(x_{t+1}, \mu_k^t, \textstyle\sum_k^t) \tag{7}$$

$$p(w_k|x_{t+1}) = \begin{cases} 1; \ if \ \ \eta_k is\ the\ matched\ Gaussian\ function \\ 0; \ otherwise \end{cases} \tag{8}$$

In (4), (5), (6), (7), and (8), α is the inverse of the time constant that specifies the change. If the considered pixel does not match any defined Gaussian distribution, the Gaussian distribution that has the smallest probability is replaced with a new one. The value of the considered pixel is its mean. Its variance is initially set to a high value, and its weight is set a small value. The adaptive nonparametric Gaussian mixture steps are outlined in algorithm 1.

Algorithm 1: Adaptive nonparametric Gaussian mixture algorithm

```
Input:
- The set of video frames
- The number of Gaussian K
Output:
- The foreground (The moving object)
START
- Set the weights to small values
- Compute μ_k and Σ_k , the mean and covariance of the k^th Gaussian
color in the scene
For each current frame
        For each new pixel
                1- Compute the fitness using (3)
                2- Compare new pixel with the Gaussian models
                3- If match is found,
                  The first Gaussian component that matches the
                  considered pixel is updated using (4), (5), (6), (7),
                  and (8).
                  Otherwise,
                  The Gaussian distribution that has the smallest
                  probability is replaced with a new one.
        END
- Define the Background as the colors that have the largest weights
- Background subtraction
END
END
```

2.2 Object Tracking using Kalman Filter

The Kalman filter estimates past, present and future location using a set of recursive mathematical equations [18]. These equations are time update equations and measurement update equations. The first ones predict the next location, prior estimate, while the second ones incorporate the feedback information to correct the posteriori estimate of the location.

2.2.1 Time Update Equations

Let $\mathrm{X}_{\mathrm{pred}}^{\mathrm{t}}$ be the vector specifying the prediction location. It is defined as

$$X_{pred}^{t} = [x, y, dx, dy] \quad (9)$$

where(x, y) is the predicted position of the moving object at t and (dx, dy) the corresponding velocity at t. It is estimated using

$$X_{pred}^{t} = A * X^{t-1} + W^{t-1} \quad (10)$$

where X^{t-1} is the moving object location at $(t-1)$, and A define the transition matrix and is expressed as

1	0	1	0
0	1	0	1
0	0	1	0
0	0	0	1

(11)

In (10), W^{t-1} represents the noise. The predicted error at t is computed using

$$Error_{pred}^{t} = A * Error^{t-1} * A^{T} + Q \quad (12)$$

where Q is the noise covariance and $Error^{t-1}$ is the error at $(t-1)$ obtained from the Measurement update equations at $(t-1)$.

4.2.2.2 Measurement Update Equations

In order to incorporate the feedback information to correct the posteriori estimate of the location, The Kalman gain is first computed using

$$K_{Gain} = Error_{pred}^{t}\left(Error_{pred}^{t}\right) \quad (13)$$

where $Error_{pred}^{t}$ is as computed in (12). The posteriori estimate of the location,X^{t}, is updated using

$$X^{t} = X_{pred}^{t} + K_{Gain} * \left(Z^{t} - H * X_{pred}^{t}\right) \quad (14)$$

In (14) X_{pred}^{t}, and K_{Gain}, are as defined in (10) and (13), respectively. Z^{t} is the location of the moving object at t. H is the transformation matrix used to map state vector parameters into the measurement domain and is expressed as

1	0	1	0
0	1	0	1
0	0	0	0
0	0	0	0

(15)

Finally, the error is updated using

$$Error^t = (I - K_{Gain} * H)^* Error^t_{pred} \quad (16)$$

where K_{Gain}, and $Error^t_{pred}$ are as expressed in (13) and (12) respectively. The Kalman filter algorithm steps are described in algorithm 2.

