Introduction

A video-processing framework combines stream processing, batch processing, and deep learning to realize deep intelligence that can help reveal knowledge hidden in video data. Evaluations of performance, scalability, and fault tolerance showed the framework's effectiveness.





Introduction(1/3)

 Application such as smart transportation and security surveillance collect vast amounts of video data daily. Surveillance videos are the biggest source of big data.



Introduction(2/3)

• Video analysis research has extensively explored such topics as feature extraction and video summary.

 Recently, video- and image-processing research has been deeply influenced by the success of deep learning initiated by Geoffrey Hinton and Ruslan Salakhutdinov.



Introduction(3/3)

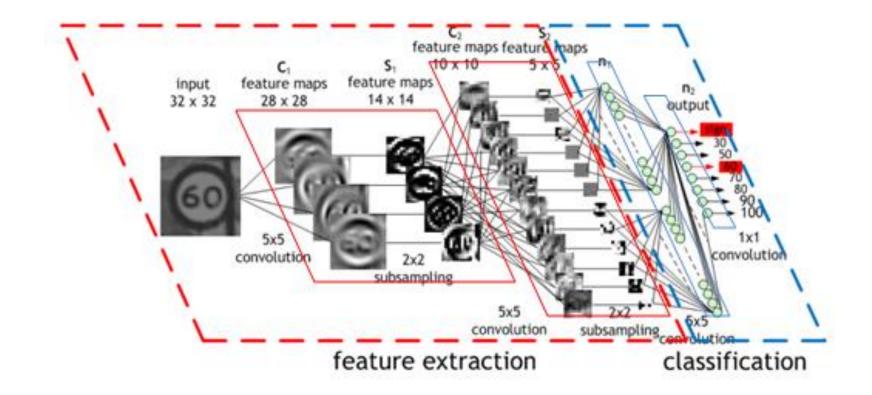
 Owing to the volume, velocity, and complexities of video data, some video-processing research has employed the latest computing technologies, such as cloud computing, using offline processing or stream processing.

What is CNN?





What is CNN?



Five key quality attributes

Performance Availability Scalability Modifiability Portability and usability





Performance

• There are two types of performance requirements.

• The first is batch processing of large volumes of historical video data .

• The second type is for real-time processing situations which is performance critical.



Availability

• The framework must be reliable to allow hardware failures. It must provide dependable services to users.





• The cloud must be able to scale up, with the ability to add videosensing devices and processing nodes dynamically.



Modifiability

• Because big data processing techniques are evolving quickly, the framework must allow easy changes of its functionalities so that future modifications are easy.



Portability and usability

 The framework must also provide a unified way to manage video equipment and video data. It must also support different Linux-style OSs.

 (Other important quality attributes exist—for example, safety and testability— but aren't part of this article's focus.)

software architecture styles

Service-oriented architecture(SOA) Publish-subscribe MapReduce Shared Data Layered architecture





Service-oriented architecture

 Owing to the complexities of video data processing and the various technologies involved, the framework must employ an SOA. This will enable modifiability, and functionality upgrades won't affect users.An SOA can also help achieve portability.



Publish-subscribe

 To decouple event consumers and providers, a publish-subscribe mechanism should handle events while monitoring the framework's running status. This will help achieve the framework's availability such that users can detect malfunction states and initiate appropriate responses.



MapReduce

 The framework must analyze enormous volumes of video data. MapReduce is a large-scale distributed-computing paradigm based on the divide-and-conquer strategy. It can efficiently process distributed large datasets in parallel. So, it can help meet performance, scalability, and availability requirements.



Shared Data

 Different processing components—for example, background subtraction and video summary—will use video data. So, the framework uses the Shared Data pattern to achieve sharing of video data, which can help improve performance.



Layered architecture

 Framework functionalities might evolve separately, and the processing of big video data can also be separated into different types and might evolve independently. So, the framework uses a layered architecture to separate the different concerns. This can support modifiability, portability, and usability.

Mapping architecture styles to quality attributes

Architecture style	Supported quality attributes
Service-oriented architecture	Portability, modifiability
Publish-subscribe	Availability, modifiability
MapReduce	Performance, scalability, availability
Shared Data	Performance, availability
Layered architecture	Modifiability, portability, usability

Architecture

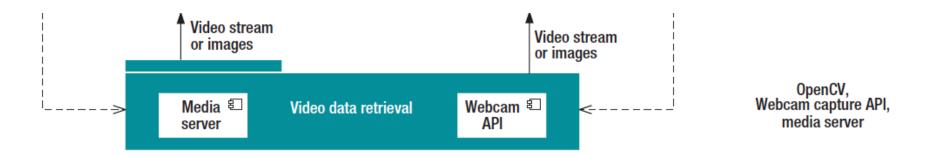
Bottom layer Data-processing layer Top Layer





