

From manual to automatic pavement distress detection and classification

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Abstract—Detection and classification of distresses is a fundamental activity in the road pavement management. Even in the early stages of deterioration, road pavement needs to be monitored to identify problems, evaluating the actual conditions and predicting what the future conditions will be. Monitoring activities through manual/visual inspections are time consuming, costly and cause of safety concerns. For these reasons, distress identification is usually limited to few sections randomly selected. The introduction of new high efficiency equipment for distress detection and classification is opening new perspective in road pavement analysis and management. Automatic pavement monitoring and Mechanistic design are introducing new pavement performance indicators and criteria for distress classification. Previous studies show lack of correlations between indexes derived from manual and automatic pavement monitoring. Therefore, capability to derive manual distress parameters from automatic monitoring systems is of great interest in the definition and testing of criteria and methodological approaches. In this paper, a background is reported by referencing examples of North American and Italian tests for the detection and classification of distresses from manual survey and capabilities of the state-of-the-art Automatic Road Analyzer (ARAN 9000) as well. An infield experiment and calibration of a Probabilistic Neural Network Classifier is presented for deriving distress measures from automatic systems.

Index Terms—Automatic Road Analyzer, Distress classification and rating, Pavement Condition Index, Pavement Management System, Neural Network,

I. INTRODUCTION

Periodical pavement condition inspection is one of the most important steps in implementing a comprehensive Pavement Management System (PMS). Such an inventory system involves dividing the pavement network into logical segments, recording descriptive segment inventory data, and collecting pavement performance information relating to these segments. These processes provide critical information to determine maintenance and rehabilitation requirements and

project priorities, and to carry out long term planning. The purpose in performing, manual or automated, pavement condition surveys is to document the actual conditions and to build progressive deterioration curves. Therefore, consistency in locating, defining, and recording the surface defects is critical.

In literature, different indexes are reported for the overall evaluation of pavement condition. The difference between each other is given by the number of distresses included in the computation and the required precision in the distress identification and rating based, also, on the techniques applied for the survey. Pavement Condition Index (PCI) from ASTM 2011 [1] is a relevant example of computation of pavement performance based on visual and manual survey of a limited part of the network assumed as statistically significant. Apart from the complexity of the methodology for the index computation, all manual procedures are based on the same principle: distresses must be visually identified on the pavement surface, and rated if required, basing on mostly qualitative or quantitative parameters in order to calculate a unique number able to represent/classify the sample unit under investigation. As mentioned, due the time restrains, the procedure of survey, identification and rating of distresses must be carried out for a fixed number of sample units covering from 20% to 10% of the whole network extension basing on the desired reliability in the computation (usually 95% confidence). In Italy, one example of manual for distress collection is the SITEB distress inventory manual [2]. SITEB manual defines both the distresses classification and rating (low/medium/high) basing on qualitative and/or quantitative measures which depend on the distress considered and survey technique (visual vs. instrumental) [3].

The introduction of new high efficiency equipment for distress detection and classification is opening new perspective in road pavement analysis and management. Speed of execution, precision of the measurement, restricted number of operators, safety conditions for operator and road users, no needs for sampling the survey area and chance of multiple measures in a same run are only a part of the advantages in the use of new technologies/equipment for pavement analysis. For example, the introduction of laser profilometers is moving the attention on the International Roughness Index (IRI) [4] which gives a global evaluation of the pavement unevenness related to the ride quality. Not only the pavement monitoring issues, but also the introduction of the Empirical-Mechanistic design of pavements is moving the

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distress selection from comprehensive indices (e.g., PCI and PSI) to disaggregate distress classification related to pavement deterioration models (e.g., IRI, alligator cracking area and severity, linear cracking width and length, rut depth). For these reasons, the effort of the road agencies and the research community is moving towards those distress identification and analysis instead of the previous distress categories based on manual/visual procedures and empirical design approaches. Even if the future of pavement monitoring relies on automatic detection, manual inspection and derived distress indexes remain of interest both for low budget road agencies and for retrospective evaluation of pavement distress curves based on historical data. Therefore, the problem of integration of the old databases with the new measurement systems is still of great interest.

Below, a literature review is presented taking as reference two of the most representative indexes: PCI from manual/visual inspection, and IRI from automatic survey. Given the controversial results in the correlations between those parameters and the lack of studies referring to the SITEB manual, the present research moved a step forward, focusing on the capacity to relate automatic survey of distresses to indices dealing with manual survey. After several trials with failing of traditional statistical regression approach, only a nonparametric classifier (the Probabilistic Neural Network, PNN) was able to provide acceptable results pointing out the complexity of the problem and encouraging to further investigate the topic.

II. OLD INDEXES (PCI) VS NEW ONE (IRI)

The relationship between IRI and PCI was investigated by different authors, finding controversial results. The correlation between PCI and IRI is of interest because it may represent a link between the old manual approach and the new automatic approach for pavement analysis. Dewan et al. [5] in 2005 conducted a study using data from Californian Highways and Freeways developing a linear relationship between the PCI and IRI. The model showed that IRI is a good predictor of the PCI based on the strong correlation between the two variables and an R^2 value of 66% for the model. Furthermore, the p-value and the t-test showed the acceptability of IRI as a predictor variable of PCI at a 99% significance level. Based on the Dewan research work the FHWA set some qualitative correlation between PCI and IRI reported in the following Table I.

TABLE I.
FHWA PAVEMENT CONDITION CRITERIA.