Algorithm 2: The Kalman filter algorithm

Input:
- The set of video frames

Output:
- Object trajectory

START
For each current frame
    For each new pixel
    1- Compute X^t_{pred} , the vector specifying the prediction location using (10)
    2- Compute the predicted error at t is using (12)
    3- Compute the Kalman gain using (13)
    4- Compute the posteriori estimate of the location, X^t, using (14)
    5- Update the error using (15)
    END
END
END

3. RELATED WORKS

In the literature, several objects tracking on videos approaches are proposed. They are intelligent systems that allow video analysis for either surveillance and monitoring applications, or for control applications. For example, the authors in [25], propose an intelligent surveillance system that assists in detecting and tracking suspicious aerial vehicles that threaten the country border. The object detection is based on background subtraction [26]. Then, the moving objects are tracked using Mean-Shift approach [23]. Similarly, in [27], the authors propose an approach for intrusion detection. The system triggers an alarm if an object invades a pre-defined area. The authors use Gaussian Mixture Model algorithm [28] to detect the object. Also, in [29], an object tracking approach is proposed for mobile robots. In fact, in order to allow the robot, perceive its environment, the moving objects are tracked using particle filters [26]. Besides, the authors in [30] propose a visual based tracking system that allows analyzing and studying animal behavior. For the purpose of automatic navigation, the authors in [31] propose a navigation system based on moving object tracking. It detects moving objects and predicts their trajectory in order to avoid collision using optical flow approach [28].

The use of technology is increasing every day. In fact, emerging devices impact our daily life and helps us perform various tasks. One of the areas where technology can help is children monitoring. Several related systems have been proposed to help the childcares monitor the kids in order avoid accidents and make their task easier. These are camera-based approaches, and gadget based approaches. In the following, we outline them.

3.1 Camera Based Approaches

An Automated Child Monitoring System is proposed in [4]. It uses a Raspberry Pi microcomputer and a camera communicating through Passive Infrared (PIR) sensors and Servomotor. The camera revolves around the child's movements throughout the room. A GSM module is also used so that the childcare can get SMS alert whenever any sensor is activated. Childcare can access by logging in to a website and the video can be broadcast live online. We should mention here that the videotape is not used for tracking the baby. It only used to broadcast the scene to the childcare. In fact, the sensors are the one who locates the child. Moreover, in [10], the authors have used a sensor bracelet, a camera, and a receiver for tracking and providing audible and visual contact with a child. The camera is attached to the child by a clothing article such as a button or pocket to get and transmit video signals to the monitor. The receiver includes a GPS switch, activated to display the latitude-longitude coordinates of the child, who wears a GPS receiver/transmitter and antenna. Similarly, in this system, the video tapped is no used for tracking, but for just transmitting the scene perceived by the child. Besides, in [11], the authors propose a car seat monitoring system. It monitors children seated in the rear seats of the car. The monitoring device is designed to relay an image of the rear seats of the car to the viewing device in the front seats of the car. The proposed system is not intelligent and it does generate an alerting message. For this system also, the video is only used for monitoring. Furthermore, in [12], the proposed child monitoring system provides a way to communicate video and audio between the child and the care provider. Similarly, as the system proposed in [12], the proposed system is not intelligent, and does not deliver an alerting message. Moreover, the video is only used for reporting the scene to the care provider.

