Detection of Real-world Fights in Surveillance Videos

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1. Motivation

- Surveillance cameras (**CCTVs**) are commonly used in many places to enforce security, however their **efficiency is highly questionable**
- "Everyday, over **99% of surveillance videos** being recorded **are never watched** by anyone due to the limitations of traditional surveillance systems." (Vi Dimensions)
- Severe issue for some events, for example **missing fights** can lead to **impunity or serious injuries to those involved**

2. Related Work

- Previous research has **unrealistic or deficient characteristics**:
  - **Too broad definition of violence**, such as explosions, gunshots, etc.
  - Used **fights with artificial movements**, acted by movie actors or researchers
  - **Convenient video properties**: good viewpoint, high resolution, centralized, no occlusion, at close-range and etc
  - **Short clips** from trimmed videos

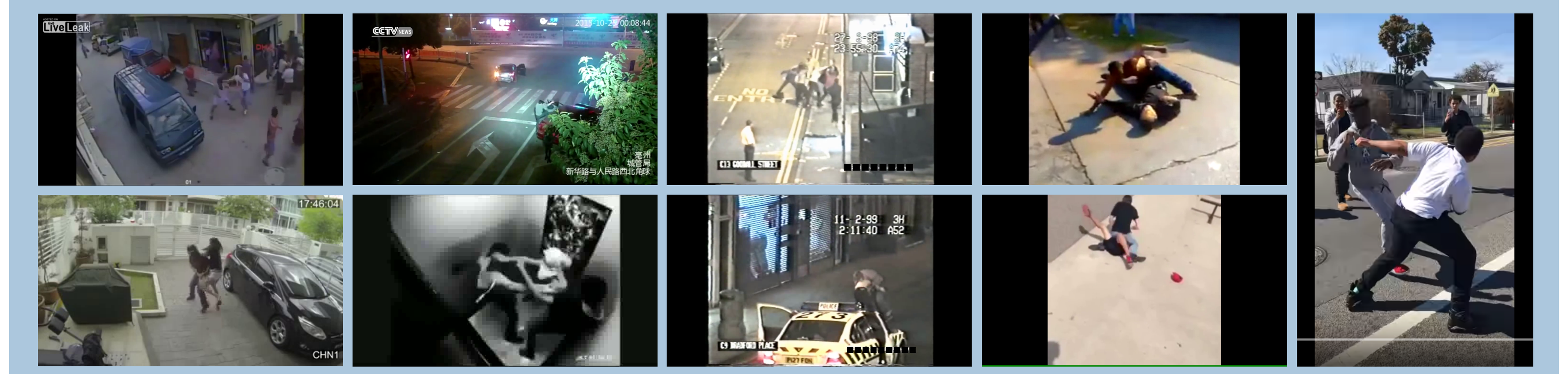
Related Datasets Details

	Name	Size	Characteristics
Trimmed	Hockey Fights	1,000 clips	Hockey players
	Movies	200 clips	Trimmed action movies
	Violent-Flows	246 clips	Crowd violence
Untrimmed	VSD	25 movies	Complete Hollywood movies
	RE-DiD	30 videos	Urban fights + Cars/Mobiles
	BEHAVE	4 videos	Acted fights + CCTVs
	CCTV-Fights	1,000 videos	Urban fights + CCTVs/Mobiles

3. Contributions

- **Creation of CCTV-Fights** dataset:
  - Challenging real-world fights
  - More than 8 hours of CCTV footage
  - Temporally annotated with begin and end of all fight instances
- **Foundational benchmark evaluation** of traditional methods
  - Feature extraction methods ranging from Deep Learning to Local Interest Points
  - Combined with different classifiers, including end-to-end CNN, LSTM and SVM

4. Novel Dataset: CCTV-Fights



- Diverse range of actions
- Multiple fights instances in the same video
- Fight segments temporal annotations
- Short and long videos (5 secs to 12 mins - 2 mins average)
- Videos from Non-CCTV sources as support data
  - Mainly mobile cameras, some very few car-cameras and drone/helicopter.

CCTV-Fights Statistics

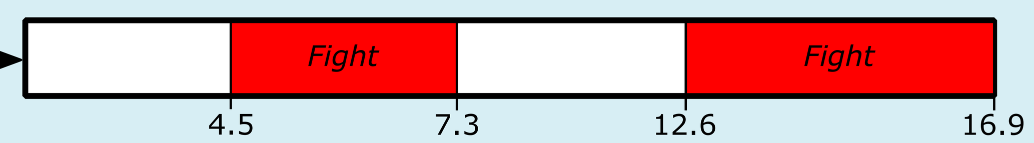
	Videos	Duration (hours)	Fight Instances
All	1,000	17.68	2,414 (2.41)
CCTV	280	8.54	747 (2.67)
Non-CCTV	720	9.13	1,667 (2.32)

5. Benchmark Methodology

Extract Features
- **Two-Stream** CNN: VGG16 [*Simonyan and Zisserman 2014*]
  - Spatial (Frames) + Temporal (Optical Flows)
- 3D-CNN: **C3D** [*Tran et al. 2015*]
- Local interest-points: **TRoF** [*Moreira et al. 2017*]

Classify Frames
- CNN Classification Layer
- LSTM
- SVM

Generate Segments
- Smooth scores with mean filter
- Merge continuous frames that satisfy a certain threshold



6. Experimental Results

Benchmark Results on CCTV-Fights

- mAP (Mean Average Precision):
  - Measurement of correct segments
- F-measure:
  - Precision and recall of fight frames

Features	Classifier	mAP	F-Measure
Two-Stream	CNN	**79.5%**	75.0%
	SVM	76.6%	72.8%
	LSTM	76.0%	**75.9%**
C3D	SVM	64.5%	58.6%
	LSTM	61.0%	58.1%
TRoF	SVM	69.2%	63.3%
	LSTM	63.8%	63.5%

Performance per Stream

Stream	mAP	F-Measure
Spatial	68.6%	61.0%
Temporal	**80.8%**	**75.3%**
Two-Stream	79.5%	75.0%

- Superior performance from Temporal Stream
- No advantage from fusing streams

Results by Videos Source

- Training strategies for **Temporal Stream**:
  - **All:** Both sources at the same time
  - **1-tiered:** Only with CCTV
  - **2-tiered:** First train with both, then fine-tune only with CCTV

Model	Source	mAP	F-Measure
All	All	80.8%	75.3%
	Non-CCTV	85.9%	79.6%
	CCTV	73.7%	66.7%
1-tiered	CCTV	72.1%	63.5%
2-tiered	**CCTV**	**75.6%**	**67.7%**

7. Conclusions

- Information from **explicit motion has a major positive impact** on performance
- Current **spatial features underperformed** greatly and could not positively complement the motion features
- **Sequential information could not be leveraged** by LSTM
- Information from **Non-CCTV sources benefit training** models that better generalizes for the CCTV videos, particularly through a 2-tiered training strategy

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