



Overview of our researches on Machine-Learning and DataMining for Self-driving cars and Intelligent Transport Systems

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Machine-Learning and Datamining for Intelligent Vehicles (& ITS)

Automated driving (or smart functions) require <u>semantic</u> interpretation of car environment:

– Locally around vehicle:

- automated detection and understanding of road signaling
- categorization of objects around (cars, pedestrians, etc...)
- forecasting of moving « objects » trajectories/behaviors
- On broader space-time horizon:
 - precise ego-localization (cf. GPS uncertainty/outage)
 - predict traffic evolution on large area for optimal route choice/adaptation
- Inside the car:
 - driver identification (for automatic switch of settings)
 - Recognize activity/gestures of driver, for monitoring his attention and/or for gestual commands

Machine-Learning and Datamining for Intelligent Vehicles & ITS @CAOR

Past and current research @CAOR/Mines_ParisTech

- Locally around vehicle:
 - Detect & recognize Traffic Signs, traffic lights, etc...
 - Localize objects of important categories (cars, pedestrians, motorbikes, bicycles, etc...)
- On broader space-time horizon:
 - Visual precise ego-localization
 - Predict traffic evolution on large area for optimal route choice/adaptation
- Inside the car:
 - Recognize gestures of driver for gestual commands



- Visual detection & recognition of traffic signs and object categories (cars, pedestrians, etc...)
- In-car Human Gestures & Activities recognition
- Road traffic mining and forecasting
- Onroad precise visual car ego-localization



. . .

- Very little intrinsic variation of object

 → main recognition challenge = <u>robustness to</u> <u>illumination & contrast changes + small 3D rotations</u>
- Large number of classes (~100)
- Input feature for classification ?
 - Vector of pixel values
 - HoG (Histogram of Orientations of Gradients)
- ML algo used @CAOR:

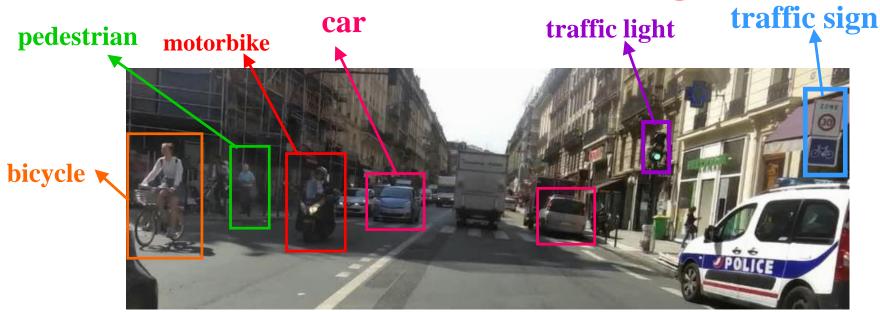
Histogram of Oriented Gradient (HoG) features + Support Vector Machine (SVM) for detection + Random Decision Forest (RDF) for recognition



TSR démo



Real-time scene understanding for ADAS and self-driving cars



- Key componant for Advanced Driving Assistance Systems (ADAS) and self-driving cars
- Very large intra-class variability: person or car model, shape, colors → challenge = find sth common to all instances AND discriminant v.s. other categories
- Strong real-time constraint: process at least ~10 frames/second



Machine-learning for visual recognition of object categories



Classifier training, e.g. using « boosting », applied to image examples extracted from videos

