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Human Action Recognition in Surveillance Videos using Abductive Reasoning on Linear Temporal Logic

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Abstract—Real time motion tracking is a very important part of activity recognition from streaming videos. But little research has been done in recognizing the top-level plans linking the atomic activities evident in various surveillance footages. This paper proposes a novel approach for high-level action recognition in surveillance videos combining Linear Temporal Logic (LTL) and Abductive Reasoning. Although both LTL and Abductive reasoning have been used separately for plan recognition in various Artificial Intelligence (AI) systems and mobile robots, the framework proposed in this paper combines the two by first mapping the surveillance videos to LTL formula and then using probabilistic and logical reasoning to identify complex events like burglary/escapade or deal with arbitrary events like occlusion or random stops.

Keywords— Human action recognition, Object Tracking, Plan recognition, Linear Temporal Logic, and Abductive Reasoning.

1. Introduction

VIDEO surveillance systems have become increasingly important for national security. Object tracking and action recognition are two important parameters for any such surveillance system. Once an object is tracked and its motion has been classified into a standard category by comparing it against a database of actions, the difficult part is to link these actions or group of actions spatio-temporally to discover events that are unusual or seek attention. In many cases, such linking is done by human operators who have to sit continually in front of these surveillance cameras and keep watching for unusual events. However, for hours and hours of video data, this becomes a Herculean task and hence calls for an automated system that could track the objects, classify the motion, and reason about the top level actions in these surveillance videos. Although many trackers (Zhou, 2006) and motion classifiers (Junejo, 2008) are available today, none of them have the ability to reason about the top level plans involving complex events like burglary or escapade. In this paper, we present a novel approach on reasoning about the top level plans combining Linear Temporal Logic and Abduction based reasoning.

The rest of the paper is organized as follows. The related work is discussed in Section 1.1 while section 2 contains a formal description of Linear Temporal Logic. Section 3 contains the basics of our approach to mapping the surveillance video frames to LTL. Section 4 discusses abductive reasoning and its use for performing probabilistic computations for reasoning about complex events in surveillance videos. Section 5 illustrates the proposed Bayesian Framework used for inference. The implementation details and results are illustrated in Section 6. Section 7 concludes the paper with discussions of the model and future work.

1.1 Related work

A theory for reasoning about actions that is based on Dynamic Linear Time Temporal Logic (DLTL) is proposed in (Giordano et al., 2001). They propose an approach for reasoning about actions and change in a temporal logic by modeling the temporal projection problem and planning problem as a satisfiability problem in DLTL. Another work that is quite related to our work is that proposed in (Raghavan and Mooney, 2011) on abductive plan recognition using Bayesian Logic Programs (BLPs). However, their work is based on Bayesian logic programs whereas we use a different approach that is based on Linear Temporal Logic (LTL).

Logical reasoning was first used for activity recognition in (Kautz, 1987). It provided a formal theory of plan recognition describing it as a logical inference process of circumscription. All actions and plans are uniformly referred to as goals, and a recognizer's knowledge is represented by a set of first-order statements called event hierarchy encoded in first-order logic, which defines abstraction, decomposition and functional relationships between types of events. However, our work is based on the use of LTL in portraying the temporal relations between the actions in event space. A method for robbery detection was proposed in (Chuang, 2007) that primarily focuses on baggage detection and hence might raise false alarms even for a not so unusual event like a normal visit to a store or bank. Their approach lacks the ability to chain multiple activities that is inherent in a composite event like robbery.

A process recognition strategy based on Linear Temporal Logic is proposed in (Kreutzmann et al., 2011). However, it is different from our work in the fact that we combine abductive reasoning with LTL to reason about complex events. An approach for motion classification using Motion History Image was proposed in (Ahad et. al., 2010) while (Shao et. al, 2012) proposed a method based on Motion and shape analysis. A probabilistic framework for plan recognition is proposed in (Bui, 2003) which is based on Abstract Hidden Markov Model. However, our approach is distinct and novel in that it combines LTL and abductive reasoning to detect and predict complex real-life events like burglary or escapade or distinguishing between temporary and permanent parking of a car in surveillance videos.

