Vehicle Detection Using Satellite Images

Filippo Galassi
1.1 Motivations (1)

Why vehicle detection?

Transportation management
- Development and maintenance of road networks

Urban areas
- Parking lots assessment
- Traffic flow management

Non urban areas
- Detection of vehicles

Evacuation routes

Military applications
- Surveillance
1.1 Motivations (2)

Why satellite imagery?

- “Relatively” cheap
- Homogeneity
- Interpretation of images
- Context over a large area
- Several datasets available
- Passive sensor
- Research from aerial imagery
1.2 Problems

**General problems:**

- Vehicles size
  - Vehicles hardly separable when grouped
  - Low contrast

- Vehicle velocity brings to motion blurring

- Light conditions

- Weather dependent

- False alarms from neighboring objects
1.3 Assumptions

**General assumptions:**

- Incorporating auxiliary databases information
  - GIS road vector map
  - Auxiliary data from local sensor
- Panchromatic images used for detection
- Weather condition causing no interferences
- Vehicles with rectangular shape

- **Specific assumption for each method**
2 Overview

**STATIONARY VEHICLES**

- Mean Shift Segmentation
  - Chen H, 2018
- Adaptive Boosting
  - Leitloff J, 2010
- Deep Neural Networks
  - Jiang Q, 2015
  - Jin X, 2007
- Hysteresis thresholding
  - Larsen S O, 2009
  - Eikvil L, 2008
  - Gao T, 2017
- Maximally-stable extremal region
  - Karim S, 2018
- Watershed Image Segmentation

**Feature Extraction**

**MOVING VEHICLES**

- Gradient-based
  - Leitloff J, 2010
  - Wei A, 2018
- multi-morphological-cue based
  - Wei A, 2018
- Dynamic association
  - Zhang J, 2019
- Kalman filter-based TSE
  - Seo T, 2018

2 Overview

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3.1 Method 1: Vehicle Detection [Leitloff et Al, 2010]

Goal
- Vehicles detection in typical traffic situations in urban areas
- Traffic activity estimation

Assumptions
- Precise road information data
- Traffic queues defined as follow
  - Low curvature, constant width and sufficiently long
  - Repetitive pattern both in gray value contrast and width
  - Representable as line in scale
- Median road surface brightness taken as reference grey value
3.1 Method 1: Overview [Leitloff et Al, 2010]

- GIS data
- PAN image
- Test image
- Training data

- Region of Interest
- Line detection and filtering
- Kernel Fitting

- AdaBoost training
- Classification
- Grouping

- Detected vehicles

- Activity estimation (non-grouped vehicles)
3.1 Method 1: Preprocessing [Leitloff et al, 2010]

- Implementation of the GIS
  - Extraction of the road axes: manual registration due to coarse resolution

- Training of the *Gentle Adaptive Booster* algorithm (Gentle AdaBoost)
  - A set is given as input
  - A weak classifier is estimated by weighted least square fitting
  - Iterative process through weights that are updated until the desired training/test error is reached
  - The final strong classifier is a linear combination of all the weaker classifiers

\[
F(x) = \sum_{m=1}^{M} f^m(x)
\]

During the classification, the sign of \(F(x)\) determines the predicted label, while its absolute value is a confidence measure for this prediction.
3.1 Method 1: Gentle AdaBoost classifier [Leitloff et Al, 2010]

Classification

- Base classifier
  - Binary decision trees
  - HOG, co-occurrence matrix, Haar-like features
- Boosting parameters to initialize the classification
  - Size of samples $\rightarrow$ variation is not needed
  - Number of nodes $\rightarrow$ testing different number of nodes

The optimal configuration has been found empirically (13x13 pixels and 4 nodes)

- Maps displaying the confidence of a pixel belonging to a vehicle or to the rejection class
- Closed contours as boundary of potential vehicle regions are created
- According to the expected vehicle size and the orientation of the corresponding road segment
3.1 Method 1: Extraction of Queues [Leitloff et Al, 2010]

- Differential geometric approach
  - Geometry and radiometry
  - Width function

- Extraction parameters
  - Primary smoothing factor
  - Thresholds from the second derivative

