Sectioning Procedure on Geostatistical Indices Series of Pavement Road Profiles

Mauro D'Apuzzo, Rose-Line Spacagna, Azzurra Evangelisti, Daniela Santilli, and Vittorio Nicolosi

Abstract Road sectioning plays a crucial role in Road Asset Management Systems and nowadays high-speed laser-based devices are able to quickly collect a huge amount of data on pavement surface characteristics. However, collected data cannot be directly employed in road maintenance planning but synthetic values have to be derived and this implies a high computational effort in identifying effective synthetic indices and road homogeneous sections. To this purpose, the Geostatistical tools, in terms of Variogram scheme have been applied for characterizing road surface. "Range" and "Sill" values, deriving from the Variogram application, have been proposed as pavement surface characteristics synthetic indices (namely the macrotexture) to identify different road surfaces. Once that Variogram scheme has been applied, a dynamic sectioning procedure can be employed to detect homogeneous road pavement sections and compared with more traditional descriptors. Preliminary results obtained by an experimental smart road, seem to highlight that the Variogram variables can be promising in both road texture characterization and homogeneous section identification.

M. D'Apuzzo · R.-L. Spacagna · A. Evangelisti (✉) · D. Santilli
Department of Civil and Mechanical Engineering (DICeM), University of Cassino, Cassino, Italy
e-mail: aevangelisti.ing@gmail.com

M. D'Apuzzo
e-mail: dapuzzo@unicas.it

R.-L. Spacagna
e-mail: rlspacagna@unicas.it

D. Santilli
e-mail: daniela.santilli@unicas.it

V. Nicolosi
Department of Enterprise Engineering "Mario Lucertini", University of Rome "Tor Vergata", Rome, Italy
e-mail: nicolosi@uniroma2.it

S. Balzano et al. (eds.), *Statistical Learning and Modeling in Data Analysis*,
Studies in Classification, Data Analysis, and Knowledge Organization,
https://doi.org/10.1007/978-3-030-69944-4_8

Keywords Pavement management · Road surface macrotexture · Geostatistics variogram scheme · Spatial data analysis · Dynamic sectioning

1 Introduction

A Pavement Management System (PMS) is a decision support system that provides effective help to road managers for planning maintenance interventions on a road pavement network in order to reach predefined performance goals that are consistent with budget constraints within a short-, medium-, and long-term scenarios. Nowadays, a PMS acts as a "sub-module" of a more general Transportation Infrastructure Asset Management System comprising all the different facilities (such as safety barriers, lighting or hydraulic systems, geotechnical structures, and so on). However, its basic principles rely on the possibility to describe pavement condition by means of several parameters that can be measured and collected along the road on a routine basis. Among the different parameters collected according to the existing Road Standards and Guidelines [2, 3], pavement surface characteristics [19] are the most significant as they affect several functional properties of road pavements such as the vehicle riding comfort and the tire-road friction, noise, and rolling resistance. Pavement surface characteristics are mainly measured by spectrally decomposing the acquired longitudinal road profiles in order to evaluate the different texture scales. The macrotexture scale, which is associated with the road profile wavelengths lying between the 0.5 and 50 mm range [7, 8, 11, 19], appears to be one of the most critical as it affects skid resistance, splash and spray phenomenon, hydroplaning, tire-pavement noise, and rolling resistance. As a matter of fact, different macrotexture descriptive indices can be derived: one of the most known and used is an indirect measure called Mean Profile Depth (MPD) evaluated according to [2], although more reliable macrotexture synthetic indices have been recently proposed [7] together with new methods for the texture prediction [8]. On the other hand, in the past decades, measuring methods and techniques for pavement condition evaluation made great strides and several High-Speed Laser-based (HSL) measuring devices have been developed and employed. Due to technologies, operating conditions, and intrinsic heterogeneous nature of the road pavement surface, the one-dimensional sampled profile can be affected by noise and invalid readings. For these reasons the HSL data usually undergo a pre-processing (filtering) procedure, according to several approaches [7, 16]. However, the huge amount of data collected cannot be directly used in the databases, but must be previously analyzed, in order to identify the statistically significant values to be associated with each homogeneous road section (pavement condition parameters as almost constant). Several sectioning methods are available in the literature; however, different aspects have to be still investigated in order to identify better synthetic indices for the texture characterization. In this paper, an innovative approach is proposed to describe the macrotexture of road surface employing geostatistical tools for characterizing one-dimensional road profiles. Then the sectioning process has been applied on both traditional synthetic index

(MPD) and spatial index obtained by the geostatistical approach showing a better performance of the latter proposed approach.

