



Extraction of Road Geometric Parameters from High Resolution Remote Sensing Images Validated by GNSS/INS Geodetic Techniques

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Abstract. Roadway geometric data, user behavior and crash data provide the main input for developing existing highway safety evaluations. In particular, roadway geometric data can be useful in providing a quantitative guidance for alignment consistency and for having an initial indication of critical point presence along a road.

Furthermore the article 13 of the Italian Road Code requires an implementation of Road Cadastre for which it is necessary to know the planimetric and altimetric alignments.

This paper presents a methodology to obtain geometric road information from high resolution images using automatic techniques for the extraction of road geometric parameters.

The paper starts from the Road Cadastre characteristics and definitions and the analysis of the existing studies regarding remote sensing methodologies. Then two strategies, tested on road sections in Italy, are presented. The first one is based on the concept of spectral signature, while the second one is based on the Fractal Dimension of the image treated only as a numerical matrix.

The results were validated by GNSS/INS geodetic techniques, using also real time kinematic data.

Keywords: Road cadastre · High resolution satellite images · Geographical information system · GNSS · INS

1 Introduction

Roadway geometric data, user behavior and crash data provide the main input for developing existing highway safety evaluations. As regard user behavior, several studies have highlighted some relationships linking the driver behavior to the road geometric features.

The parameter chosen to represent the user behavior was the operating speed. Based on numerous speed surveys, some models were obtained to predict the operating speed

of the vehicles as a function of the main horizontal geometric features of the road. In particular, interesting regression equations were studied to predict the environmental speed as a function of the CCR (curvature change rate), which represents the general characteristics of an homogenous section belonging to the road. The geometric characteristics of the roads used to develop the prediction models of the operating speed were obtained from the original design plan or from the analysis of the high resolution digital cartography. However, when the design plan is not available and the alignment is very long, a new methodology to obtain quick horizontal geometric road information with high precision could be extremely useful.

Moreover, the Road Administrations have also the necessity to know the as-built data of their roads to program the road maintenance and to improve the travelling safety. For this scope, a new quick methodology for the reconstruction of the road geometry could be useful to the writing of a road cadastre (Ministry of Public Works 2001) that, if constantly updated, could be a fundamental device for the improvement of the road safety evaluation.

In summary road geometric characteristics and in particular the geometrical characteristics of the road axis, the width of the roadway and the shoulders, are essential both for road safety studies and Cadastre.

Technical cartography is not a good tool because these elements cannot be extracted with high accuracy, moreover it is not possible to reconstruct the signing from cartography.

Moreover for example the Ministerial Act 01/06/2011 (Modalities of institution and updating of the Road Cadastre) does not give expressly a definition of road axis, but only “an illustrative definition” from which it is possible to give an enumerative definition:

- In the case of road cross section organized in a single carriageway with two run directions, the road axis is given by the separation axis between the internal lanes with opposite run directions (that does not necessarily coincide with the geometric axis of the roadway, nor with the section geometrical axis);
- In the case of a road cross section organized in a single carriageway with one run direction, the road axis is given by the geometric axis of the roadway (that does not necessarily coincide with the geometric axis of the section);
- In the case of road cross section organized on two separate carriageways, and if one decides to represent the road segment with a single road element, the road axis is given by the axis of the median.

Thus for Italian Road Cadastre the definition of road axis depends on road typology (category) and lane numbers for every sense of running, while for ministerial decree 05/11/2001 (Ministero delle Infrastrutture e dei Trasporti), “Functional and Geometric rules for road construction”, the geometric axis of the road is the central point of the part of carriageway.

From these definitions it is possible to make some consideration of practical interest, namely: to be able to correctly detect the road axis, the signing must be complete and present (Fig. 1). Not always the road geometric axis coincides with the road sign of the axis, also because sometime the axis sign does not exist.