- Dilation and erosion to enhance the queue structure

- Extracted lines are collinearly grouped and approximated by polygons
3.1 Method 1: Width Function [Hinz et Al., 2005]

- Width is determined through the detection of vehicle side in the gradient image
- The profile is spanned perpendicularly to the line direction
- The maximum value is supposed to correspond to the vehicle boundary
- The distance between two maximum represents the queue width
- If no maximum is found the gaps are closed by bilinear interpolation

![Diagram showing the process of width function determination](image)
3.1 Method 1: Single Vehicles from Queues [Leitloff et Al, 2010]

- Single vehicles extracted by fitting Gaussian kernels

\[ f(a_f, \sigma_f, \mu) = \frac{a_f}{\sqrt{2\pi\sigma_f}} \exp\left(-\frac{1}{2} \left(\frac{x - \mu}{\sigma_f}\right)^2\right) \]

- \(a_f\) is the amplitude
- \(\sigma_f\) Second-order moment
- \(\mu\) First order moment
- \(x\) Position along the polygon

- Fitting the parameters to both the width and the contrast functions
- Iterative Reweighted Least Square fitting to compute the accuracies
- Distinction of false and correct hypotheses through predefined thresholds based on geometric and radiometric vehicles properties
3.1 Method 1: Traffic Activity Estimation [Leitloff et Al, 2010]

Goal

- Estimation of movement
- Estimation of speed

Exploitation of the time gap that appears between the acquisition of the panchromatic and multispectral data

Images are geo-coded and co-registered with road data taken from GIS

- Information about region of interests, roads, junctions and parking lots

Assumptions

- limited to such vehicles that are not contained in queues
- Active traffic acting along roads
- Data to be 100% complete and correct
3.1 Method 1: Traffic Activity Estimation (1) [Leitloff et Al, 2010]

Vehicle position extraction
- Vehicle center is manually selected on the panchromatic image
- Corresponding position in the multispectral (MS) image needs to be computed

Determination of vehicle position in MS image
- RGB images -> Intensity-Hue-Saturation (IHS) color space
  - High color saturation of an object strongly influences the distance from the coordinate origin in the color space
- The blob structure in the saturation image becomes clearly visible
3.1 Method 1: Traffic Activity Estimation (2) [Leitloff et Al, 2010]

Determination of the translation vector between vehicle blob in the PAN and MS

- A template containing the vehicle is cropped from the PAN image
- Smoothing the resulting image to make comparison possible (pan image higher resolution)
- Compute the gradient direction in both the resulting images
- Pixel-wise comparison between gradients direction images (HIS and PAN image)
- Position showing highest similarities in the gradient direction is chosen
  - Maximum distance check

Corresponding detection with given position in pan image (green) and detection in MS images (red)
3.1 Method 1: Traffic Activity Estimation (3) [Leitloff et Al, 2010]

**Accurate position estimation**
- Least square fitting to refine the matched position
  - Accuracy can be derived

**Movement Estimation**
- Time delay panchromatic and multispectral sensor
- Distance of the position in the two different corresponding images is calculated
- Accuracy of the calculation computed by simple error propagation
  - Variance in position in MS image and PAN image known

Profiles and accurate position for panchromatic (green) and similarity image (red)
3.2 Method 2: Watershed Segmentation (1) [Wang et Al, 2016]

**Goal**
Detection of urban road vehicles based on watershed image segmentation

**Problem**
Low ground resolution

**Assumption**
Shadows cast by small vehicle are considered as parts of the corresponding vehicle

**Major steps**
- Mask determination
- Image segmentation
- Feature extraction & rule-based classification
3.2 Method 2: Preprocessing [Wang et Al, 2016]

**Determination of road masks**
- Implementation of GIS maps
- Constrain the detection to the road region

**Determination of vegetation masks**
- Vegetation mask retrieved from GF-2 multispectral imagery
- Areas with vegetation are identified and masked out to avoid problems of vehicle occultation

Picture representing the acquired image and the implemented GIS information
3.2 Method 2: Watershed Segmentation [Wang et Al, 2016] (2)