2. Linear Temporal Logic

Linear Temporal Logic (LTL) is a modal temporal logic with modalities referring to time. It is used to encode the formulae about future of paths and is used to represent real-world entities in the formal language that helps in instantiating model checking clauses. It was first proposed in (Pnueli, 1977) as a tool for formal verification of computer programs. The advantage of using Linear Temporal Logic in modeling surveillance videos lies in the fact that each video frame can be shown to be logically related to the previous and next frames with relations that can be represented in the temporal domain. The clauses of LTL used in this paper are:

X □ → □ holds at the next instant

G □ → □ holds on the entire subsequent path

F □ → □ eventually has to hold (somewhere on the subsequent path)

An object’s spatial location is marked by the 2-tuple (x,y) representing the pixel coordinates of its centroid.

3. Mapping surveillance videos to LTL

The first step in our approach is to map the surveillance video frames to Linear Temporal Logic. This requires developing a mechanism to represent the entities and actions in the formal language of LTL.

3.1 Symbols used to represent the real-world entities

$O \rightarrow \{O_1, O_2, \ldots O_n\}$ represents the various objects that are considered part of the foreground.

$O \in \{C\} \cup \{H\} \cup \{A\}$ where C represents the set of cars, H for humans and A for animals.

$L \rightarrow \{L_1, L_2, \ldots, L_n\}$ represents the object locations.

$V \rightarrow \{V_1, V_2, \ldots, V_n\}$ represents the velocities of the corresponding objects quantified with the help of the optical flows (Lucas and Kanade, 1981).

3.2 Atomic Propositions

isAt(t_i, O_j, L_k) $\rightarrow$ Object O_j is at location L_k at time instant t_i where t_i belongs to the finite domain.

isClose($\square_i$, $\square_j$) $\rightarrow$ Entities $\square_i$ and $\square_j$ are in close proximity to each other, defined by a threshold τ (close proximity is defined in terms of the unit in which the entities are defined) which may be Euclidean distance, appearance labels, or just the magnitude.

isLinear(V_i) $\rightarrow$ Object O_i has a velocity V_i that is linear for a certain period of time within a pre-defined threshold.

Mag(V_i) $\rightarrow$ Magnitude of the velocity of Object O_i.

3.3 Integrity Constraints

Each frame represents a time instant t_i. An object cannot be present simultaneously at two locations in the same frame. This can be represented mathematically as:

$$\text{isAt}(t_i, O_j, L_k) \wedge \text{isAt}(t_i, O_j, L_m) \Rightarrow L_k \Leftrightarrow L_m \qquad \ldots (1)$$

3.4 Complex events represented as a combination of composite atomic propositions

3.4.1 Occlusion (Event E_1) :

Occlusion occurs if at time t_i, Object O_j is at location L_k and at the next instant, the object is not visible at any location L_k close to L_j.

$$\mathbf{E_1} \rightarrow \text{isAt}(t_i, O_j, L_k) \wedge \mathbf{G}\ ([\forall\ j]: \text{isClose}(L_j, L_k) \wedge \neg\ \text{isAt}(t_{i+}, O_j, L_j) \wedge t_{i+} \Rightarrow \mathbf{X}\ t_i) \qquad \ldots (2)$$

3.4.2 Human entering a vehicle (Event E_2):

A human entering a vehicle is detected at time t_i if an Object O_i at location L_k belongs to the set of humans while there exists another object O_j close to it that belongs to the set of cars, and at the next instant of time, the human is not visible near the previous location.

$$\mathbf{E_2} \rightarrow \text{isAt}(t_p, O_i, L_r) \wedge \text{isAt}(t_p, O_j, L_k) \wedge (O_i \in H) \wedge (O_j \in C) \wedge \text{isClose}(L_j, L_k) \wedge [\forall\ m : \text{isClose}(L_m, L_r) \wedge \neg\ \text{isAt}(t_{p+}, O_i, L_m)] \wedge t_{p+} \Rightarrow \mathbf{X}\ t_p \qquad \ldots (3)$$