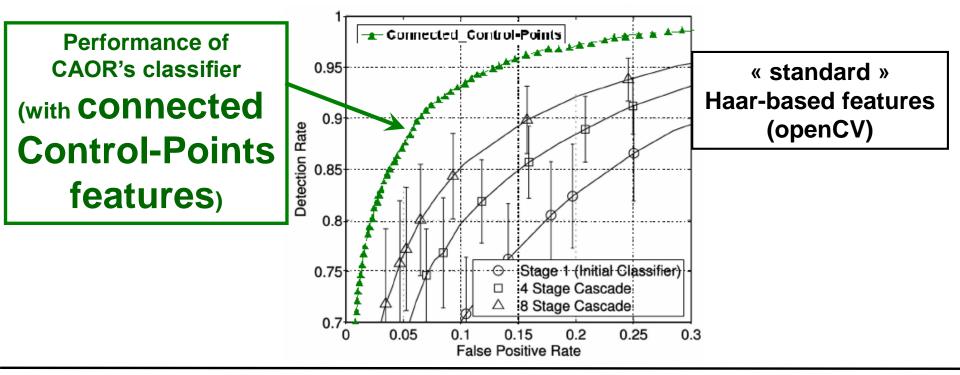
(boosting principle: assembling and weighting many elementary « weak » classifiers into one « strong « classifier)

$$H(x) = \operatorname{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$$





Public pedestrian examples database collected by Daimler, with 4800 positive image examples and 5000 negative (all of size 18x36 pixels)



Object category detection démo



<u>Pedestrians (daytime)</u>: ~80% detection with less than 2 false alarms per frame

<u>Cars (backviewed)</u>: ~ 95% detection with less than 1 false alarm per frame





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Micro-

gestures

(fingers)

areas

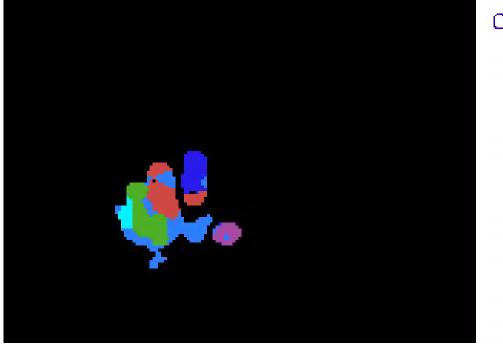
Gestures recognition *inside* car

Goal = <u>touchless HMI (for infotainment, etc...)</u> that avoids perturbing attention/driving (e.g. fingers gestures while holding the driving wheel)

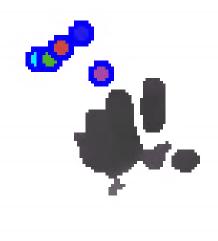


Macrogestures area (swipes, etc...)





Current fps : 29.411764



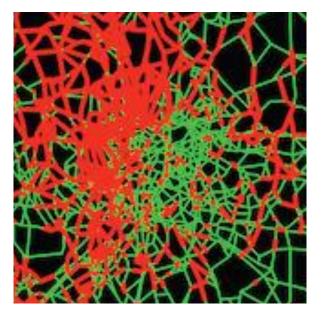
<u>3D « time-of-flight » camera (PMD camBoard Nano)</u> + segmentation/labelling of fingers by <u>RandomForest</u> + gestures recognition by <u>HMM or/and DTW</u>



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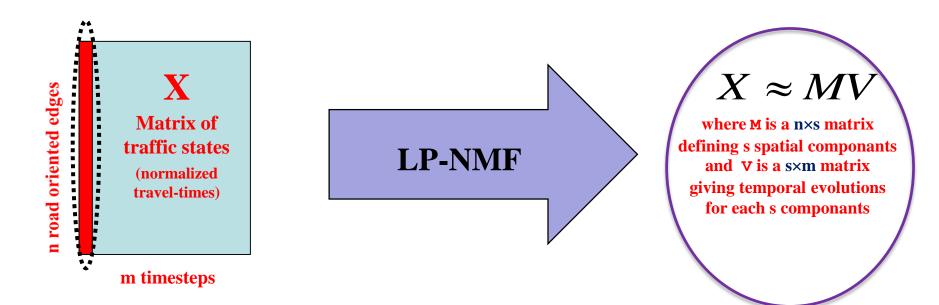
 Goal: forecast large-scale (~70km) long-term (~1h-2h) evolution of traffic, for re-planning of fastest itinerary