Image segmentation

1. Input of gray image
2. Small Sobel operator - gradient image
3. Marker computation: morphological filter to reduce noise and fix the minima points
4. Marker controlled watershed transformation to obtain the initial segmentation
5. Region merging
   - Similarity criteria
   - Initial regions were iteratively merged to refine segmentation results
3.2 Method 2: Morphological Filter [Wang et Al, 2016]

- Non-linear operator
  - Erosion, dilation, opening, closing
- Object oriented transformation
- It is defined by a structuring element which designs the shape and the size of the filter
- Simplify the input image by erasing the scene and preserving other structures in the image
  - In this case object similar to vehicle
- Particularly this filter reduce the noise components keeping the geometrical features of the objects in the scene.
3.2 Method 2: Classification [Wang et al, 2016]

Feature extraction and rule-based classification

- Spectral and geometric features have been used as input to the hierarchical classifier
  - Mean value, from panchromatic image
  - Area
  - Length-to-width ratio
  - Rectangular fit

Diagram:
- Image Objects
  - Object mean value > threshold 1
  - Bright Objects
  - Geometric relations (area, length to ratio, rectangular fit)
  - Resulting vehicle
  - Dark Objects
  - Object mean value < threshold 2
3.3 Method 3: Hysteresis Thresholding (1) [Larsen S O et Al, 2009]

**Goal**
Vehicle detection under different imaging and traffic conditions

**Assumption**
Objects overlapping masks edges are considered as part of the background

**Major steps**
- Pre-processing
- Segmentation
- Feature extraction
  - Prediction of vehicle shadows
- Classification
3.3 Method 3: Hysteresis Thresholding (2) [Larsen S O et Al, 2009]

**Preprocessing**
- Road mask to restrict vehicles detection to roads
- Vegetation mask to remove objects obstructing the view
  - Removing all objects below a certain NDVI threshold

Panchromatic image where all non-road pixels are set to black

**Segmentation**
- Based on Otsu’s method for unsupervised threshold selection
- Selecting a weak and a strong threshold (Hysteresis thresholding)
  - two threshold for dark objects
  - two thresholds for bright objects
- Keeps only well connected edges and filters out noisy ones
3.3 Method 3: Feature Extraction [Larsen S O et Al, 2009]

**Feature extraction**

Potential areas of interests are described from a set of features:

- Geometrical features
- Radiometric features
  - Mean value intensity
- Obvious non-vehicle segments are discarded used as rule-based pre-classification step
- **Shadow mask** to remove blobs shadows
- Dark objects overlapping mask edges are removed
3.3 Method 3: Shadow Mask (1) [Larsen S O et Al, 2009]

- Based on information about elevation and direction of the Sun
- Shadow mask is just a binary mask representing pixels assigned to shadow. It is derived from two conditions:

1. Overlapping condition
   - From the dilation of the image we obtain two classes: bright segments and dark segments (expected shadow)
   - An image containing only the shadow segments is filtered out and compared with an image containing dark objects that lies next to bright ones

2. Distance condition

If the pixels overlap and are below a certain distance threshold from bright vehicles classified as shadow pixels
3.3 Method 3: Shadow Mask (2) [Larsen S O et Al, 2009]
3.3 Method 3: Classification [Larsen S O et Al, 2009]

Classification

- Maximum likelihood classifier
- Definition of 6 classes:
  - Bright car
  - Dark car
  - Bright truck
  - Bright vehicle fragment
  - Vehicle shadow
  - Road mark
- Shadows often confused with dark vehicles

Post-classification

- To reduce the number of misclassifications
- Distance to nearest shadow feature:
  - Segments included in the shadow mask having zero distance are labelled as shadow
  - Improve of vehicle fragments and road marks separation
4.1 Dataset – Method 1

QuickBird satellite

- Panchromatic band: 0.6 m resolution
- Multispectral band: 2.4 m resolution
- Area: Munich, Technische Universität
- GIS: German Authoritative Topographic Cartographic Information System (ATKIS)

Images from [Leitloff et al., 2010]
4.2 Dataset – Method 2

**GF-2 satellite**

- High resolution data
  - Multispectral, res 3.24 x 3.24 m
  - Panchromatic, res 0.81 x 0.81 m