2 Geostatistical Tools for Road Pavement Characterization

Geostatistics is a field of the Statistics focused on the study of spatial or regionalized phenomena, which are characterized by a spatial correlation [5]. Thanks to this peculiarity, several applications within environmental aspects have been performed [21, 22] and encouraging results have been achieved from preliminary attempts for the road profiles analysis [10]. In this case, the spatial structure of the pavement texture has been studied using the geostatistical tools, highlighting a correlation between the pavement characteristics (grain size and binder) and the spatial properties of the Variogram. This spatial tool describes the relation between two measured point at "h" distance. The experimental variogram $\gamma(h)$ is estimated following Eq. 1:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (Z(x_i + h) - Z(x_i))^2 \tag{1}$$

where Z(x_i) is the measured variable at location x_i, Z(x_i+h) is the measured variable at location x_i+h, and N(h) is the number of couple of points at h distance. The spatial structure is obtained by modeling the experimental variogram according to the specific functions proposed in literature [5, 18]. The most common simple models are reported in Table 1.

Those variogram models are increasing function with distance, characterized by two properties: the range "a" and the sill "C". The range represents the distance beyond which the data exhibit a spatial correlation, and the sill is the value of the variogram reached the range. Several methodologies are available to automatically fit the chosen model with the experimental variogram. The optimal definition of the

Table 1 The most common simple variogram models

Model	Equation	
Spherical	$\gamma(h) = \begin{cases} C\left[\left(\frac{3h}{2a}\right) - \left(\frac{h^3}{2a^3}\right)\right], & for \quad 0 \le h < a \\ C, & for \quad h \ge a \end{cases}$	(2)
Exponential	$\gamma(h) = C\left[1 - e^{\left(-\frac{3h}{a}\right)}\right]$	(3)
Gaussian	$\gamma(h) = C\left[1 - e^{\left(-3\frac{h^2}{a^2}\right)}\right]$	(4)
Cubic	$\gamma(h) = \begin{cases} C\left[7\left(\frac{h}{a}\right)^2 - \frac{35}{4}\left(\frac{h}{a}\right)^3 + \frac{7}{2}\left(\frac{h}{a}\right)^5 - \frac{3}{4}\left(\frac{h}{a}\right)^7\right], & for \quad 0 \le h < a \\ C, & for \quad h \ge a \end{cases}$	(5)

sill and the range can be obtained by using standard minimization procedures [18]. In this paper, the calculations have been performed with R software [20] and RGeostats plugin [17]. The automatic variogram modeling is based on an iterative least square algorithm, called foxleg [9]. Both MPD and the variogram model properties, are considered as indices of the pavement texture and used to identify the homogeneous pavement sections.

3 Brief Overview on Road Sectioning Methods

Pavement condition data usually vary along the road alignment and since data sampling has always been pursued by means of a discrete approach sectioning method were borrowed by typical industrial process control techniques. The key aspect is based on the identification of the transition point between two adjacent homogeneous sections, namely the "break points". Break points can be detected by means of graphical or statistical approach. The Cumulative Difference Method (CDA) proposed by the American Association of State Highway Transportation Officials (AASHTO) [1] and the method of CUMulative SUMs (CUMSUM) [4] use a graphical approach and became very popular because of the ease of implementation and use in PMS, however, this approach gives rise to some problems related to objective identification of transition points. Statistical approaches offer more sound and automated methods to identify the position of breakpoints since their basic principle relies on the fact that pavement data collected can be described as time series characterized by structural changes. These latter methods can be further distinguished in the following:

- linear, if the algorithm to detect and statistically verify the break points is sequentially applied along the road chainage, thus by an analysis approach based on a moving window,
- non-linear, if the method is applied to the entire dataset thus providing the optimal partition that meets predefined requirements and statistical criteria.