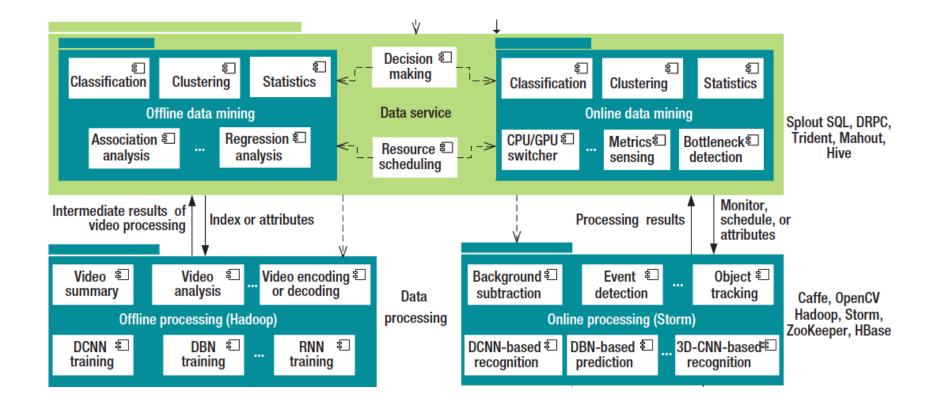
Bottom layer

• The bottom layer is the data retrieval layer. It's a generalization of video data collection, in which a media server and webcam API receive different types of video data from various cameras.





Data-processing layer(1/5)





Data-processing layer(2/5)

• The data-processing layer comprises the offline-processing package, based on Apache Hadoop.

 The online-processing package, based on Apache Storm stream processing(http://storm.apache.org).



Data-processing layer(3/5)

 Some video-processing tasks—for example, video summary and encoding and decoding of large amounts of video data—occur during offline processing.

 The online-processing package handles some lightweight videoprocessing tasks—for example, background subtraction. On the basis of the offline neural-network training results, this package achieves real-time recognition, including the recognition of events, objects, and behaviors.



Data-processing layer(4/5)-The key classes for online processing

• ForegroundObjectBolt-removes the background.

• PrioriKnowledgeFilterBolt-locates the moving targets and filters out the object of classification according to the prior knowledge.

• ClassificationBolt-classifies the moving targets.

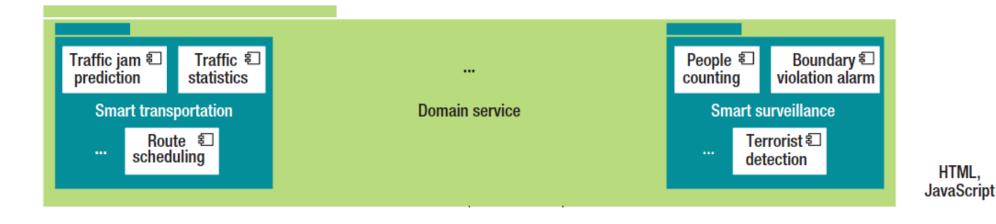
Data-processing layer(5/5)-Class diagram

BaseRichSpout	BaseRichBolt	ClassificationCaffe		
prepare(Map conf, TopologyContext context, OutputCollector collector) : void execute(Tuple tuple) : void declareOutputFields(OutputFieldsDeclarer declarer) : void	open(conf : Map, context : TopologyContext, collector : SpoutOutputCollector) : void nextTuple() : void declareOutputFields(OutputFieldsDeclarer declarer) : void	recognize(model_file : String,trained_file : String,mean_file : String,label_file : String,mat_addr : long) : String n_Recognize(model_file : String,trained_file : String,mean_file : String,label_file : String,mat_addr : long) : String		
Ţ.	ForegroundObjectBolt			
VideoCaptureSpout	mog2 : BackgroundSubtractorMOG2 fg : Mat	PrioriKnowledgeFilterBolt	ClassificationBolt	
camera : VideoCapture mat : Mat collector : SpoutOutputCollector	collector : OutputCollector execute(input : Tuple) : void	<pre></pre>	classification : Classification collector : OutputCollector execute(input : Tuple) : void	
open(conf : Map,context : TopologyContext,collector : SpoutOutputCollector) : void nextTuple() : void declareOutputFields(OutputFieldsDeclarer declarer) : void	DomainTopology builder : TopologyBuilder conf : Config			



Top Layer

• The top layer is the domain service layer, which developers can use to create different domain applications such as smart transportation and smart campuses.



The configuration of the experiment's cloud infrastructure.

experiment's cloud infrastructure DCNN training performance Camera's Scalability Fault Tolerance





The configuration of the experiment's cloud infrastructure.

Nine IBM 3650 servers(64 Gbytes of RAM, 24 cores, and 12 Tbytes of storage) deployed as a cloud. Each node ran the Ubuntu 14.04 server and a modified version of the Caffe deep-learning tool.