- Acquisition
  - Chaoyang District (Beijing, China)
  - 5th December 2014

- Panchromatic band is used for detection
4.3 Dataset – Method 3

**QuickBird satellite**

- Panchromatic and multispectral bands
- Five different images from Norway (2002-2006)
- Typical Norwegian traffic conditions
  - Narrow roads, close to forests, low traffic density

<table>
<thead>
<tr>
<th>Location</th>
<th>Image area $[km^2]$</th>
<th>road</th>
<th>Length of road mask [km]</th>
<th>Traffic density [vhc/km]</th>
<th>Date [dd.mm.yy]</th>
<th>Latitude</th>
<th>Mean Sun elevation [°]</th>
<th>Mean off nadir view [°]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bodø</td>
<td>32</td>
<td>RV80</td>
<td>9</td>
<td>-</td>
<td>21.07.03</td>
<td>67</td>
<td>43</td>
<td>4.4</td>
</tr>
<tr>
<td>Kristiansund</td>
<td>29</td>
<td>RV70</td>
<td>5,6</td>
<td>20,9</td>
<td>19.06.04</td>
<td>63</td>
<td>50</td>
<td>7.9</td>
</tr>
<tr>
<td>Østerdalen</td>
<td>59</td>
<td>RV3</td>
<td>31,4</td>
<td>1,4</td>
<td>10.08.04</td>
<td>62</td>
<td>43</td>
<td>7.3</td>
</tr>
<tr>
<td>Eiker</td>
<td>154</td>
<td>RV35</td>
<td>20,5</td>
<td>7,3</td>
<td>07.06.02</td>
<td>60</td>
<td>53</td>
<td>12.9</td>
</tr>
<tr>
<td>Sollihøgda</td>
<td>52</td>
<td>EV16</td>
<td>26,6</td>
<td>6,7</td>
<td>05.10.02</td>
<td>60</td>
<td>47</td>
<td>12.5</td>
</tr>
</tbody>
</table>

[Larsen S O et al., 2009]
5.1 Results - Method 1 (1)

- The classification algorithm results
  - Normalized range of \([-1;1]\)
  - Zero crossing representing vehicle regions

- Only some vehicles in a row are detected as individual cluster

- Extraction of queues and their vehicle to solve this problem

Image from [Leitloff et Al, 2010]
5.1 Results - Method 1 (2)

Classification

\[
\text{correctness} = \frac{TP}{TP + TF}
\]

\[
\text{completeness} = \frac{TP}{TP + FN}
\]

<table>
<thead>
<tr>
<th>Manual count</th>
<th>Automatic Count</th>
<th>Correctly classified</th>
<th>Correctness</th>
<th>completeness</th>
</tr>
</thead>
<tbody>
<tr>
<td>268</td>
<td>221</td>
<td>210</td>
<td>95.3%</td>
<td>82.5%</td>
</tr>
</tbody>
</table>

* True positives
O False negative
+ False positive

Image from [Leitloff et al, 2010]
5.1 Results - Method 1 (3)

**Activity estimation**

- Only selected results are showed
  - Possible clear visual interpretation

- Picture 1
  - Isolated vehicles
    - The upper one shows no colour bias
    - Position in the two channels is identical
  - Lower one with a derived speed of 57km/h
    - Result reasonable

- Picture 2
  - Missing detection of grouped error (line extraction Error)
  - 90 km/h derived speed
    - Above the speed limit

Images from [Leitloff et al., 2010]
5.2 Results - Method 2 (1)

Segmentation results

- Comparison between watershed and multiresolution segmentation
- Watershed segmentation showing better results
  - Dark vehicles can be better separated from the pave road compared to other method

Images from [Wang et Al, 2016]
5.2 Results - Method 2 (2)

<table>
<thead>
<tr>
<th>Sub-image ID</th>
<th>Manual counts</th>
<th>Detected vehicles (missed)</th>
<th>Omission</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>115</td>
<td>98(17)</td>
<td>15%</td>
</tr>
<tr>
<td>#2</td>
<td>91</td>
<td>79(12)</td>
<td>13%</td>
</tr>
<tr>
<td>#3</td>
<td>84</td>
<td>73(11)</td>
<td>13%</td>
</tr>
<tr>
<td>#4</td>
<td>62</td>
<td>57(5)</td>
<td>8%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>352</strong></td>
<td><strong>307(45)</strong></td>
<td><strong>12%</strong></td>
</tr>
</tbody>
</table>