- Input data:
 - current traffic state + evolution since beginning of day
 - history of travel-times on hundreds of days



 with Locality-Preserving Non-negative Matrix Factorization (LP-NMF)

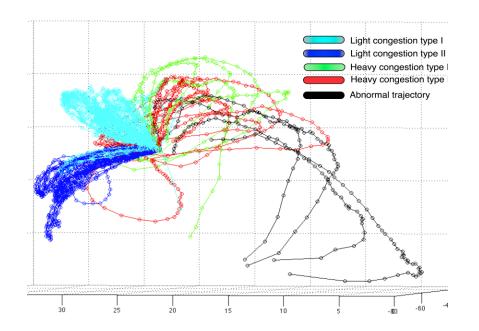


→ Each traffic state of full area (vector in $]0;1]^n$ with n~5000) mapped onto a compact representation in \Re^s (with s~15)



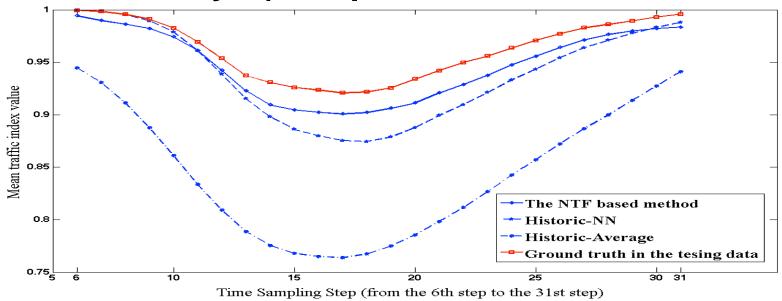
Partitioning of days into several typical temporal evolutions

- Each day in historic mapped onto a <u>trajectory</u> of d successive points in *R*^s
- Apply clustering (e.g. K-means) on the set of trajectories → partition days of history into several big types of daily evolutions





- Given beginning of day (b vectors in]0;1]ⁿ), estimate start-of-trajectory as b vectors (p_i) in R^s
- Find in history the K most similar start-of-days in ^S (efficient search as s<<n)
- 3. Future assumed to be linear combination of those K rest-of-days (with ponderations = similarities)