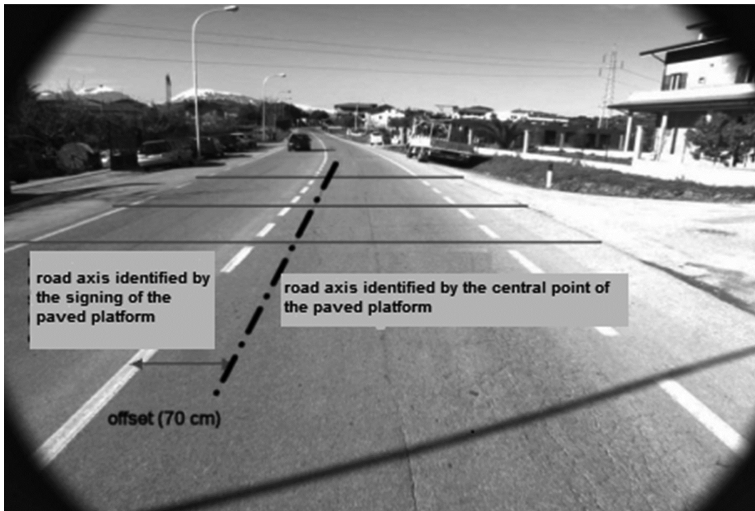


Fig. 1. Comparison between the road axis identification by means of the pavement signing and of the central point of the paved platform.

The remarking of the signing, can invalidate a pre-existing Cadastre (also in the cases in which the other parameters interesting for the Cadastre, like the roadway width, travel direction and the number of lanes, are not changed).

Being the materializations of the axis points not foreseen, it is necessary to give a documentation of the road situation at the time of the surveys together with the data given for allowing the operation of testing that will consist in a “congruence check with the national geodetic networks”.

To obviate this it is possible to apply techniques that allow extracting the axis and signing width both using directly and indirectly techniques.

The techniques used till now for these aims foresee the use of instrumented vehicles running along the road; the vehicle positions, surveyed by GNSS (Global Navigation Satellite System), allow to reconstruct the geometric parameters of the elements (including signing measurements).

Besides of this technique, the authors experimented the potentiality of the geometric characteristic survey using the analysis of high resolution satellite images.

This technique allows surveying also the signing, thus overcoming the uncertainty deriving for instance from the analysis of cartography and reducing in the same time the acquisition time to respect to the GNSS surveying. Furthermore, this technique could be used to verify the accuracy of the signing layout.

2 Existing Studies

The extraction of roads from spatial data sources like aerial or satellite images has been in scope of research for more than thirty years. Many approaches are based upon techniques like edge detection or texture analysis (Dial et al. 2001). Other methods use

dynamic programming or LSB-Snakes improving the results of the road extraction process (Grüen 1997), Gruen and Li (1995).

The use of knowledge-based approaches seemed to gain more importance by means of rules and models (Hinz et al. 2001).

Predefined information is acquired at a generic global level (e.g. connectivity) and at a local level (e.g. context), respectively (Hinz and Baumgartner 2002; Vosselmann 1997).

Valuable properties can be derived from other existing spatial data sources like vector data (Zhang et al. 2001). Some work has been done on the extraction of continuous surfaces like roads from laser scanning surveys; (Pattnaik et al. 2003), Hatger and Brenner (2003) suggest the use of laser scanning data to gather information on road inventory. Mobile Mapping Systems (MMS) use also laser scanner technology in order to collect dense and precise three-dimensional point clouds that gather both geometric and radiometric information of the road network. A methodology for the automatic detection and classification of road signs from point cloud and imagery data provided by a LYNX Mobile Mapper System, have been presented by Soilán et al. (2016).

Yang et al. (2015) extract urban objects (for instance poles, cars and buildings) segmenting a super voxel structure and classifying the segments according to a series of heuristic rules. Serna and Marcotegui (2014) classified up to 20 different objects using Support Vector Machines (SVM).