In the former group, the most significant are the Dichotomic method developed by Laboratoire Central du Ponts et Chaussées (LCPC) [15] and the Pruned Exact Linear Time with the Empirical Distribution of the cost function (ED-PELT) [12], whereas at the latter one belong: the Bayesian Methods [23], minimum Root Mean Square (RMS) based methods (MINRMS), or the Linear Model with Multiple Structural Changes (LMSC) Method as the method introduced by James and Matteson [13] and the method developed by Killick, Fearnhead, and Eckley [14]. A benchmarking among these different methods is reported in [6].

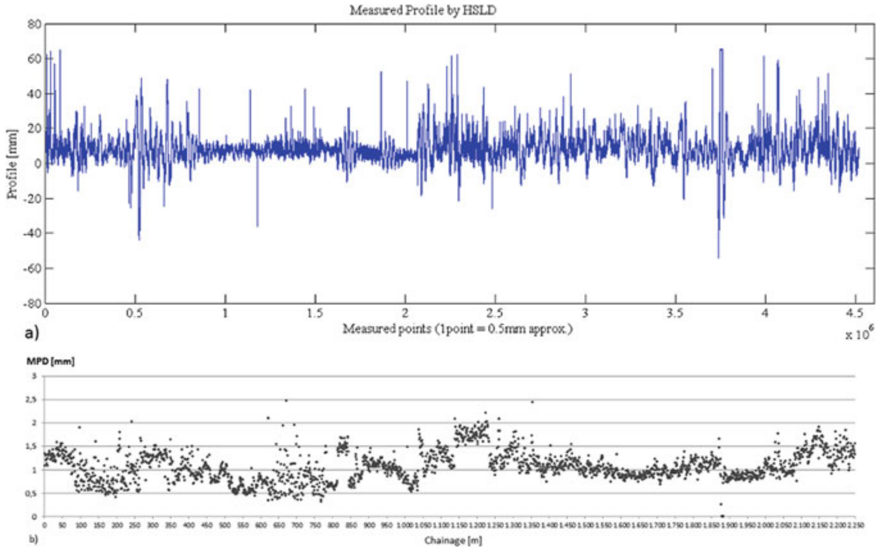

Fig. 1 **a** Measured profile by the HSL and **b** corresponding MPD values along the road profile

4 Data Collection and Analysis

The road pavement characterization is mainly based on the analysis of the road surface, which can be sampled on a one-dimensional or two-dimensional basis. In this paper, a single one-dimensional road profile has been collected with sample spacing of about 0.5 mm (see Fig. 1a) by means of an HSL device, with a laser spot of 0.2 mm and a sampling frequency of 64 kHz. Pavement profile measurement has been performed at the Virginia Smart Road, which is a full-scale, closed test-bed research facility managed by the Virginia Tech Transportation Institute (VTTI), where 24 different road pavement typologies have been laid along an overall length of about 2300 m. According to the [2], the sampled profile underwent a cleaning process, enabling to remove spikes, drop-outs, and data trend. On the filtered profile in parallel the MPD has been evaluated (see Fig. 1b) and the Geostatistical tools have been applied. Due to the one-directional sampling of the collected road profiles, the isotropy and anisotropy analysis has been inevitably reconducted to the evaluation of one-directional experimental semivariograms.

The one-directional experimental semivariograms of the profile have been calculated with a lag distance of 0.5 mm and the number of lag of 30 (15 mm) on a moving window of 1 m. The four models of Table 1 have been automatically fitted (Fig. 2).