3.2 Gadget Based Approaches

The authors in [6] propose a system that tracks the child's movement. The system consists of two modules. The first one, worn by the child, is a bracelet. This gadget sends signals relative to the distance and direction of the child. The second module, which is in the possession of the childcare, triggers an alarm if the distance between the child and childcare increase beyond a maximum threshold. The second module displays the direction and distance of the child movement. Similarly, the authors in [8] and in [9], propose a monitoring system based on a bracelet gadget. It alerts the childcare when a child moves beyond a limited range. On the other hand, the authors in [5] propose a system that monitors the departure of a child from an exit. The child should wear a tag that responds to electromagnetic fields. When he reaches the exit, the alarm is triggered. Similarly, the child monitoring system proposed in [7] uses an adhesive bandage gadget. It is a transmitter device that tracks the child movement. A portable receiver device should be with the childcare. Moreover, the signal strength of a radio frequency signal transmitted by a device attached to the child is used in [8] to track the child movement. More specifically, if the received radio frequency is too weak, meaning that the child wandered far away from the monitoring device, the childcarer is notified through an audio tone or through vibration. The monitoring device displays also the location of the child using eight LEDs, which indicates the relative direction. Additionally, the system proposed in [9] uses a microphone device. The device is worn by the child and transmit an audio signal to the receiver hold by the childcarer. The communication is done through a wireless connection and radio frequency or infrared optical signals.

The approaches reported in the literature either use a camera device or radio/ audio transmitters to monitor the child's movements. However, the camera based approaches report only the scene to the childcare provider. Besides, the child tracking is performed either through sensors, radio receiver/transmitter, or GPS device. Moreover, we notice that the alerting messages, if any, is only triggered when the child goes far away. In fact, these systems are not intelligent. They do not track the child through the video, and they do not detect the fact that the child is approaching a danger. Nevertheless, the availability of videotaping device nowadays should be explored to make the child tracking task intelligent using object tracking in videos.

4. INTELLIGENT CHILD MONITORING SYSTEM

We propose a monitoring system that uses a video as an input. The video is recorded using laptop cam. It videotapes the child moving and tracks its trajectory. As shown in figure 1, the proposed system detects the child using background subtraction based on adaptive nonparametric Gaussian mixture [13]. Then, it tracks him using Kalman Filter [18]. While tracking the child, the system computes the distance from the child to the different dangerous item and/or the boundaries of the safe area that have been specified by the user. When the computed distance is smaller than a certain threshold, a voice recorder message that can be heard by the childcarer and the child is triggered. The voice message should not scare the child but it should be an affirmative directive to which the child is used to react positively. That is why; we intend to let the childcare to record a personalized voice message. It should contain a message familiar to the child such as "Oh!Oh!", "Don't touch" , "Get back" , or "Stop". The message will be repeated till the child is out of the dangerous region. Algorithm 3 describes the steps of the proposed approach.

The proposed approach includes two main components. The first component of the system detects the child if he moves. This is a moving object detection problem where the child is the moving object (also called foreground) and the reaming parts of the recoded scene are the background objects. It is based on an adaptive nonparametric Gaussian mixture model [13]. It aims at discarding repetitive motions that are small such as moving tree leafs. The second component of the system tracks the child when moving. This is an object tracking problem where the child is the moving object to be tracked. We use Kalman filter technique [18] to perform this task. It is a recursive approach, which consists of two steps: prediction and correction. It performs child tracking by predicting the child's location using information about the previous location, and by estimating the error of the predicted location with respect to the real new location. It is the most widely used approach for object tracking because it gives efficient results [19].