	Node								
	1	2	3	4	5	6	7	8	9
Roles	Name- Node Nimbus DRPC server Resource- Manager	DataNode Supervisor DRPC server Node- Manager	DataNode Supervisor DRPC server Node- Manager	DataNode Supervisor DRPC server Node- Manager	DataNode Supervisor DRPC server Splout SQL Node- Manager	DataNode Supervisor DRPC server Node- Manager	DataNode Supervisor ZooKeeper DRPC server Node- Manager	DataNode Supervisor ZooKeeper DRPC server Node- Manager	DataNode Supervisor ZooKeeper DRPC server Node- Manager Webserver



DCNN training performance

 As the image size grew and the network became more complex, the recognition rate increased. However, the training and recognition time also grew.
Considering the accuracy and real-time-performance trade-off, Network 1 was a practical choice.

Network	lmage size (pixels)	No. of layers	Training time	Recognition time (ms)	Accuracy (%)
1	32 × 32	14	1 h, 1 min, 30 s	6.82	92.36
2	224×224	20	4 h, 57 min, 43 s	959.76	95.85



Example: How many cars had passed the cameras since 9 o' clock?

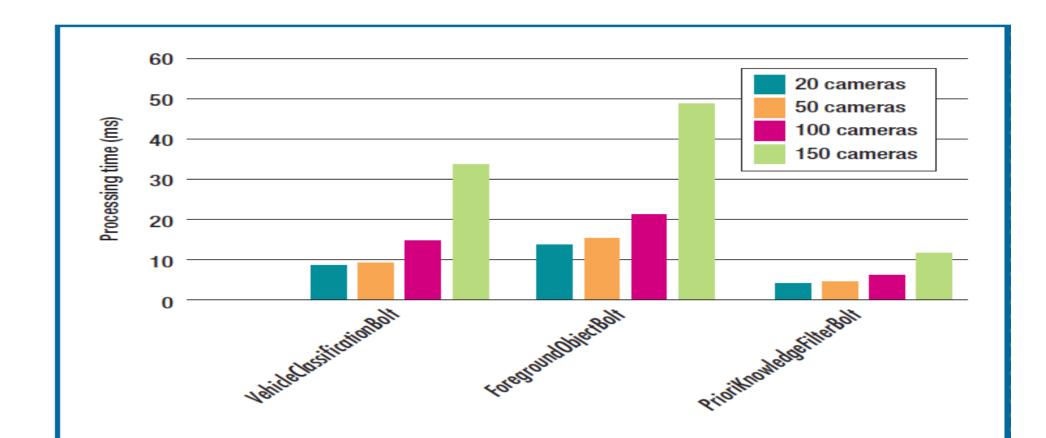
Overall, it took approximately 43 ms (11.13 + 3.93 + 7.79 + 10.00 + 10.00) from video frame acquisition to target recognition.

	Online-processing class*			
Run	ForegroundObjectBolt	PrioriKnowledgeFilterBolt	VehicleClassificationBolt	
1	10.724	4.069	7.862	
2	11.541	3.754	8.000	
3	11.118	3.980	7.510	
Average	11.130	3.930	7.790	



Camera's Scalability

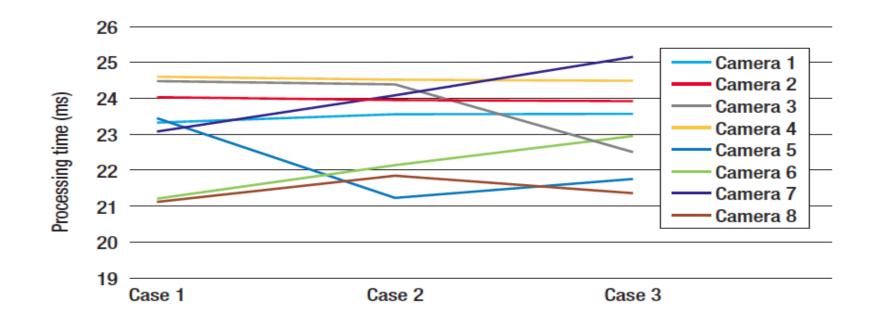
• The test bed's performance scaled as we added cameras.





Fault Tolerance

- Case1 used seven supervisors.
- Case 2 used six supervisors.
- Case 3 used only four supervisors.



Conclusion

Conclusion Challenge





Conclusion

- These evaluations also showed that our framework was effective and efficient for continuous real-time video processing.
- The SOA is enacted with clearly designed interface contracts and loosely couples components in different layers.
- Publish-subscribe decouples Storm generated events and event consumers that monitor the cluster status to optimize scheduling.
- MapReduce achieves parallel processing of video data, and we've employed it for implementations of some algorithms.
- The Shared Data pattern shares video data among processing components spanning multiple layers, implemented with the SOA.
- Finally, the layered architecture helps separate different data-processing concerns.



Challenge

• Integrating the SOA in a layered architecture posed two challenges:

 how to enable different features to interact harmoniously in different layers through well-defined interface contracts.

 how to use shared data to provide effective data partitioning for MapReduce.