In order to identify the appropriate model, statistical tests in term of the Pearson correlation coefficient (ρ), the Kendall rank correlation coefficient (τ), the Spearman's rank correlation coefficient (r_s), and the R^2 (also in term of angular coefficient and intercept), have been calculated and summarized in Table 2. As can be seen, the

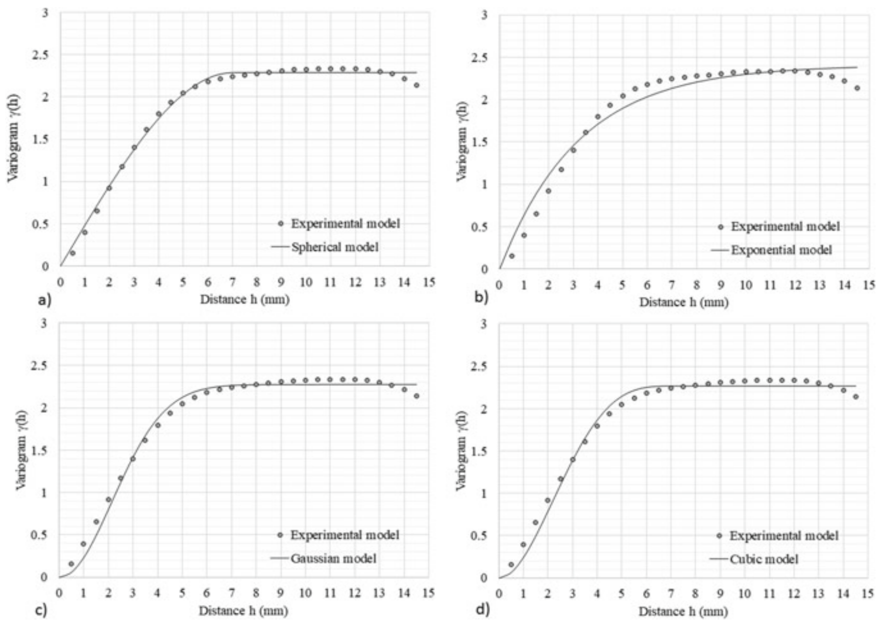

Fig. 2 Experimental semivariogram of a meter of road pavement and **a** Spherical, **b** Exponential, **c** Gaussian and **d** Cubic variogram Models

Table 2 Average values of the statistical descriptors for comparison between the different variogram models

Model	ρ	τ	r_S	R^2	Ang. Coeff.	Intercept
Spherical-Fig. 2a	**0.9880**	**0.7869**	**0.8660**	**0.9763**	**0.9756**	**0.0004**
Exponential-Fig. 2b	0.9877	0.7041	0.8038	0.9757	1.0342	–0.0410
Gaussian-Fig. 2c	0.9787	0.7071	0.8015	0.9582	0.9176	0.0491
Cubic-Fig. 2d	0.9780	0.7737	0.8566	0.9568	0.9166	0.0496

Spherical Model is more appropriate to describe the experimental semivariogram evaluated on the road profiles.

The Range and Sill evaluated by the Spherical model have been represented in Fig. 3. As it is possible to see, the Range and Sill (R&S) series describe two different features of the same measured profile thus providing additional information on structural changes that can be used by sectioning methods.

In order to perform the sectioning process, among the aforementioned statistical methods, the LCPC Method, the ED-PELT, and the methods proposed in [13, 14], on both MPD and the R&S series, have been employed and compared. In this case, the comparison in terms of the number of identified real break points has been summarized in Table 3.