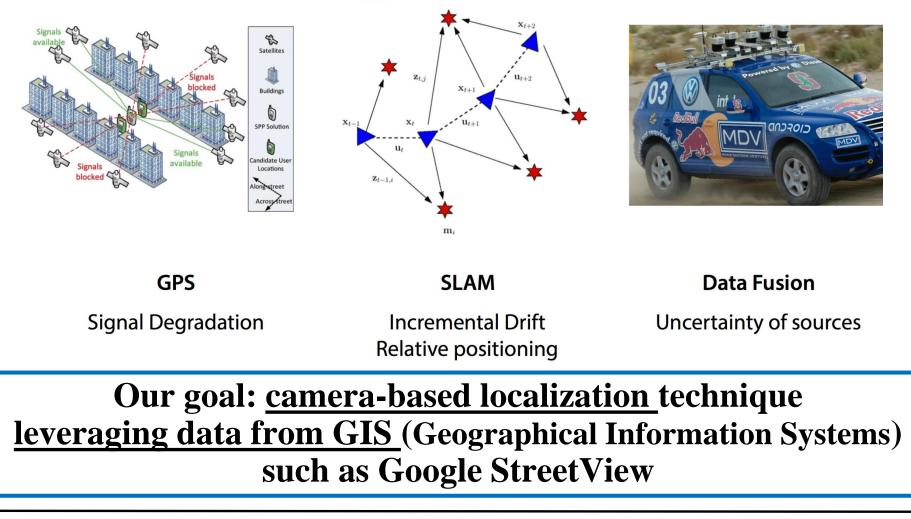




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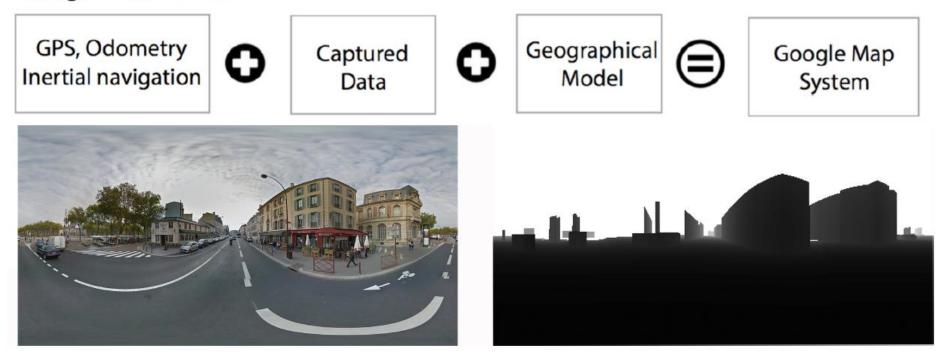


Work in collaboration with VeDeCom (phD thesis of Li YU)





Google Street View



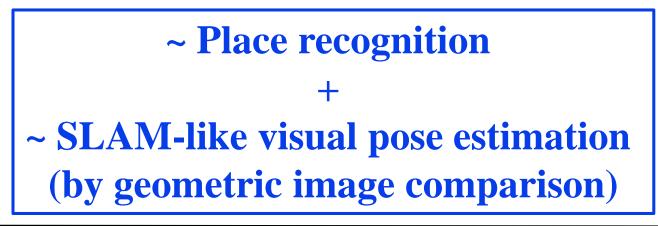
An example of Street View panorama (13312*6656) and its depth map(<200m) at the localization [48.801631, 2.131509] with a yaw degree(158.39°) w.r.t the north direction.



<u>Real-time mining</u> of nearest reference images from GIS by approximate matching of current image from car

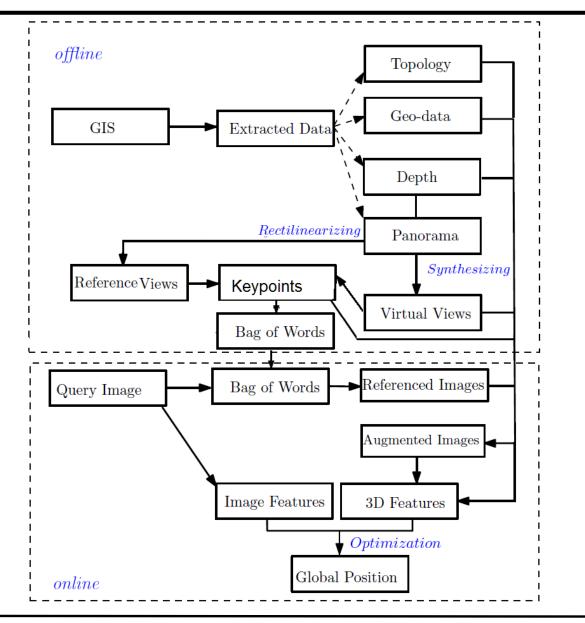
+

Estimation of precise pose (position+heading) by comparison current_image/reference_images





