Towards a Forensic Event Ontology to Assist Video Surveillance-based Vandalism Detection[1]

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Content

Context

- CCTV cameras are playing a key role in crime investigations
- Lack of a formal, comprehensive and accurate representation of the knowledge in the forensic domain
- The Desired state: Automated video surveillance system:
  - Analyse
  - Recognise
  - Extract
  - Classify events

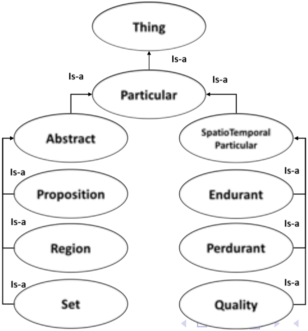
Contribution

1. Development of a new comprehensive knowledge representation framework
   - Modelling a novel systematic ontological framework for standardising the event vocabulary for forensic analysis
   - Extended from the DOLCE ontology
   - Relies on the linguistic and cognitive modelling of philosophical knowledge
   - Ultimate goal: to facilitate modelling, indexing, classification and retrieval of forensic data by analysts
2. Evaluation: knowledge model for classifying high-level events regarding the composition of some lower level events using
   - Manually built and automatically learned General Concept Inclusion (GCI) axioms

A Forensic Event Ontology

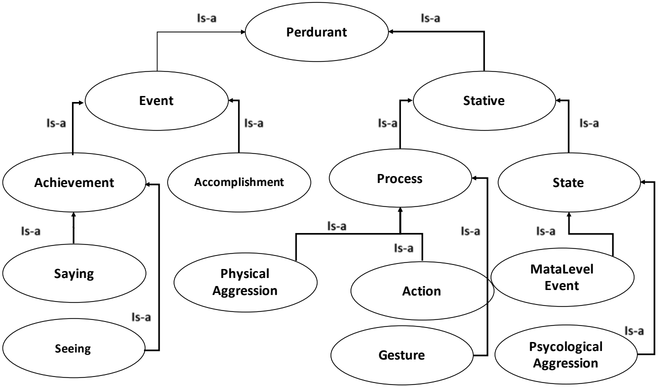
Classification of Event Types:

- State [- telic,- stages]
- Process [- telic, + stages]
- Accomplishments [+ telic, + stages]
- Achievements [+ telic, - stages]



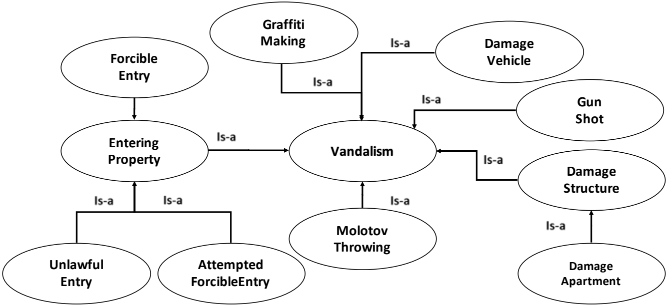
- State [-telic,-stage] This action category represents a long, non-dynamic event in which every instance is the same: there cannot be any distinction made between the stages. States are cumulative and homogenous in nature.
- Process [-telic, +stage] The action category, like State, is atelic, but unlike State, the action undertaken are dynamic. The actions appear progressively and thus can be split into a set of stages for analysis.
- Accomplishment [+telic, +stage] Accomplishments are telic and cumulative activities, and thus behave differently from both State and Process. The performed action can be analysed in stages and in this way, they are similar to Process. Intuitively, an accomplishment is an activity which moves toward a finishing point as it has variously been called in the literature. Accomplishment is also cumulative activity.
- Achievement [+telic, -stage] Achievements are similar to Accomplishment in their telicity. They are also not cumulative with respect to contiguous events. Achievements do not go on or progress, because they are near instantaneous, and are over as soon as they have begun.

Excerpt of Perdurant Subclass



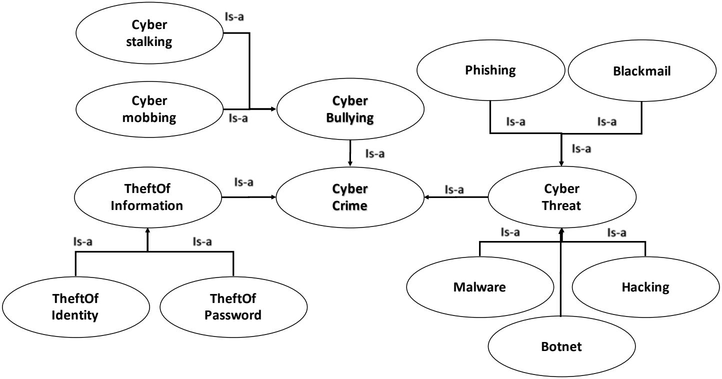
Excerpt of Vandalism Subclass

- Direct subclass of CrimeAgainstProperty. The latter is a subclass of class CrimeCategory, which is subclass of Accomplishment.