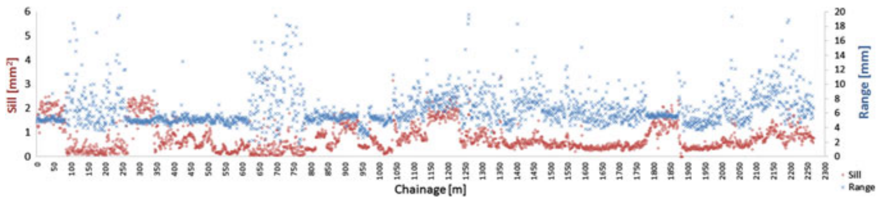

Fig. 3 Sill and range representation along the road profile

Table 3 Identification of the homogeneous segments with different sectioning methods on both MPD and R&S series

Sectioning methods	Series	
	R&S	MPD
ENVCPT package—mean	17/24	15/24
ENVCPT package—AR1	17/24	8/24
ENVCPT package—AR2	16/24	7/24
CHANGEPOIT.NP package (mean)	17/24	13/24
ECP package	11/24	15/24
LCPC	**20/24**	**15/24**

The LCPC method, with a significance level (α) = 5% and sample size of 25, appears to be the more efficient in the identification of the homogeneous pavement road sections, moreover, the R&S indices provide more satisfactory results than the MPD for 5 sectioning methods on 6 tested.

5 Conclusion

In Pavement Management Systems, pavement condition data are nowadays collected by means of high-performance measuring devices. However, the acquired huge amount of data requires a sectioning analysis in order to obtain synthetic descriptors to be used in the planning of maintenance interventions for specific road sections. The basic idea is to apply a Variogram scheme, derived from the Geostatistics field, to the filtered road profile in order to obtain a transformed dataset that is characterized by two statistical descriptors (Range and Sill—R&S). It is believed that this dual representation can better highlight the structural changes in the dataset in order to improve the effectiveness of road sectioning procedures, with respect to more traditional descriptors such as the MPD. A preliminary experimental validation of this procedure has been carried out on real pavement data collected by means of the HSL Device on the Virginia Smart Road (an experimental track that is composed of several pavement sections). Different variogram models have been applied and compared and the Spherical one was more appropriate to describe the road texture; its relative R&S indices have been selected, together with the MPD, for the following sectioning process. In order to detect homogeneous road sections, different methods have been used and compared. The obtained results showed that the R&S indices produce more satisfactory results than MPD (for 5 sectioning procedures on 6) and the LCPC method detects the highest number of real breaks. However, further investigations have to be carried out in order to improve the proposed procedure and to extend the validation to a wider dataset.

Acknowledgements The authors would like to thank Prof. Gerardo Flintsch and the staff of the Virginia Tech Transportation Institute for providing pavement profile data.

References

1. AASHTO: Guide for design of pavement structures, American Association of State Highway and Transportation Officials, Washington D.C. (1986)
2. ASTM E1845-15: Standard Practice for Calculating Pavement Macrotexture Mean Profile Depth, American Society for Testing and Materials (ASTM) International, West Conshohocken, PA (2015). www.astm.org. https://doi.org/10.1520/E1845-15
3. ASTM E965: Standard Test Method for Measuring Pavement Macrotexture Depth Using a Volumetric Technique. American Society for Testing and Materials (2006). https://doi.org/10.1520/E0965-96R06
4. Austroad: Consistency in approaches to road network segmentation and data aggregation – review of current practice. Austroad pubblication No. AP-R276/05, Austroad Inc., Sydney (2005). ISBN 1921139072
5. Chilès, J.P., Delfiner, P.: Geostatistics: Modeling Spatial Uncertainty. Wiley, New York (1999)
6. D'Apuzzo, M., Nicolosi, V.: Detecting Homogeneous Pavement Section Using Econometric Test for Structural Changes in Linear Model. Transportation Research Board 91st Annual Meeting Paper no 12-2125, 0–18, Transportation Research Board, Washington DC, United States (2012)
7. D'Apuzzo, M., Evangelisti, A., Flintsch, G.W., de Leon Izeppi, E., Mogrovejo, D.E., Nicolosi, V.: Evaluation of Variability of Macrotexture Measurement with Different Laser-Based Devices. Airfield and Highway Pavements: Innovative and Cost-Effective Pavements for a Sustainable Future. 294-305. TRIS, ASCE (2015). https://doi.org/10.1061/9780784479216.027
8. D'Apuzzo, M., Evangelisti, A., Nicolosi, V.: Preliminary investigation on a numerical approach for the evaluation of road macrotexture, vol. 10405, pp. 157–172 (2017). https://doi.org/10.1007/978-3-319-62395-8. In Lecture Notes in Computer Science (Including Lecture Notes in Artificial Intelligence and in Bioinformatics)-ISBN:978-3-319-62394. In Lecture Notes in Artificial Intelligence - ISSN:0302-9743
9. Desassis, N., Renard, D.: Automatic variogram modeling by iterative least squares: univariate and multivariate cases. Math. Geosci. **45**, 453–470 (2013). https://doi.org/10.1007/s11004-012-9434-1
10. Ech, M., Morel, S., Pouteau, B., Yotte, S., Breysse, D.: Laboratory evaluation of pavement macrotexture durability. Revue Européenne de Génie Civil, **11**, 5, 643–662 (2007). http://dx.doi.org/10.1080/17747120.2007.9692949
11. Evangelisti, A., Katicha, S., Izeppi, E., Flintsch, G., D'Apuzzo, M., Nicolosi, V.: Measurement error models (MEMs) regression method to harmonize friction values from different skid testing devices (2016). https://doi.org/10.1002/9781119318583.ch12, pp. 159-173. In Materials and Infrastructures, vol. 1,5A - ISBN:9781119318583