Pipeline of our algorithm

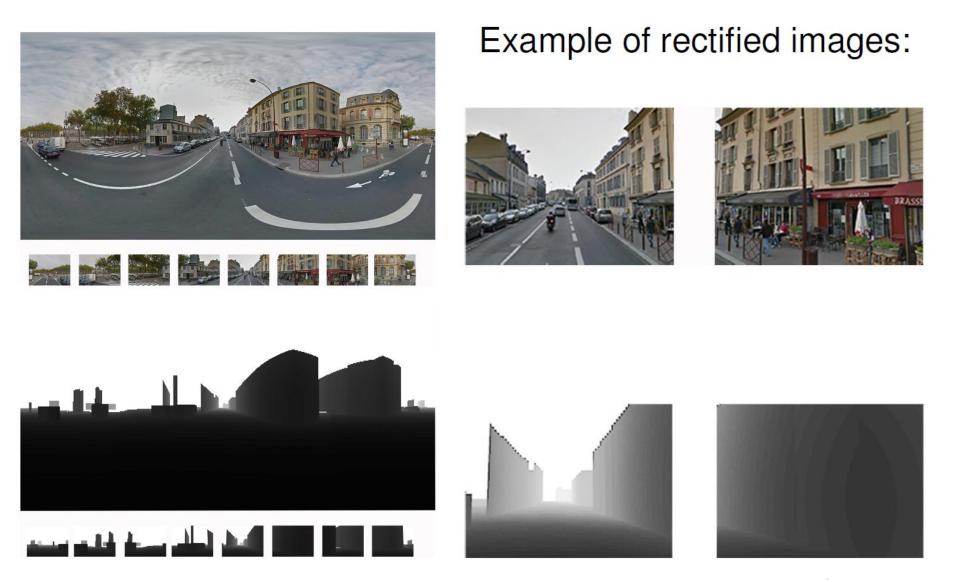




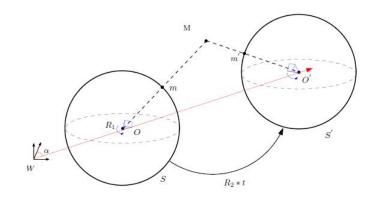
- Generate rectified images from panoramas
- Generate synthetized intermediate images <u>between</u> panoramas
- Compute keypoints on obtained reference images
- Build bag-of-words descriptors for them



Rectifying StreetView images



Synthetizing intermediate views





Translation distance	2m	4m	6m	8m
Invalid camera position	0	3	11	27
Uniform distribution	N	Y	Y	N
Ratio of virtual views with null pixels	0	0.125	0.5	1

4-meter forward/backward virtual panoramas are constructed from the original ones

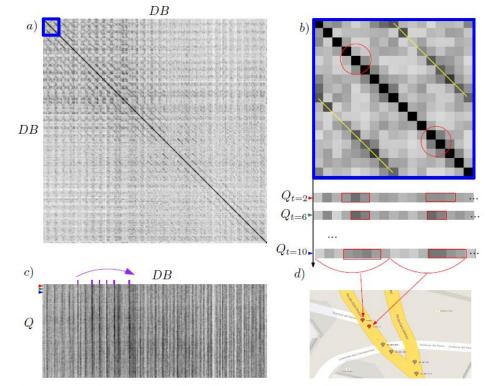


Database construction

	Construct 2 ind	ependent	bags of words
No.	1	2	
Detectors	SIFT	MSER	
Descriptors	484202	91026	
Para	ameterization		
Size of bags	5000	2000	
IF-I	TF weighing		
Combin	ation of two bag	JS	SIFT - local point
Search b	y cosine similari	ty	MSER - local region
	Detectors Descriptors Para Size of bags IF-I Combin	No.1DetectorsSIFTDescriptors484202ParameterizationSize of bags5000IF-ITF weighingCombination of two bag	DetectorsSIFTMSERDescriptors48420291026ParameterizationSize of bags50002000



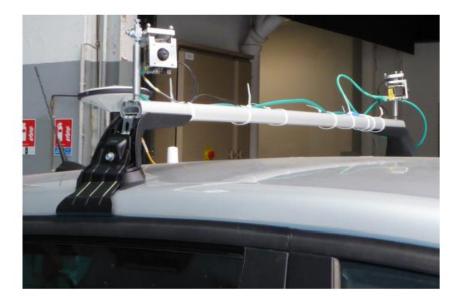
Search efficiency optimization



Topologic relationship co-similarity matrix helps to reduce 89.7% impotent searching.