3.4.3 Burglary or escapade (Event E_3):

Burglary or escapade is a composite event detected when one or more of the aforementioned events occur in the course of time with other atomic events of interest like carrying an object and velocity of cars and humans exceeding a threshold.

$$\mathbf{E_3} \rightarrow O_i \in H \wedge (Mag(V_i) > Threshold\ T_1) \wedge H_O \text{ detected} \wedge E_2 \wedge \mathbf{X}\,(O_j \in C) \wedge \mathbf{F}\,(Mag(V_j) > Threshold\ T_2) \qquad \ldots(4)$$

where,

$T_1 \rightarrow$ Threshold for Human velocity

$T_2 \rightarrow$ Threshold for car velocity

$H_O \rightarrow$ Human carrying object

4. Abductive Reasoning

Abduction is a *logical reasoning* framework first proposed in (Pierce, 1901). In abduction, an explanation *a* for an observation *b* is derived by presuming that *a* may be true because then *b* would eventually follow. Thus, to abduce *a* from *b* involves determining that the occurrence of *a* is sufficient (or nearly sufficient) for the eventual occurrence of b, but not necessary for *b* to occur.

Given a theory *T* (in LTL) describing normal/abnormal behavior in an environment and a set of observations *O*, an abduction engine computes a set Σ of LTL formulas that form possible explanations for *O* and is consistent with *T*. A probability distribution on the set Σ (also called a belief state) is used to determine the most likely explanation. Technically, E is a minimal set of LTL formulas that together with T entails O; i.e., $T \wedge \Sigma \models O$.

Here, we assume a Bayesian framework with *prior probabilities* wherein we first determine the prior probabilities of all actions A_i that can eventually lead to a particular observation O and choose the A_i with maximum apriori probability.

While the LTL-based framework in Section 3 provides a deterministic plan recognition technique that is not flexible enough to incorporate probability distributions of the various apriori events, in most real-world scenarios, the atomic propositions are associated with probabilities provided either by the sensors or by the tracking/atomic action recognition system. This enables us to combine logical abduction with Bayesian inference to determine the most probable top-level plan.

4.1 Example cases where probabilistic reasoning might help

4.1.1 Burglary or escapade:

In the example of burglary or escapade in the previous page, in the deterministic case we just consider the velocities of the human being entering the car and the velocity of the car henceforth. However, a great determining factor is the location of the incident. So, once again like the previous example, by matching the label on the ROI (Region of Interest) around the scene against a database of standard locations, we try to figure out if the point is a bank or jewelry or an antique shop because these places have a higher probability of witnessing a burglary than other places.

4.1.2 Filling up tracks under occlusion:

Both humans and cars could be occluded during tracking. For instance, humans could be occluded by a tree or a building. Similarly, moving cars could also be occluded by a tree or another car. So, we construct a map of the respective objects based on their speeds and appearance. The ones having closest speeds and closest in terms of appearance while going into occlusion and reappearing have highest probabilities of being identified as the same object.

4.1.3 Filling up tracks on vehicles that might have remained stationary for arbitrary periods of time:

Suppose a car comes to a standstill at a point. We can't keep tracking it forever. So, matching the label on the ROI around the car against a database of standard locations, we try to figure out if the point is a traffic signal or a parking lot. There's a high probability of a car waiting temporarily at a signal or permanently stopping at a parking lot.

4.2 Probabilistic reasoning to perform abduction

The use of conditional probabilities to perform probabilistic Horn abduction was proposed in (Poole, 1993). Probabilistic Horn Abduction is a framework for integrating probabilistic and logical reasoning into a coherent practical framework. We use this same idea in our paper but use an altogether different approach by performing probabilistic reasoning on the Linear Temporal Logic formulas defined in Section 3.