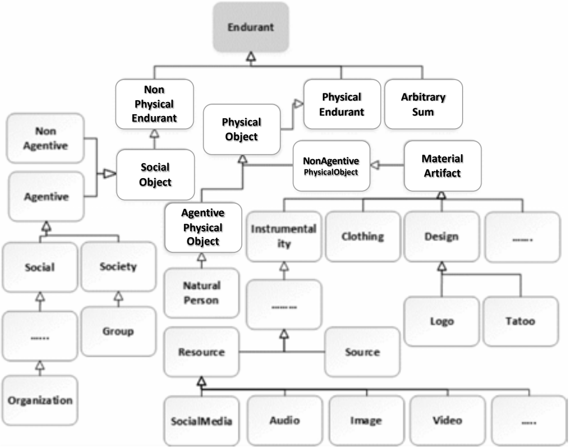


Excerpt of CyberCrime Subclass

- Direct subclass of CrimeCategory. The latter is a subclass of class Accomplishment.

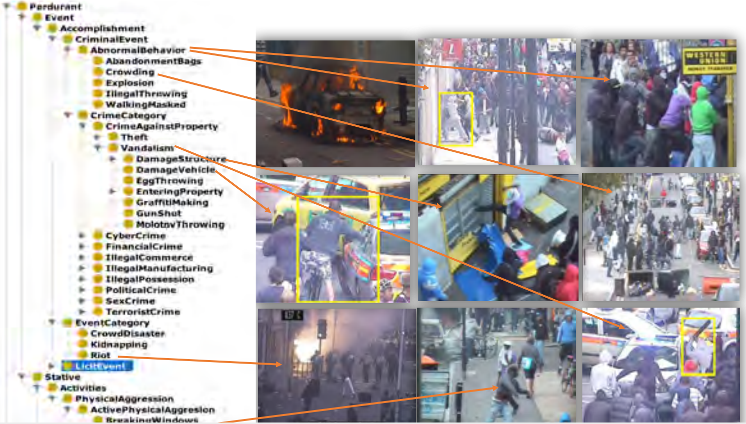


Excerpt of Endurant Subclass



Assisting Video Surveillance-based Vandalism Detection

Annotating Media Objects, viz. Surveillance Videos:



Manually built GCIs for Vandalism Event Detection

Example of DamageVehicle and DamageStructure scenes in CCTV.

DamageVehicle:

$$\text{Perdurant} \sqcap \exists \text{participant}.(\text{Vehicle} \sqcap \exists \text{participantIn}.(\text{BreakingDoor} \sqcup \text{BreakingWindows})) \sqsubseteq \text{DamageVehicle}\,.$$

"If an event involves a vehicle that is subject of a breaking door or breaking windows then the event is about a damaged vehicle"

Manually Built vs Learned GCIs for Vandalism Event Detection

DamageStructure:

$$\mathsf{Perdurant} \sqcap \exists \mathsf{participant}.(\mathsf{Structure} \sqcap \exists \mathsf{participantIn}.\mathsf{Kicking}) \sqsubseteq \mathsf{DamageStructure}\ .$$

"If an event involves a structure that is subject of kicking, then the event is about a damaged structure"

Vandalism:

$$\mathsf{Perdurant} \sqcap \exists \mathsf{part}.(\mathsf{Crowding} \sqcap \mathsf{DamageStructure}) \sqsubseteq \mathsf{Vandalism}$$
$$\mathsf{Perdurant} \sqcap \exists \mathsf{part}.(\mathsf{Crowding} \sqcap \mathsf{DamageVehicle}) \sqsubseteq \mathsf{Vandalism}$$
$$\mathsf{Perdurant} \sqcap \exists \mathsf{part}.(\mathsf{Explosion} \sqcap \mathsf{Throwing}) \sqsubseteq \mathsf{Vandalism}\ .$$

Experiments

We conducted two experiments with our ontology

- We evaluate the classification effectiveness of manually built GCIs to identify crime events
- We try to learn GCIs instead automatically from examples
- Setup:
  - 140 videos about the London riot 2011, from 35 CCTV cameras
  - contains features such as latitude, longitude, start time, end time and street name
  - videos have been annotated manually: 106 events

Table: Criminal event classes considered.

Vandalism (13, 57)	Riot (4, 21)	AbnormalBehavior (2, 80)
Crowding (1, 64)	DamageStructure (3, 9)	DamageVehicle (3, 16)
Throwing (1, 30)		

- The first number in parenthesis reports the number of GCIs we built for each of them
- The second number indicates the number of event instances (individuals) we created during the manual video annotation process

Table: Ontology Metrics.