Acquisition system used





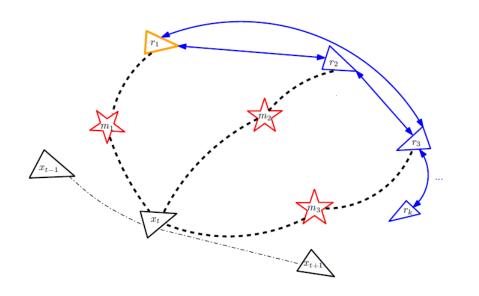
Left: Capturing system by MIPSee Camera(57.6°FoV, 20fps); A Real Time Kinematic GPS as ground Truth; Right: A sample of current image (640*480).



Real-time localization method

Coarse to fine Localization:

- Topologic localization: Bag of words => Referenced images
- Metric localization: RANSAC PnP => pose



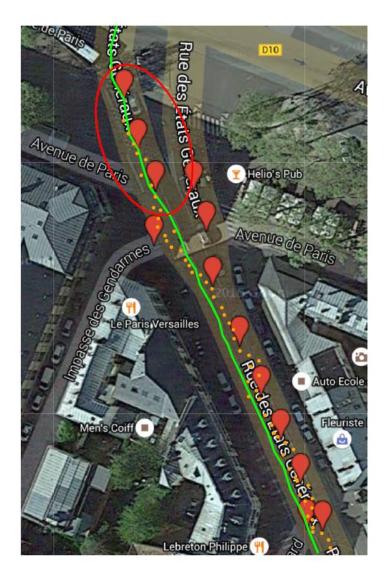
Red: observations Blue: camera position of Google Black: camera position of vehicle

$$\Theta^{\star} = \arg\min_{\Theta} \sum_{i} \pi \left(\|\mathbf{m}_{i} - \mathbf{P}(\mathbf{M}_{i}, \Theta)\| \right)$$

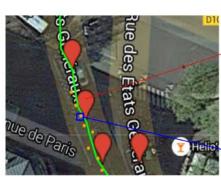


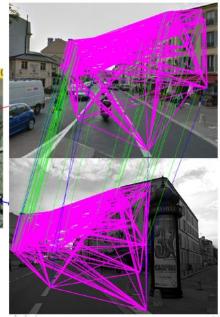
Results with only original panoramas

localization



-13 panoramas in a 287m street
-Ground truth in green
-Average error <6.5m, 58.6% <2m
-Standard GPS <8m
-58/423 images improved with metric







Results with « augmented » StreetView



		Original Street View	Augmented Street View
Continuity		137/1046	281/1046
Average Erro	or .	3.82m	3.19m
Ratio in [0m	1m	21.89%	41.28%
Ratio in [1m	,2m	28.47%	27.40%
Ratio in [2m	,3m	44.53%	19.22%
Ratio in 3m	,4m	5.11%	12.10%

- 1046 query images
- 498m trajectory
- 28 existing panoramas
- 53 virtual panoramas synthesized

with augmented Street View:

More query images are localized 68.68% positions lie within the error [0m, 2m[



- Feasibility of meter-level real-time urban localization with just monocular camera
- Interest of leveraging images in GIS such as Google StreetView

Ongoing and future work:

- compare our method with deep-learning (PoseNet)
- automatic update of GIS database when structural change detected ?



General conclusions and ongoing/future research

CAOR has addressed many domains of Machine-Learning / Datamining applications for intelligent vehicles & ITS:

- computer-vision / pattern recognition for visual scene semantic understanding, visual ego-localization of car, driver gestures recognition
- traffic-mining and forecasting

Ongoing and future work:

- unified recognition for driver fingers_micro-gestures & hand_macrogestures
- deep-learning for localization (~PoseNet),
 + possibly other Self-driving cars functions
- Categorization of 3D points clouds from LIDAR ?
- deep-learning for analysis & recognition of gestural time-series (+possibly other types, eg trajectories?)



Questions ?