Case 1: Burglary or escapade

Let us denote a bank by the label B and an antique shop or Jewelry shop by AS. So, the probability that the event E is a burglary or escapade is given by

$$P(E{=}\text{Burglary/Escapade}) = P(\mathbf{F}\ (\text{isAt}(t_i, L_i, B) \vee \text{isAt}(t_i, L_i, AS))) \wedge P(E_3) \quad \ldots\ (5)$$

Here, $P(\mathbf{F}\ (\text{isAt}(t_i, L_i, B))) = \mathit{dist}(L_i - PL)$ and $P(\mathbf{F}\ (\text{isAt}(t_i, L_i, AS))) = \mathit{dist}(L_i - AS)$

Also, E_3 denotes the deterministic event presented earlier in equation 4 and **F** denotes the eventually clause in LTL.

A careful investigation into the above equation yields the unknowns $P(\text{Mag}(V_i) > \text{Threshold } T_1)$ and $P(H_O \text{ detected})$ that are yet to be defined.

We define them as follows:

$P(\mathrm{Mag}(V_i) > \text{Threshold } T_1) = 1$, when $\mathrm{Mag}(V_i) > \text{Threshold } T_1$

$= 0$, otherwise.

And, $P(H_O \text{ detected})$ is obtained from the template matching algorithm that yields both the appearance labels discussed before as well as the human carrying object.

Case 2: Filling up tracks under occlusion

Suppose at the instant an object O_i is last seen before being occluded, it has velocity u_i and appearance label $a1_i$. For each object that has a velocity $u \in U$ and appearance label $a1 \in A1$, after coming out from occlusion has a velocity $v \in V$ and corresponding appearance label $a2 \in A2$. Also let us define the track join operator as Δ.

So, $T_i \,\Delta\, T_j \rightarrow$ joining tracks T_i and T_j. Hence,

$$P(T_i \,\Delta\, T_j) = (P(\mathbf{F}\,(\mathrm{isClose}(u_i, v_j)))) \wedge (P(\mathbf{F}\,(\mathrm{isClose}(a1_i, a2_j)))) \; [\forall\, i,j\text{: } u_i \in U \text{ and } v_j \in V \text{ and } a1_i \in A1 \text{ and } a2_j \in A2] \quad \ldots (6)$$

Here, $P(\mathbf{F}\,(\mathrm{isClose}(u_i, v_j))) = \min\,(|u_i-v_j|)/\,(|u_i-v_j|)$

And, $P(\mathbf{F}\,(\mathrm{isClose}(a1_i, a2_j))) = \min\,(|a1_i-a2_j|)/\,(|a1_i-a2_j|) \quad [\forall\, i,j\text{: } u_i \in U \text{ and } v_j \in V \text{ and } a1_i \in A1 \text{ and } a2_j \in A2]$

The above equation uses normalization to ensure that the probability always remains less than or equal to 1 as well as the fact that closer the velocities of each object higher the probability of track joining. The operator **F** denotes the eventual modality defined in LTL.

Case 3: Filling up tracks on vehicles that might have remained stationary for arbitrary periods of time

As illustrated earlier, a location is marked as L_i. Also, let us denote a parking lot by the label PL and a traffic signal or level-crossing as S. Also, let us denote the wait time for keeping the tracks active on a stationary vehicle as δt. So, for a parking lot,

$$P(\delta t = t_{temp}) = P(\mathbf{F}\,(\mathrm{isClose}(V_i, 0) \wedge \mathrm{isAt}(t_i, L_i, PL))) \quad \ldots (7)$$

And for traffic signal,

$$P(\delta t = t_{perm}) = P(\mathbf{F}\,(\mathrm{isClose}(V_i, 0) \wedge \mathrm{isAt}(t_i, L_i, S))) \quad \ldots (8)$$

Where, $P(\mathbf{F}\,(\mathrm{isClose}(V_i, 0))) = 1/\lceil V_i \rceil$ and $P(\mathbf{F}\,(\mathrm{isAt}(t_i, L_i, PL))) = 1/\mathit{dist}(L_i - PL)$, provided V_i and $\mathit{dist}(L_i - PL)$doesn't fall beneath 1 and $\mathit{dist}(L_i - PL)$ denotes the distance between L_i and PL. So as L_i approaches PL the probability measure keeps increasing.