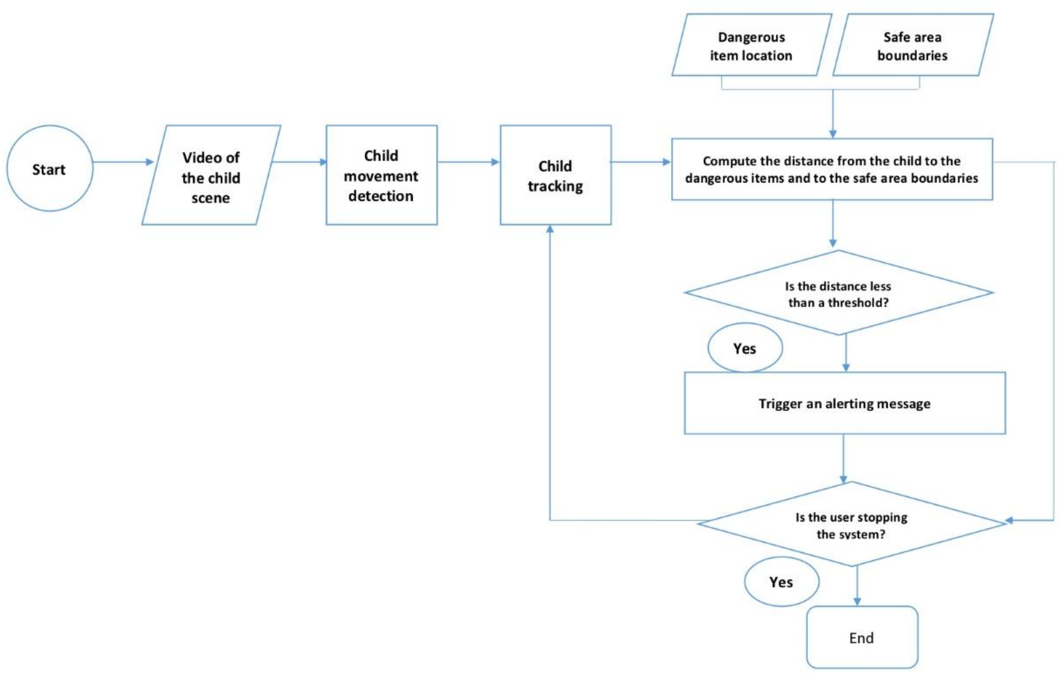

FIGURE 1: Flowchart of the proposed system.

Algorithm 3: The proposed intelligent child monitoring system

Input:
- Dangerous item location and area boundaries
- Threshold

Output:
- Voice alerting message if any

START
- Videotape the child scene
- Detect the Child usingadaptive nonparametric Gaussian mixture for foreground detection
- Repeat
  1. Track the child using Kalman filter
  2. Compute the distance from the child to the different dangerous item and/or the boundaries of the safe area
  3. If the distance is smaller than the threshold
     Trigger a voice recorded message
     Otherwise, go to step 2
- Until the user stops the system

END

5. EXPERIMENTS

A set of 21 videos are collected using laptop cam. Each video contains a child playing in an inside house scene. For a certain time interval, [t1-t2], a dangerous event occurs such as the child touches a dangerous item, or goes out of a pre-specified safe area. Table 2 reports a detailed description of the considered videos. For each video, it specifies its duration in seconds, the number of frames considered, a description of the dangerous event that occurred, and its time interval. Each video is split into a set of frames. Then, each frame will be labeled as positive or negative. "Negative frames" are the frames just before the dangerous event occurs. More specifically, if the child approaches a dangerous item, or adventures outside the safe area at a certain time interval, [t1-t2], all the previous frames, that occur before the time t1, are considered as negatives. The positive frames are the frames between t1 and t2, when the voice alert should be triggered. On the other hand, the "negative" frames are all the remaining frames where the child is away from the dangerous event. We should mention here that these labels are used for the assessment of the proposed system. They are not used by the proposed approach.

Data	Duration (s)	No of frames	Description of the dangerous event	Dangerous event time interval
1	19	456	The child goes to the stairs	[13-19]
2	36	864	The child touches dangerous items on the table	[20,24]
3	23	552	The child hides behind of the chair	[2-3] [11-12]
4	16	384	The child goes to the stairs	[13-17]
5	33	792	The child touches dangerous items on the table	[11-30]
6	10	240	The child goes out of his bed.	[5-10]
7	20	480	The child adventures outside the safe area	[14-20]
8	25	600	The child adventures outside the safe area	[18-25]
9	30	720	The child adventures outside the safe area	[24-29]
			The child touches dangerous items on the table	[16-20]

10	51	1224	The child goes to the window	[30,39]
11	51	1224	The child adventures outside the safe area	[32,36]
12	67	1608	The child touches dangerous items on the table	[11-14]
13	23	552	The child touches dangerous items	[10-19]
14	9	216	The child goes to the door	[26,27] [34,38]
15	45	1080	The child plays with the food on the table	[15-17]
16	16	384	The child plays with the food on the table	[4-7]
17	6	144	The child plays with the bag	[19,35]
18	44	1056	The child touches dangerous items	[11-15]
19	24	576	The child goes to the window	[13-21]
20	21	504	The child plays with the plug	[16-22]
21	17	408	The child plays with the plug	[8-15] [16-18]

TABLE 1: Dataset Description.