- Overall omission rate is 12%
- Validation done manually

Table from [Wang et Al, 2016]
5.2 Results - Method 2 (3)

Classification results

- Good vehicle classification
- Some miss-detection due to omissions in the segmentation process

<table>
<thead>
<tr>
<th>Image ID</th>
<th>Manual count (detected vehicles)</th>
<th>Automatic classified as vehicles</th>
<th>Correctly classified as vehicles</th>
<th>Correctness</th>
<th>Overall accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>115(98)</td>
<td>105</td>
<td>92</td>
<td>88%</td>
<td>80%</td>
</tr>
<tr>
<td>#2</td>
<td>91(79)</td>
<td>83</td>
<td>73</td>
<td>88%</td>
<td>80%</td>
</tr>
<tr>
<td>#3</td>
<td>84(73)</td>
<td>77</td>
<td>66</td>
<td>85%</td>
<td>78%</td>
</tr>
<tr>
<td>#4</td>
<td>62(57)</td>
<td>60</td>
<td>54</td>
<td>90%</td>
<td>87%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>352(307)</strong></td>
<td><strong>325</strong></td>
<td><strong>285</strong></td>
<td><strong>88%</strong></td>
<td><strong>81%</strong></td>
</tr>
</tbody>
</table>

Table from [Wang et Al, 2016]
5.3 Results - Method 3 (1)

- Testing on four set of satellite scenes sub-images (299 objects)
- 73 noise samples, segments not belonging to any of the defined classes, to see whether these samples are classified into vehicle or not

- Overall accuracy: 90%

Including noise:
- Overall accuracy: 72%

<table>
<thead>
<tr>
<th>Given label</th>
<th>Bright vehicle</th>
<th>Dark vehicle</th>
<th>Vehicle shadow</th>
<th>Road mark</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>True label</td>
<td>127</td>
<td>0</td>
<td>0</td>
<td>12</td>
<td>139</td>
</tr>
<tr>
<td>Bright vehicle</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dark vehicle</td>
<td>0</td>
<td>67</td>
<td>10</td>
<td>0</td>
<td>77</td>
</tr>
<tr>
<td>Vehicle shadow</td>
<td>0</td>
<td>10</td>
<td>70</td>
<td>0</td>
<td>80</td>
</tr>
<tr>
<td>Road mark</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>total</td>
<td>127</td>
<td>77</td>
<td>80</td>
<td>15</td>
<td>299</td>
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<tr>
<td>Noise</td>
<td>17</td>
<td>16</td>
<td>18</td>
<td>22</td>
<td>73</td>
</tr>
<tr>
<td>SUM</td>
<td>144</td>
<td>93</td>
<td>98</td>
<td>37</td>
<td>372</td>
</tr>
</tbody>
</table>

[Larsen S O et Al, 2009]
5.3 Results - Method 3 (2)

Validation

- Manual count as the most reliable
- In-road equipment to estimate the average traffic situation
  - Assuming no queues and homogeneous traffic density
- Fragments that belong together and trucks are counted as one vehicle

<table>
<thead>
<tr>
<th>Location</th>
<th>Automatic count</th>
<th>Manual count</th>
<th>Agreement</th>
<th>Estimated from In-road Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kristiansund#1</td>
<td>16</td>
<td>22</td>
<td>14</td>
<td>25</td>
</tr>
<tr>
<td>Kristiansund#2</td>
<td>18</td>
<td>32</td>
<td>17</td>
<td>27</td>
</tr>
<tr>
<td>Østerdalen</td>
<td>43</td>
<td>44</td>
<td>30</td>
<td>51</td>
</tr>
<tr>
<td>Eiker</td>
<td>39</td>
<td>57</td>
<td>36</td>
<td>57</td>
</tr>
<tr>
<td>Sollihøgda#1</td>
<td>63</td>
<td>64</td>
<td>48</td>
<td>58</td>
</tr>
<tr>
<td>Sollihøgda#2</td>
<td>26</td>
<td>30</td>
<td>24</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>202</td>
<td>249</td>
<td>169</td>
<td>221</td>
</tr>
</tbody>
</table>