12. Haynes, K., Fearnhead, P., Eckley, I.A.: A computationally efficient nonparametric approach for changepoint detection. Stat. Comput. **27**(5), 1293–1305 (2017). ISSN 1573-1375. https://doi.org/10.1007/s1122201696875, https://doi.org/10.1007/s11222-016-9687-5
13. James, N.A., Matteson, D.S.: ECP: An R package for nonparametric multiple change point analysis of multivariate data. J. Stat. Softw. **62**(7) (2014). https://www.jstatsoft.org/
14. Killick, R., Fearnhead, P., Eckley, I.A.: Optimal detection of changepoints with a linear computational cost. J. Am. Stat. Assoc. **107**(500), 1590–1598 (2012)
15. Lebas, M., Peybernard, J., Carta, V.: Méthod de traitement des enregistrements de mesure de densità en continu. Bulletin Liason Laboratoire des Ponts et Chaussées n. 114, Juillet-août (1981)
16. Losa, M., Leandri, P.: The reliability of tests and data processing procedures for pavement macrotexture evaluation. Int. J. Pavement Eng. **12**(1), 59–73, Taylor and Francis (2011). https://doi.org/10.1080/10298436.2010.501866
17. MINES ParisTech/ARMINES: RGeostats: The Geostatistical R Package. Version: 12.0.0. (2020). Free download from: http://cg.ensmp.fr/rgeostats
18. Olea, Ricardo A.: A six-step practical approach to semivariogram modelling. Stoch. Environ. Res. Risk Assess **20**, 307–318 (2006). https://doi.org/10.1007/s00477-005-0026-1
19. PIARC: Optimization of Pavement Surface Characteristics, PIARC Technical Committee on Surface Characteristics, Report to the XVIIIth World Road Congress, Brussels, Belgium (1987)
20. R Core Team: R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria (2020). https://www.R-project.org/
21. Saroli, M., Albano, M., Modoni, G., Moro, M., Milana, G., Spacagna, R.L., Falcucci, E., Gori, S., Scarascia Mugnozza, G.: Insights into bedrock paleomorphology and linear dynamic soil properties of the Cassino intermontane basin (Central Italy). In Engineering Geology - Volume 264 (2020) 105333 - https://doi.org/10.1016/j.enggeo.2019.105333
22. Spacagna, R.L., Modoni, G.: Gis-based study of land subsidence in the city of Bologna. In: Mechatronics for Cultural Heritage and Civil Engineering, pp. 235–256 (2018). https://doi.org/10.1007/978-3-319-68646-2_10
23. Thomas, F.: Statistical approach to road segmentation. ASCE J. Transp. Eng. **129**(3), 300–308 (2003). https://doi.org/10.1061/(ASCE)0733-947x(2003)129:3(300)