Also, t_{temp} and t_{perm} denote the user-defined constants representing the temporary and permanent waiting times for a vehicle and **F** denotes the eventual modality in LTL.

5. Chaining the events by mapping them into a Bayesian Framework

A Bayesian network (also known as a belief network or probabilistic causal network) captures believed relations (which may be uncertain, stochastic, or imprecise) between a set of variables, which are relevant to some problem. They might be relevant because they will be observable, because their value is needed to take some action or report some result, or because they are intermediate or internal variables that help express the relationships between the rest of the variables.

Each node in a Bayesian Network represents a scalar variable which may be discrete, continuous or propositional. Once the nodes are abstructed out, they are connected together by directed links. Each node has an associated probability vector with it. The number of elements in this vector depends upon the number of nodes that the current node depends on. So, if the current node is dependent upon say one node then, the vector has four elements – representing the cases where the previous node and the current node are true-true, true-false, false-true and false-false respectively. Similarly, a node dependent on two previous nodes may be shown to have a probability vector of length eight. An example Bayes net from our implementation has been pictured in Fig 1. Each node has a probability vector associated with it.

For instance, Probability that velocity of human is greater than threshold is given by the vector $[(1-\delta)\ (\tau_{human}-V_{min\_human})/(V_{max\_human}-V_{min\_human})\ \ \delta\ \ (V_{max\_human}-\tau_{human})/(V_{max\_human}-V_{min\_human})]$. Here, δ is a pre-defined constant that determines the hardness of assumption. Hence, a value of 0.2 for δ means that even if an event E_1 is false, another event E_2 that depends upon it has a probability of 20 percent of being true and hence has a chance of 80 percent of being false. Hence each element of the probability vector of E_2 that depends upon E_1 is the conditional probability of E_2 with respect to E_1. The probability vectors are determined by an expert and later updated based on incoming data.

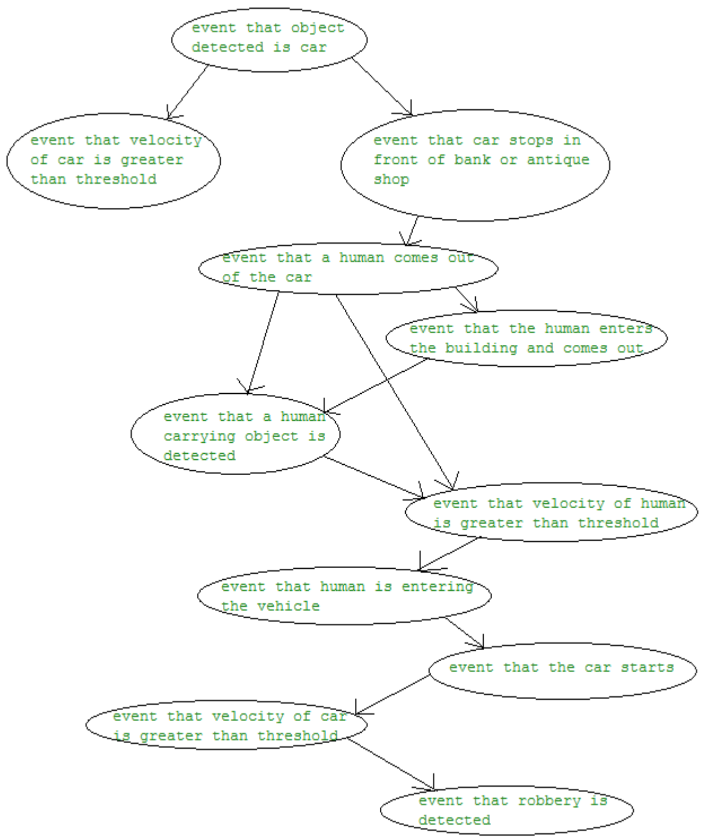

Fig 1. The Inference Engine for Burglary detection

6. Implementation

The action recognition module proposed in this paper uses our tracking[1] and motion classification modules[2]. The plan recognition module produces significantly accurate results distinguishing between car stops at an intersection and a parking lot. It is also able to track a car again after an occlusion by linking the tracks using appearance and velocity labels through our inference engine. Our module can also distinguish a normal visit to a store from that of a burglary/escapade.