Other works focus on the detection of a single object class within a point cloud. Street lights (Yu et al. 2015), curbs (Zhou and Vosselman 2012; Wang et al. 2015) or trees (Reitberger et al. 2009) can be detected using LiDAR data. Regarding traffic signs, Pu et al. (2011) distinguished several classes of planar shapes corresponding to the possible shapes of traffic signs. Riveiro et al. (2015) used a linear regression model based on a raster image for classifying traffic signs based on their shapes. However, the resolution of a point cloud is not enough to distinguish the specific meaning of a traffic sign, therefore these analyses need to be integrated by the study of optical images.

Wen et al. (2015) detect traffic signs based on their retro reflectivity, and project the 3D data on 2D images in order to classify the previously detected traffic signs. There exists a vast literature regarding traffic sign recognition in RGB images. The Traffic Sign Recognition Benchmark (GTSRB) (Stallkamp et al. 2012) gathered more than 50,000 traffic sign images and established a classification challenge. The best results were achieved by Cireşan et al. (2012). They combined various Deep Neural Networks (DNN) into a Multi-Column DNN, getting a recognition rate of almost 99.5% (Sermanet and Lecun 2011).

Information from a street database was acquired to set up predefined regions along roads. Subsequently, least squares regression was applied to those regions in order to compute appropriate values for longitudinal and transversal slopes. Apart from that, few approaches investigate discontinuities like breaklines and introduce constraints like curvature or slope for the extraction of linear features.

The availability of images at resolutions close to that of aerial photographs make them suitable for a variety of applications ranging from water quality monitoring to monitoring of urban changes.

The excellent characteristics of such data, like its high resolution (1 m), real time data availability, three-dimensional measuring possibility by stereographic observations, flexibility of data acquisition, the high sensitivity and the availability of multi-spectrum covering up to NR (near infrared), improved the use of satellite remote sensing images in roads and in new technological areas (Kumagai et al. 2001).

Derivation of data like the road network data can be of use in the car navigation systems. So far, the extraction of the road information was mostly carried out manually by the operators, resulting in rather high costs.

The possibilities of automating process of road parameters extraction have been studied by many authors. One possibility is to divide the image of the aerial photograph into meshes considering that the contrast in the shade values between the road and the surroundings is quite strong. Using the Maximum A Posteriori probability technique and a Dynamic Programming technique for each mesh, the features of the road are extracted.

Various researches include the tracing of the starting segments of the roads in the mesh with the road feature to extract the major roads automatically.

Kumagai et al. (2001) carried out the process of automatic extraction of roads in regions containing some areas and road features, by applying some techniques of the image processing technology.

Grüen and Li (1997) proposed a semi-automated system for road extraction based on dynamic programming and least squares B-spline (LSB) snakes. The automatic completion of road networks based on the generation and verification of link hypotheses given in (Wiedemann and Ebner 2000; Wallace et al. 2001) present an approach designed for a wide variety of imagery. It is based on an object-oriented database which allows the modelling and utilization of relations between roads as well as other objects. Road extraction using statistical modelling in the form of point processes and Reversible Jump Markov Chain Monte Carlo was proposed by Stoica et al. (2004).

Some of the proposed techniques are suitable for the extraction of roads in mostly agricultural as well as arid areas, the latter also comprising mountainous regions, based on line/edge extraction, generation and verification of connection hypotheses and global grouping detailing.

Generally, due to the large differences in the appearance of roads in different areas, a single model for automatic road extraction is not sufficient. It could be useful to distinguish between agricultural, mountainous, and desert areas Bacher (2004).

In mountainous areas the roads are strongly affected by the topography. Roads often turn with a large curvature or even with sharp bends. In the images the roads are mostly represented as bright and only seldom by dark lines.

In desert areas roads mostly appear as bright or dark lines with few disturbing objects. The distinction from other linear objects is often difficult.

In agricultural areas roads appear as elongated structures. They often have no bar-shaped profiles in the images, but can be seen directly as collinear edges of field borders.