[Larsen S O et Al, 2009]
5.3 Results - Method 3 (3)

[Image of satellite view with highlighted areas]

[Larsen S O et Al, 2009]
6.1 Discussion – Method 1 (1)

**Traffic activity estimation**
- Only selected results are showed where clear visual interpretation is possible
- Non-numerical evaluation
- Visual interpretation not always possible
- Less then half a pixel to verify a movement
  - Minimum velocity of 20km/h

**Single vehicle detection**
- Excellent correctness showing high robustness of the algorithm
- High completeness
  - Most of the isolated cars are detected
- Most misdetections due to
  - Low contrast to the background caused by vehicles color
  - Complexity of the scenes (trees, strong reflections)
6.1 Discussion – Method 1 (2)

General Outcome

- The presented approach for vehicle detection from spaceborne optical imagery shows very good results.
- Single vehicles can be extracted from queues very reliably.
- Critical shadows and reflections might be excluded a priori by including also light conditions.
- A drop-off in completeness in the case of more difficult scenes is expected.
  - Few trees and shadows occurrence.
- Speed detection seems to be too optimistic.
- Movement estimation can be performed from Space imagery.

6.2 Discussion – Method 2

The segment-based vehicle detection is a promising approach

- Test the implementation on different roads type
- Approximately 12% of vehicles are miss – detected
  - Low contrast with background
  - Fragmented objects (too small)
- Dark vehicles are more difficult to segment because of lower contrast
- Ground truth obtained by visual interpretation
6.3 Discussion – Method 3 (1)

General outcome

- The results are promising for the improved monitoring of the national road system in the future

- The automatic vehicle detection algorithm tends to underestimate the number of vehicles

- In those images where the automatic count is close to the manual count, the agreement is worse

- Performance dependent on lighting conditions

- Contrast enhancement should be implemented as preprocessing
6.3 Discussion – Method 3 (2)

**Classification**
Most vehicles were correctly classified thus the main reason for underestimation is believed to lie in the segmentation routine.

**Segmentation**
The proposed segmentation routine fails to capture vehicles of very low contrast to the local background.

**Problems**
- Poor contrast for gray tone level thresholding
- Partially shadow covered vehicles
- Segment overlapping road edges, hence discarded
- Relation between histogram and intensity classes too optimistic
### 6.4 Comparison – method 1 & 2

<table>
<thead>
<tr>
<th>Method 1</th>
<th>Method 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>- QuickBird satellite</td>
<td>- GF-2 satellite</td>
</tr>
<tr>
<td>- Classifier training and road mask</td>
<td>- Vegetation and road masks</td>
</tr>
<tr>
<td>- Adaptive boosting classification</td>
<td>- Model-based classification</td>
</tr>
<tr>
<td>- Activity estimation</td>
<td>- Queues extraction not considered</td>
</tr>
<tr>
<td>- Detection discriminated between grouped vehicles</td>
<td>- Grouped vehicles showed the lowest accuracy</td>
</tr>
</tbody>
</table>

**Method 1 shows higher completeness and correctness and also a clearer and more detailed description of the algorithm**

**Method 3 tested on different scene (non-urban). Hence, not compared**
Stationary vehicles

- Monitoring of traffic conditions is possible
- High resolution imagery makes vehicle detection possible from satellites
- Implementation of auxiliary databases are needed
  - GIS, Vegetation mask, Shadow mask
- Illumination conditions information would be important

Main limitations

- Radiometric contrast between vehicles and background
- Segmentation of grouped vehicles
- Influence from neighboring objects, e.g.
  - Vegetation, road marks, injunctions
- Sensed truth, not 100% reliable
7 Personal opinion (2)

Moving vehicles

- High resolution satellite imagery can provide movement estimation of vehicles
- Application seems to optimistic
- Implementation of new satellite constellation
  - Delivery of first videos from space

Main limitations

- Low resolution
- Few research on this application
References (1)

References (2)

References (3)