Axioms	9889
Logical axiom count	7176
Class count	483
Object property count	148
Data property count	51
Individual count	1800
DL expressivity	SHIQ(D)

SubclassOf axioms count	532
EquivalentClasses axioms count	5
DisjointClasses axioms count	11
GCI count	38
Hidden GCI Count	5

SubObjectPropertyOf axioms count	93
InverseObjectProperties axioms count	20
TransitiveObjectProperty axioms count	5
SymmetricObjectProperty axioms count	2
ObjectPropertyDomain axioms count	19
ObjectPropertyRange axioms count	18

SubDataProperty axioms count	11
DataPropertyDomain axioms count	1
DataPropertyRange axioms count	5

ClassAssertion axioms count	1793
ObjectPropertyAssertion axioms count	2964
DataPropertyAssertion axioms count	1706

AnnotationAssertion axioms count	195

Evaluation

- Leave-one-out cross validation method

Manual GCIs results:

Event	TP	FP	FN	TN	$\|C\|$	$\|trueC\|$	$Precision_C$	$Recall_C$	$F1_C$
Vandalism	42	0	15	168	42	57	1.00	0.74	0.85
DamageVehicle	11	0	5	209	11	16	1.00	0.69	0.81
DamageStructure	9	0	0	216	9	9	0.89	0.89	0.89
Crowding	60	1	4	160	61	64	0.98	0.94	0.96
Throwing	30	0	0	195	30	30	1.00	1.00	1.00
Riot	5	0	16	204	5	21	1.00	0.24	0.38
AbnormalBehaviour	70	22	10	123	92	80	0.76	0.88	0.81
	$Precision_{micro}$	$Recall_{micro}$	$F1_{micro}$	$Precision_{macro}$	$Recall_{macro}$	$F1_{macro}$			
	0.91	0.82	0.86	0.96	0.78	0.86			

Learning GCIs:

- Used DL-Learner CELOE algorithm
- The best-selected GCIs found by CELOE for each of the target classes are:

$$
\begin{array}{l}
\mathrm{PhysicalAggression} \sqcap \exists \mathrm{immediateRelation}.\mathrm{Structure} \sqsubseteq \mathrm{DamageStructure} \\
\exists \mathrm{immediateRelation}.\mathrm{Vehicle} \sqsubseteq \mathrm{DamageVehicle} \\
\exists \mathrm{immediateRelation}.\mathrm{Vandalism} \sqsubseteq \mathrm{AbnormalBehavior} \\
\exists \mathrm{immediateRelation}.\mathrm{Arm} \sqsubseteq \mathrm{Throwing} \\
\exists \mathrm{immediateRelation}.\mathrm{Group} \sqsubseteq \mathrm{Crowding}\ .
\end{array}
$$

- No learned rules for Riot and Vandalism

Automatically learned GCIs results:

Event	$Precision_C$	$Recall_C$	$F1_C$
DamageVehicle	0.69	0.98	0.81
Damage Structure	1.00	1.00	1.00
Crowding	0.96	1.00	0.98
Throwing	0.86	0.99	0.92
AbnormalBehavior	0.69	0.99	0.81

$Precision_{micro}$	$Recall_{micro}$	$F1_{micro}$	$Precision_{macro}$	$Recall_{macro}$	$F1_{macro}$
0.753	0.964	0.845	0.599	0.709	0.649

Merging Manual and Learned GCIs:

Event	$Precision_C$	$Recall_C$	$F1_C$
Vandalism	1.00	0.74	0.85
DamageVehicle	1.00	0.69	0.81
Damage Structure	0.89	0.89	0.89
Crowding	0.98	0.94	0.96
Throwing	1.00	1.00	1.00
Riot	1.00	0.24	0.38
AbnormalBehavior	0.76	0.89	0.82

$Precision_{micro}$	$Recall_{micro}$	$F1_{micro}$	$Precision_{macro}$	$Recall_{macro}$	$F1_{macro}$
0.90	0.82	0.86	0.95	0.77	0.85

Essentially, no improvements

Conclusions

- We built an ontology for representing complex criminal events
  - Goal: to assist Video Surveillance-based Vandalism Detection
- An experiment has been conducted comparing manually built GCI vs learned GCIs
  - The results are generally promising
  - Effectiveness of machine derived definitions for high-level crime events is encouraging though needs further development
- Future Work:
  - Built fuzzy ontology version: involved entities are fuzzy by nature.
    - **Horizontal-Distance-Region** (Very Close, Close, Middle, Far, Very Far)
    - **Move** (Very Fast Movement, Fast Movement, Medium Movement, Slow Movement, Very Slow Movement)
  - Automatically learn fuzzy concept description (using fuzzy DL-Learner)
  - Development of Feature Selection (FS) methods that enables reasoning in a practical sized ontologies