Other authors propose the extraction of linear features using the Steger sub-pixel line and edge extractor. The extracted features are split into segments with curvature values below a given threshold. Then the resulting lines and edges from all image channels are fused to single data sets and the connections are constructed from them.

Goemann et al. (2005) use polynomial interpolation to determine pixels belonging to road structures in the satellite images, for the lines detection. This is a standard method for ridge detection. The image is regarded as a function $I(i, j)$. Lines are detected as ridges and ravines in this function by locally approximating the image function by its second order Taylor polynomial. The polynomial is used to approximate first and second order derivatives of the image function from the Hessian matrix of the Taylor polynomial.

The gradient and curvature information characterizing each pixel are used to classify a pixel in a number of topological classes based on their sign or magnitude. Line points are mainly characterized by a high second directional derivative, i.e. a high curvature perpendicular to the line direction.

The performance of the detector for a given dataset and the according parameter set that gives optimal results can be found. Furthermore the error propagation can be used to analyze the influence that perturbations on the intensity values have on the estimation of the parameters.

3 Method Case Studies

3.1 Road Geometry Survey Using a Mobile Mapping System (MMS)

The road geometry survey using a MMS, for the compilation of the Road Cadaster, has been performed initially as prototype, by the Centre of Excellence for the Research in TeleGeomatics and Spatial Information, University of Trieste, Italy, as required by the Friuli Venezia Giulia Region Manzoni et al. (2004). Sample roads have been surveyed in any of the four Regional Provinces.

Several public administrations adopted the same techniques in order to draw up the Road Cadastre in the areas of their competence, assigning the surveys to firms equipped with MMS.

The aim of the research presented in this paper was to compare the road geometric parameters computed from GNSS/INS road surveys by using “GIGI-One”, the GeoSNav Lab, University of Trieste, MMS, with the ones extracted from high-resolution satellite images and the relative project values.

For the absolute positioning, the Mobile Mapping System uses the POS LV (Position and Orientation System for Land Vehicles) System of Applanix Corporation, a fully integrated, Position and Orientation System, utilizing GNSS positioning integrated by inertial technology to generate stable, reliable and repeatable positioning solutions for land-based vehicle applications (Fig. 2). Designed to operate under the most difficult GNSS conditions in urban and suburban environments, it enables accurate positioning for road geometry, pavement inspection, GIS database and asset management, road surveying and vehicle dynamics.



Fig. 2. The MMS of the GeoSNav Lab, University of Trieste, and the Applanix Corporation POS LV[®] system components mounted on board the vehicle.

This integrated GNSS/INS (Global Navigation Satellite System/Inertial System) system is able to give, instant by instant, the position and asset of the vehicle.

Besides two GNSS receivers and the Inertial System, an odometer mounted on the back left wheel of the vehicle, is present, measuring the travelled distance.

The integration of each sensor data is performed by a Kalman filter, allowing to gain in any instant the best solution. GNSS data has a 1 Hz acquisition rate, while the odometer and the inertial system send data to the System CPU at a 200 Hz rate.

The centre of the footprint of the back left tire was used as reference point for the MMS positioning data.

Kinematic tests were carried out to assess the repeatability of surveyed trajectories by driving the MMS without any constraint, keeping the vehicle on the centre of the lane.

The tests have been performed both in situations of nearly contemporaneous trajectories (few minutes between a passage and the subsequent one, in order to maintain the similarity on the satellite geometries) than in different days and with different satellite constellations: the maximum differences between the so surveyed trajectories are in the order of 50 cm.

In the case of motorways with two or more lanes, as well as when the road is double tracked, to determine the road axis, the road must be travelled in both directions, on symmetrical lanes with respect to the axis, maintaining the MMS in the centre of the lane and calculating the axis as the average of the detected trajectories.

When the white line, on a single carriageway road, materializes the road axis, the survey can easily be accomplished by keeping the reference wheel on the line.