Fig 2, 3 and 4 portray cases of burglary detection in videos obtained from surveillance cameras. Fig 5 and 6 demonstrate the effectiveness of our approach in the case of occlusion for human and car respectively. Fig 7 shows a temporary car stop at an intersection while Fig 8 shows a permanent stop at a parking lot. The videos used for the experiments were obtained from public datasets like VIRAT and Youtube.

[1] https://xythos.lsu.edu/users/mstagg3/web/tracker.
[2] Provided along with the supplementary materials

Burglary

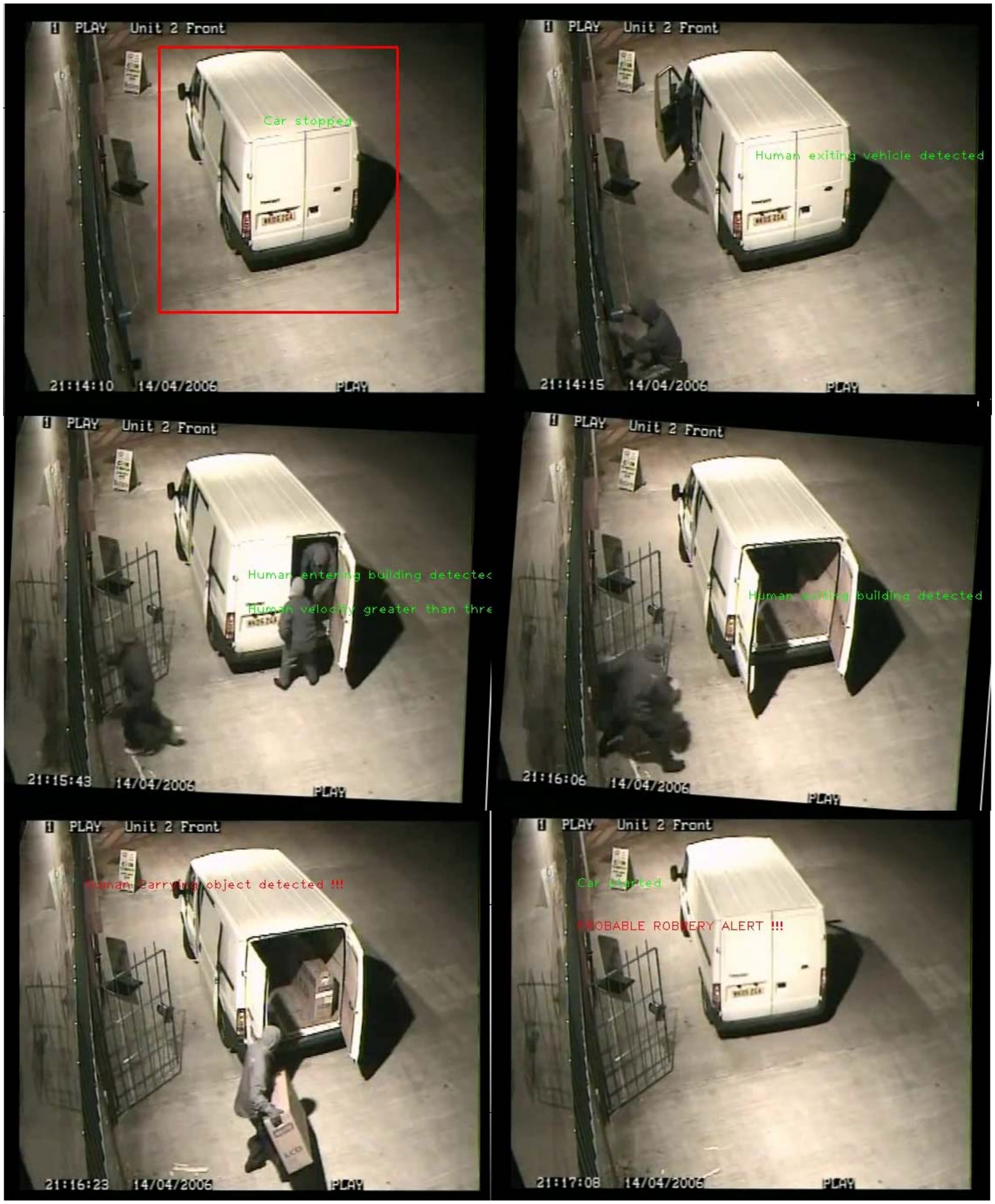

Fig 2. V_{car} > Threshold and V_{human} > Threshold and Human carrying object detected and L_i in front of store and Human entering and exiting building detected, so, probable burglary detected.

Fig 3. Human velocity greater than threshold and Human carrying object detected inside store, so, probable burglary alert

Fig 4. V_{car} > Threshold and V_{human} > Threshold and Human exiting building and escaping on a car was detected, so, probable burglary detected.