In order to assess the proposed approach, we use several statistics. Namely, we will compute the accuracy, the precision, the recall and the F- measure. For this purpose, we compute the True Positive, False Positive, False Negative and True Negative. More specifically, the True Positive, TP, is the number of times the alert is triggered when it should, and false positive is the number of times the alert is triggered wrongly. On the other hand, True negative is the number of times the alert is not triggered when it should not, and False Negative is the number of times the alert is not triggered while it should.

Each video, from the collected dataset, is provided as input to the proposed approach. The system records the frame numbers when the alarm is triggered if any. These frames are assigned to the category 1. All the other frames are assigned to the category 0. The obtained results are then compared to the ground truth (target results) using the labeled frames. Using this information, we compute the performance measures reported in table 2.

Video No	TP	FP	FN	TN	Accuracy	Precision	Recall	F-Score
1	66	2	8	309	0.9740	0.9706	0.8919	0.9296
2	94	20	2	700	0.9730	0.8246	0.9792	0.8952
3	159	57	87	417	0.8	0.7361	0.6463	0.6883
4	86	3	8	308	0.9728	0.9663	0.9149	0.9399
5	444	53	12	283	0.9179	0.8934	0.9737	0.9318
6	96	12	25	107	0.8458	0.8889	0.7934	0.8384
7	16	25	537	310	0.9396	1	0.800	0.8889
8	163	19	0	412	0.9680	0.8956	1	0.9449
9	38	10	10	494	0.9638	0.7917	0.7917	0.7917
10	162	59	30	973	0.9273	0.7330	0.8438	0.7845
11	96	29	0	1483	0.9820	0.7680	1	0.8688

12	63	9	9	484	0.9681	0.8750	0.8750	0.8750
13	211	11	5	419	0.9752	0.9505	0.9769	0.9635
14	109	28	11	956	0.9647	0.7956	0.9647	0.8482
15	36	13	6	346	0.9526	0.7347	0.8571	0.7912
16	57	0	7	95	0.8906	1	0.8906	0.9421
17	362	41	22	625	0.9400	0.8983	0.9427	0.9199
18	84	7	12	473	0.9670	0.9231	0.8750	0.8984
19	157	1	36	310	0.9266	0.9937	0.8135	0.8946
20	25	13	0	370	0.9681	0.6579	1	0.7937
21	182	0	34	543	0.9552	1	0.8426	0.9146

TABLE 2: Performance measures with respect to each considered video.

For a better display of the results, we sketch the average and standard deviation of these results as error bar plots in figure 2. As displayed in figure 2, we have almost the same average results for the precision and the recall ($\overline{P}$=0.87 and $\overline{R}$=0.9). Nevertheless, the precision is slightly smaller than the recall. Considering the standard deviation of the precision and the recall, σ_P=0.1, σ_R=0.09, we notice that there is no considerable variation in the result of the different videos. The F-measure which combines both the precision and the recall results, has an average of $\overline{F}$=0.87 with a standard deviation of σ_F=0.07.