Should signing not be present, it is possible to choose to have the output of the positioning data in correspondence of a predefined point along the vehicle axis, keeping the vehicle as much as possible in the centre of the lane during the survey.

Different drivers, following the guidelines outlined above, also run the same trajectories: this did not have a relievable influence on the captured data sets.

Each trajectory is materialized by a seeding of points, obtained by interpolating every 1-meter the data coming out from any component of the surveying system at its own acquisition frequency. For each point of the seeding, the plane coordinates in the chosen

reference system are provided, as well as the ellipsoidal heights; the progressive distance from the starting point, the longitudinal and transversal slopes and the curvature expressed as punctual attribute, are associated.

In the present study, the radius determination was performed, point by point, based on the geometric construction of the circumference through three points: the central is the examined point, the forward and backward points are at a distance of 20 m from it. This choice - instead of considering three following points of the seeding- allows smoothing the driving effects.

The trajectory surveyed by the MMS is in fact never perfectly superimposable to the road geometries, but repeated runs showed it to be a good index of the “most likely” one.

The radius determined in this way, and consequently the curvature values, are thus affected by a certain level of noise needed to be filtered.

A null curvature is assigned to the points where the curvature value is less than a threshold (in the examined cases $k_s = 0.001 \text{ m}^{-1}$). A null curvature value associated to consecutive points identifies straight roads segments.

For each point of the surveyed trajectories, the Easting and Northing coordinates, the ellipsoidal height, the radius and the curvature (computed as the inverse of the radius) are available, ordered by the progressive distance from a starting point.

A filtering technique was set up by the Authors in order to detect arches with constant curvature from the points' seeding, where present; in this way, it was possible to assign the “*curvature*” attribute to each segment.

The axis has been determined as the mean of two trajectories, so that the assigned radius value is the one resulting from the mean of the two starting values.

The progressive distance values of the first and the last point of each straight segment allow to calculate its length; the initial and final progressives of the elements with a curvature different from zero are also identified. Curved sections needed to be analysed one by one. The radius, as a function of the progressive distance, was considered point by point. By definition, the first derivative of the radius function has to be null where the radius is constant. This does not happen in practise due to the noise of the points' seeding identifying the trajectory, related to the driving uncertainty and the described methodology used for the punctual radius determination. The first derivative is not zero, but it fluctuates around the zero value due to the radius punctual value variations. It is necessary to assume a threshold for the first derivative, below which its value is consider null (first derivative < 12 in the performed test). If the first derivative of the radius function is zero, the radius value and the initial and final points of the constant-radius arc have to be estimated.

The radius can be calculated as the mean value of the punctual radii in the central half of the considered arc. Then the centre of the circle having R radius crossing two points of the seeding, whose punctual radius values have been used for the calculation of the mean radius, can be identified.

Knowing the C circle centre coordinates and the equations of the two straight lines (preceding and following the examining curve) calculated as linear regression of the surveyed points, the distances of the C centre from the straight lines can be computed.

Each of these distances $D_i = R + \Delta R_i$ can be determined and the A_i parameter can be calculated for the clothoid connecting each straight segment to the constant radius arc:

$$A_i = \sqrt[4]{24R^3 \Delta R_i \left(1 + \frac{3\Delta R_i}{14R}\right)} \quad (1)$$

The lengths S_1 and S_2 of the curves having variable radius, and the curvilinear abscissa at the beginning and end of the arc having constant curvature, can be obtained from equation $RS_i = A_i^2$.

The described methodology was applied to curves with known parameters, both in case of curves with constant radius connected by clothoids, and in case of curves with constant radius directly inserted on the straight lines.

The computed radius values resulted to be the same ones as in the project in both the cases.

In a first test phase, the equation of the two straight sections preceding and following the curve has been graphically determined by using the geometric construction of the line passing through two points of the seeding, instead of the linear regression of the points belonging to the same straight line. Using this approximation, the accuracy in the ΔR computation, and consequently in the clothoid parameter and its length, was smaller. Nevertheless, the so obtained values are very close to project ones.