Occlusion

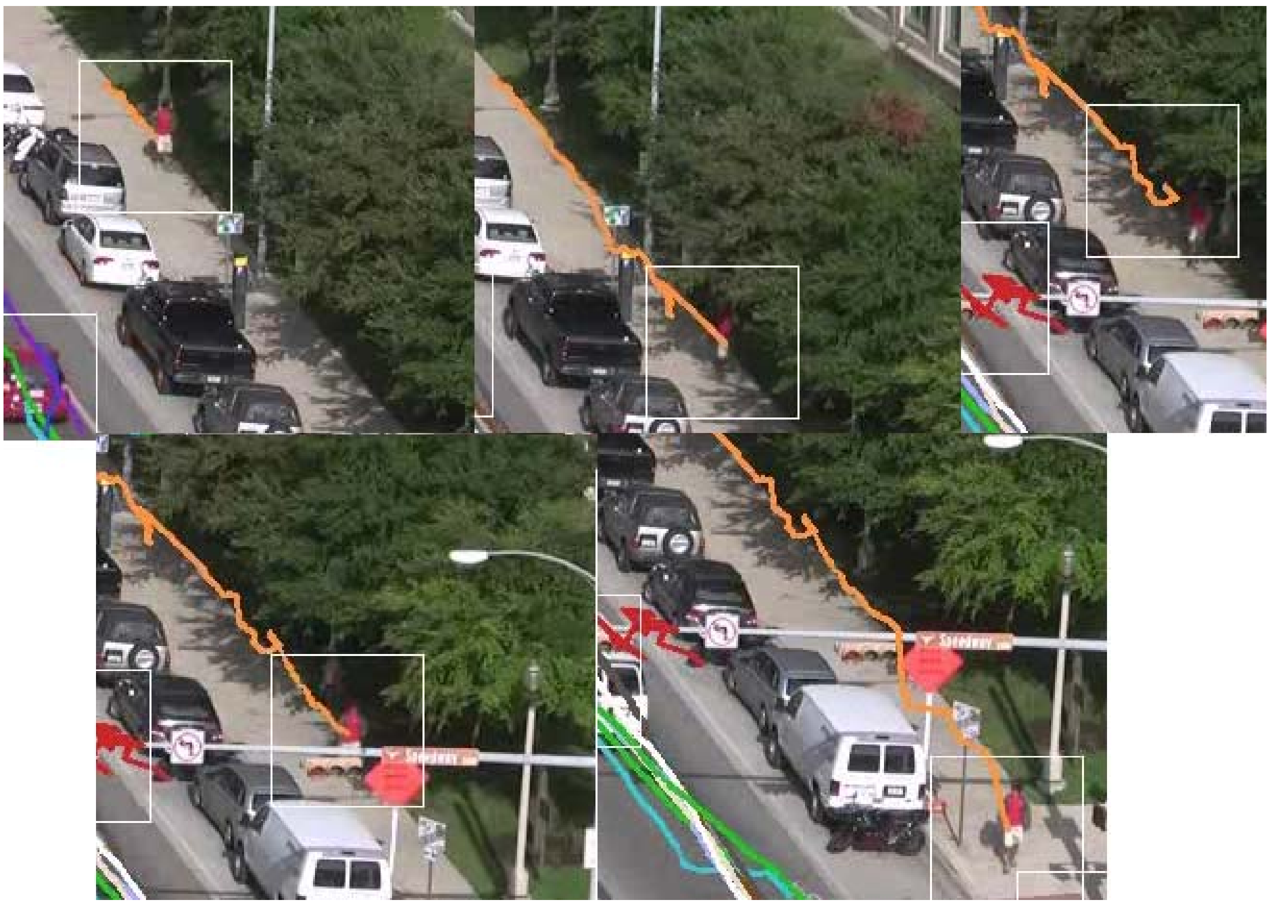

Fig 5. Tracking a human (on the side walk) through occlusion by matching appearance and velocity labels

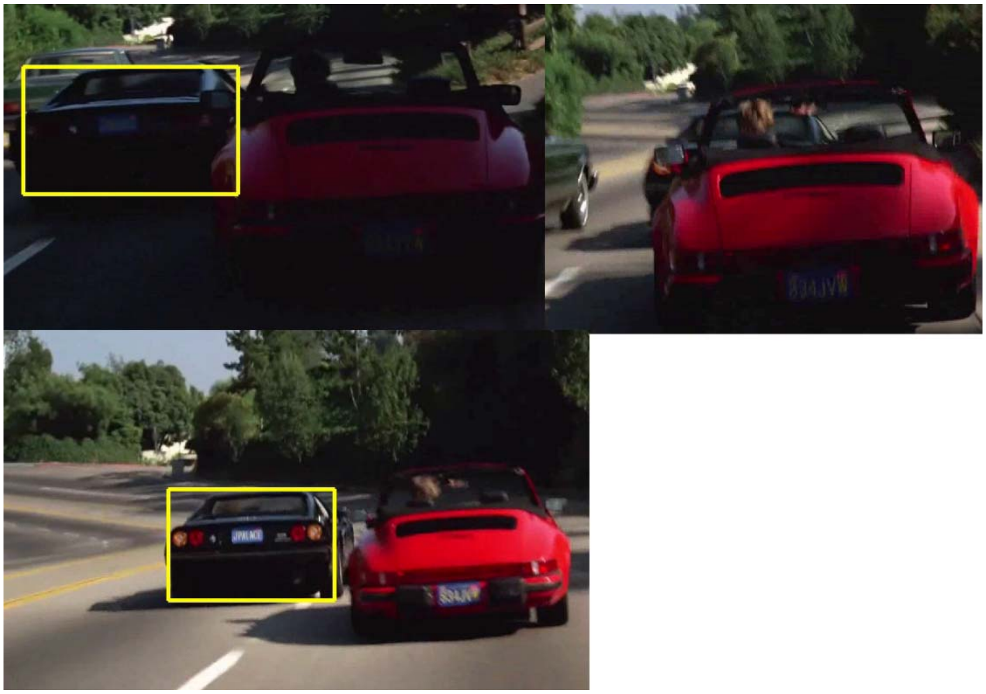

Fig 6. Velocities and appearance labels are roughly similar for the same car that proves greater likelihood of track merging after occlusion.

Intersection

Fig 7. Cars at an intersection. Waiting time for tracker $\delta t = t_{temp}$

Parking Lot

Fig 8. A car at a parking lot. Waiting time for tracker $\delta t = t_{perm}$

7. Conclusions

Our approach to high level action recognition using LTL based abductive reasoning provides a novel approach in identifying complex events like burglary or escapade in surveillance videos. The use of Linear Temporal Logic ensures in accounting for the temporal modalities between the successive frames, whereas, abductive reasoning through the integration of probabilistic and logical reasoning frameworks as proposed in (Poole, 1993) proves to be a useful tool in reasoning about the various complex real-life events that are otherwise impossible to detect in existing automated implementations.

Currently we are working on integrating the ideas proposed in this paper to develop an ensemble learning framework that can automatically detect the top-level plans associated with a wide-range of suspicious activities in surveillance videos.

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