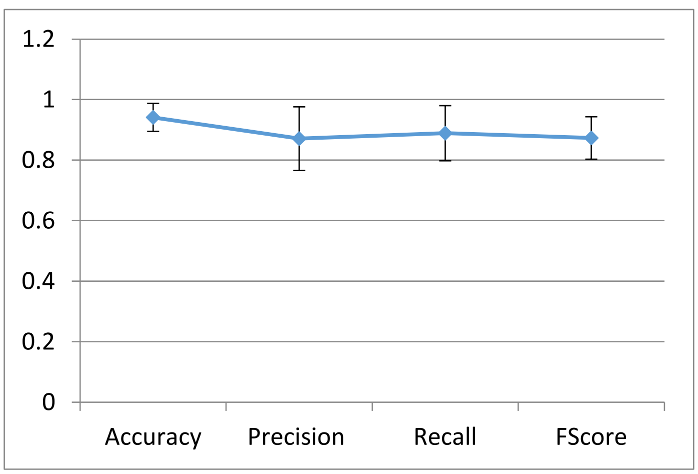

FIGURE 2: Average and standard deviation of the performance measures of the monitoring child system on the considered videos.

In order to further investigate the false positive and false negative occurrences, we visualized the videos in order to figure out the problems that miss-lead the proposed system. In the following we show and analyze three wrong alert cases. When visualizing video No 3, we noticed that the child hides for a relatively long time behind the obstacle (mattress). For a while, the system is able to predict the position of the child correctly. After that, it is not able to track him, and considers that he is out of the safe area. Figure 3 shows a frame from video No 3, where the child is hiding behind the mattress.

FIGURE 3: Selected frame from video No 3.

From the results of the proposed system on video No 6, we noticed that when the child is touching the table, the alarm is not triggered. It is explained by the fact that the distance between the child and the dangerous area is computed from the centroid of the body of the child to the border of the dangerous area. However, in this case the child reaches the tables with his hand while his body is not inside the dangerous area. Figure 4 displays a frame from video No 6.

FIGURE 4: Selected frame from video No 6.

On video No 9, the moving shadows of the child are recorded as it can be seen in figure 5. For certain frames, the shadow goes out of the safe area or reaches a dangerous point. The alarm is then trigged while the child is safe.

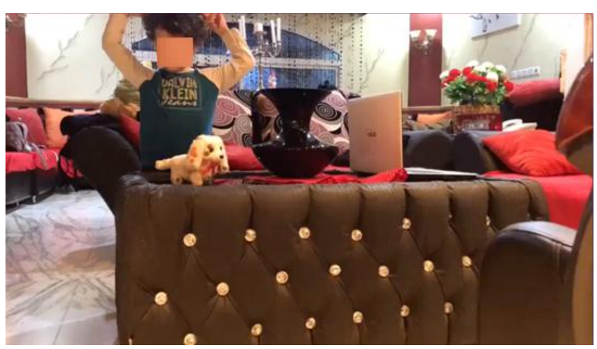

FIGURE 5: Selected frame from video No 9.

6. CONCLUSIONS AND FUTURE WORKS

Usually, children enjoy playing with dangerous items, which threatens their safety such as plugs, stairs, etc. Nevertheless, no matter how careful a parent is, he can't have his eyes on his kid all the time. Monitoring devices can be a solution that helps parents to be less stressed and perform simple tasks while the child is playing. However, the available approaches are not intelligent which means that the childcarer has to monitor the device all the time. This requires the same amount of efforts as monitoring the child directly.

In this paper, we designed a child monitoring system based on image processing techniques. The child is first detected using adaptive non- parametric Gaussian mixture for background subtraction [26]. Then, his movement is tracked using Kalman filter approach [18]. If the child adventures outside the safe area or is near a dangerous item, an appropriate voice message is delivered to both the child and the childcarer. The assessment of the proposed system on the collected dataset showed the effectiveness of the proposed approach.

As future works, we intend to improve the performance of the system in order better guarantee the security of the child and avoid inconvenient wrong alerts. For this purpose, we plan to investigate the problems that yielded the system errors. More specifically, we will investigate the way of computing the distance between the child and the dangerous area, and the way of dealing with shadows and relatively long occlusions. Besides, we plan to make the system identify the dangerous points automatically. In other words, the system will be trained to learn different dangerous item. This way, when the child approaches one of them, the alarm will be triggered without the user pre-specifying them. Another improvement of this system could be to consider another moving object in the scene. This could be another person entering the scene, or a moving toy-like train or a car.

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