A vehicle, driven on the road, runs a variable radius curve, even where it is not really designed and constructed. In such cases, the obtained ΔR values were in the order of $20 \div 30$ cm. It is possible to introduce a threshold to reduce the ΔR value to zero, thus excluding the presence of a variable radius curve where not really existing, by improving the algorithm used to determine the straight line equations like linear regressions of the points seeding.

3.2 Road Parameters Extraction from High Resolution Satellite Images

The availability of a large number of HR (High Resolution) satellite images gives a new instrument to extract road features using semi-automatic techniques.

These images give a resolution from 60 cm to 1 m, near to the one of the aerial photographs usually adopted for cartography.

One of the goals of this paper is to test HR images capability to provide information about road conditions and characteristics.

Two QuickBird images with a geometric resolution of 60 cm have been used for the tests. Their spectral resolution is 4 bands (three in the visible spectrum - blue, green and red - and a band in the near infrared wavelength). The chosen color depth is 8 bit/pixel.

Two strategies for road extraction have been tested: the first one based on the concept of spectral signature, and the second one based on the Fractal Dimension of the image, treated like a numerical matrix.

The "spectral signature" is the core concept of all remote sensing techniques. It is based on the idea that each object has a peculiar reflectance that can be observed and analyzed looking at the Digital Number that the object has on each recorded band. In

particular, it is quite easy to separate non-vegetated areas from the vegetated ones using their great difference in reflectance in red and near-infrared (NIR) bands.

A combination of these two bands gives the NDVI (Normalized Difference Vegetation Index) index, largely used in remote sensing techniques to perform a separation of green and non-green areas Altobelli et al. (2004). NDVI is calculated as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (2)$$

where RED and NIR stand for the spectral reflectance measurements acquired in the red (visible) and near-infrared regions, respectively.

The Authors used it to have a basis on which being able to separate roads from the other kind of soil uses, considering that in the studied area the main roads built inside a largely wooded area have been analyzed. After this index calculation, it was possible to use it as a basis for a typical classification using a single band (the newly calculated NDVI “band”) or a bias value that can separate vegetation from roads. Both this techniques were useful because of the peculiar soil use of the area; where more types of non-vegetated land are present, it is necessary to use of a multi spectral classification, otherwise it would be very difficult to separate roads from other soil coverage that are typical of urban areas like roofs, concrete, bare soils etc.

An unsupervised classification of the NDVI map was applied for this project, using an Euclidean Distance algorithm and then an isolation of road representing class, into a black and white map (Fig. 3).

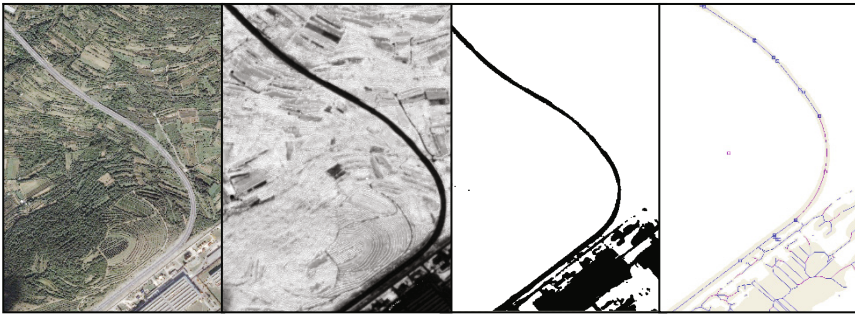


Fig. 3. Road extraction through NDVI map classification.

Even the Fractal Dimension of this area has been calculated on the NDVI map, because it represents a combination of band, so it has inside a larger quantity of information than a single band. The FD will be considered a measurement of the complexity of digital number distribution over: within the scale of the image used for this study, we expected a regular distribution of values on the artificial soil coverage (as roads are) and a more irregular distribution on the natural areas.

If the FD is regarded as a measure of input data roughness, the DN matrix can be imagined as a topographic surface, where higher or lower reflectance values (or NDVI)

can be found as peaks or valleys: the bigger the differences in value between near pixels, the higher the fractal dimension of this area.

The “Triangular prism surface method (TPSA)” was applied to calculate the area fractal dimension (Fig. 4). The “topographic surface” is split up into cells, according to a regular grid, and each area is measured. Each cell is not considered as a plane surface but calculated as a prism where z coordinates of base vertexes are the DN of the pixel located on the corner of the cell, and prism height is the mean of the corner values.

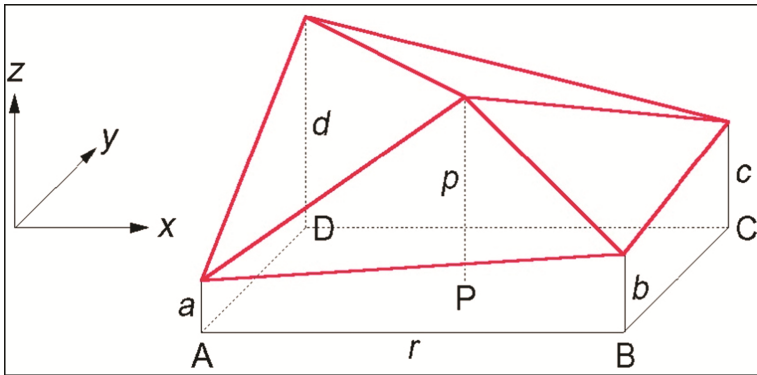


Fig. 4. Triangular prism surface method.

The area is calculated many times, according to grids of different scales so that the bases of the prisms have different numbers of pixels every time. The calculated area is then expressed through a logarithmic scale by means of a proper software routine developed by Altobelli and Pucci Poppi in 1998, and correlated with the respective dimensions of the cells on which it was calculated. The so obtained regression line coefficient is related to the Fractal Dimension as expressed below:

$$FD = 2 - b \tag{3}$$

where b is the linear regression coefficient. Roads are expected to have a lower FD respect to other kind of soil coverage in the used images, so that it is easy to separate them from other areas.

What was initially not considered is that the highest difference in the Digital Numbers occurs exactly around the road margins, describing the change of soil usage, from artificial coverage to vegetation.

A classification based on fractal dimension thus leads to the identification of road borders, rather than to an identification of the road path from which the road axes can be obtained, as happens with the classification based only on spectral signature (Fig. 5).

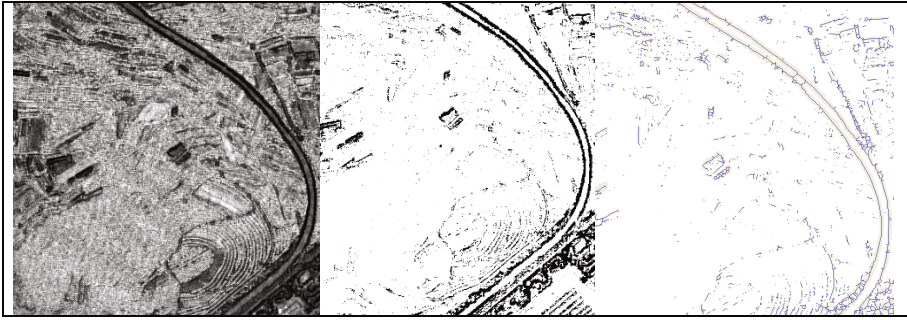


Fig. 5. Road extraction through fractal dimension techniques.

The last step of this road identification process consists of the vectorization of some of the extracted features in order to compare these results with the ones obtained through the other survey methods. The types of comparable data are for example the radii of curves. The vectorization of the map is probably the hardest part of image analyses, because classified maps often present some sort of “erosion” of the road path, due to the presence of the shadows of trees on the border. The eroded pixels sometimes cause an error in the vectorization. Vectorization softwares are sensible to any small changes towards the main orientation of pixels to be vectorized, a little abundance or lack in the road border therefore leads to an interruption in the direction of the extracted lines, or to a misinterpretation of it, such as in tracts where junctions with side roads are present. The map that should be provided to the vectorizing software therefore needs a quite important “cleaning” job, to avoid this problem as much as possible, being careful not to change the real road aspect.

Another aspect of roads that could be observed and obtained from satellite images is relative to road horizontal signings. These lines are clearly visible in high resolution images, even if the nominal pixel dimension could not theoretically permit it. This is possible because of the high difference in reflectance between the white lines and the black asphalt. The digital number of a pixel containing a line can be considered as a weighted mean of the values of the asphalt alone and the line alone. The radiometric difference is so high that the influence of a thin white area in the pixel causes a remarkable increase of the DN (note that in our case, with 8 bit images, a low reflectance is converted into a DN value near 0 and a high reflectance has a DN near 255).

The easiest way to extract this type of road feature for geometric purposes is through its manual digitalization. The image is georeferenced in the used coordinate projection system using proper GIS software functions, and the road lines are digitalized in a vector file. Otherwise, they can be extracted through a spectral based classification: another raster file can be obtained, which is a qualitative representation of the road signing characteristics, and could be particularly useful to check the signing aspect, e.g. brightness, straight positioning etc. (Fig. 6). This type of file cannot be used to precisely control the geometric characteristics of road signing, because the size of the pixel in the input map - as explained above - is wider than the extension of the signs themselves, so line positioning inside the pixels is not certain.

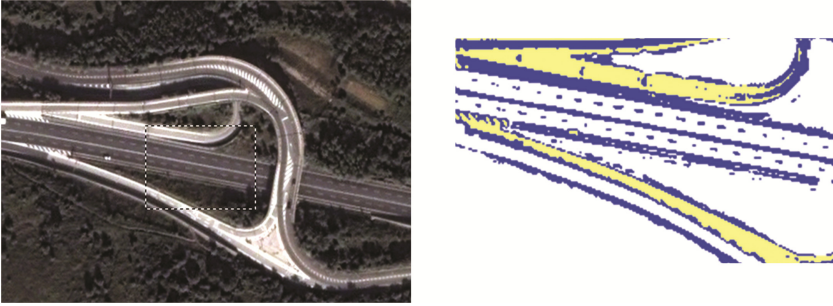


Fig. 6. Particular of road signings extraction.

In Table 1 the geometric road parameters derived from MMS surveys and Remote Sensing analysis are compared with the design project values, thus showing the agreement in curve radius extraction.

Table 1. Comparative values between design alignment, MMS and remote sensing surveys

	Curve radius	First clothoid parameter	First clothoid length	Second clothoid parameter	Second clothoid length
Project Information	250 m	160	102,4	160	102,4
MMS survey	250 m	154	95 m	161	104 m
Remote Sensing survey	252 m	Not detected	Not detected	Not detected	Not detected

4 Conclusions

The aim of this paper was to test and compare different road survey methods in order to select the more suitable one under certain conditions.

Mobile Mapping System (MMS) surveys can lead to a complete description of curve geometries with a very good accuracy, even when curvature radii are variable (clothoid), as frequently happens on motorways.

Similar results were obtained in radius determination through Remote Sensed Images where the radius is constant, and the expected accuracy was reached considering the image geometric resolution.

The analysis of road geometries through Remote Sensing Images could be useful when on site surveys are not possible. Up to now, the exact ending point of the straight lines could not be found by means of remote sensing data, and clothoids parameters could not be calculated. The adopted software and techniques need to be optimized in order to calculate these types of parameters. On the other hand, satellite images can provide further information such as road signing distribution or condition.

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