Road Quality Terms	IRI Threshold (m/km)
Good	<1.50
Acceptable	<2.70

Park et al. [6], in 2007, using data from different states of North Atlantic region, found an exponential relationship between PCI and IRI. Using IRI as a predictor variable of the PCI, they finalized that the former accounts for the majority, close to 59%, of the variation of the latter.

Arhin at al. [7] in 2015 analyzed the variation of IRI and

PCI using data from District of Columbia in a time frame from 2009 to 2012, considering their variation and finding a strong relationship between the two indicators for different road categories in urban area. Particularly, the results underlined a linear relationship between IRI and PCI with a R^2 of about 56%.

Another model with a linear relationship for IRI as a function of PCI was developed for the Bay Area cities and counties in California Dewan et al. [8] with the intent of using the model in estimating user costs/benefits in their pavement management system. The model's R^2 value was 53% with a coefficient of variation of 28%.

Shahnazari et al. [9] developed in 2012 a genetic algorithm and an artificial neural network to predict PCI using only the main distresses and their severities using a sample of Iranian Highways for the training and testing of the system. The results demonstrate the strong validity of the methodology with a R^2 of 99% for the artificial neural network and 98% for the genetic programming.

Vidya et al. [10] in 2013 built a neural network model to estimate IRI from PCI based on data obtained for construction work zones. The results shown an R^2 value of 0.86 and MSE of 0.041 which indicate that the performance of neural network was satisfactory and feasible for the prediction IRI starting from PCI data.

In 2014, Arhin et al. [11] has studied the relationship between IRI and PCI for different pavement and road typologies, by using data of Washington DC in different years (2009, 2010 and 2012). Their findings indicate a poor correlation between IRI and PCI in the logarithmic equation form chosen by the authors.

The presented literature review on the topic, even considering different road categories and road environment is related only to the correlation between IRI and PCI (Table II). The reason is that the computation of PCI, which requires manual investigation, does not allow to report partial results. In other terms, PCI is given by the combination of more distresses and severities, homogenized introducing the deducted values and their correct expression.

TABLE II
SUMMARY OF MODELS REPORTED IN LITERATURE REVIEW.

Jurisdiction	Model
California (highway and freeway) [5]	IRI=0.0171(153-PCI)
US Mid-Atl. States and Canada [6]	$\log(\text{PCI})=2.0436\log(\text{IRI})$
Washington DC [7]	$\ln(\text{IRI})=6.672-0.42\text{PSR}$
California [8]	Various linear model form
Iran [9]	Artificial Neural Network
Iran [9]	Genetic programming
Washington DC [11]	Various logarithmic model form

Given the not full successful results in the correlation between the PCI and IRI, the present paper moved a step forward by comparing some of the distresses included in the SITEB distress inventory schema with the automatic classification by limiting the investigation in this stage of the research to the ability of the automatic survey system to identify the presence of a distress if it was identified manually. At this aim, a simulation of a manual survey was performed

on the VISION software and the results were compared with some elaboration of the longitudinal pavement surface profile and the IRI.

III. NEW TECHNOLOGY AND EQUIPMENT

A. Advanced technologies for pavement monitoring

The growing needs of distress detection for effective Pavement Management Systems, under the light of the Mechanistic design for Quality Assurance/Control (QA/QC), has brought to the development of High-tech equipment to monitor and evaluate the pavement conditions in a high efficiency way. In this framework, the development of LiDAR technology has brought to a high point density (based on the laser technology) able to detect even the smallest crack on pavement surface. One of the advantages in the use of LiDAR is the georeferenced 3D reconstruction of the surveyed area with a precision close to 1mm in the 3 directions, with a 360° detection of the road environment. Unfortunately, this kind of survey generates a huge amount of data, which are nowadays still difficult to analyze and queried. Furthermore, in the case of road pavement, one of the element to take into account is that the 360° survey generates overabundant information. Moreover, to avoiding masking effects, the detection must be performed with angles as close as possible to 90° with respect to the pavement surface. As a result, development of Laser Crack Measurement Systems (LCMS) obtained the advantage to get information only from the pavement surface with a higher point density and detail at higher survey speed. The technology of LCMS allows to survey several transversal sections of the pavement surface in the direction of motion. This shape data is available every 5mm along the road in the direction of travel, at 1mm transverse resolution. The LCMS system employs high speed cameras, custom optics, and laser line projectors to acquire 2D images and high resolution 3D profiles of road surfaces that allow for automatic detection of cracks and the evaluation of macrotexture and other road surface features. Designed for both day and nighttime operation in all types of lighting conditions, the system is immune to sun and shadows and is capable of measuring pavement types ranging from concrete to dark asphalt. The LCMS can be operated at speeds of up to 100 km/h on road lanes as wide as 4 m. Each transversal profile, given by a series of points generated by LCMS is univocally identified by the linear chainage and GPS global position.

Collected data can be processed with analysis software to automate the characterization a wide range of distresses (mainly, cracks, ruts, potholes, raveling, macro-texture) [12].

Longitudinal unevenness is collected by more traditional class 1 laser profilers with accuracy complying the ASTM standards [4]. Other works [13][14][15] have also looked at a relationship between longitudinal profile and surface parameters as well as the use of more well established pavement texture measures such as SMTD, MPD and IRI, as previously discussed in the paper.

B. Equipment

ARAN 9000 is one of the most efficient equipment that allow to collect data from pavement and infrastructure features with a productivity of 200 km/day.



Fig. 1. ARAN 9000 of University of Catania.

The ARAN available at the transport Infrastructure laboratory of Catania University uses a Mercedes Sprinter vehicle where three PCs working in synchrony to collect data coming from the installed systems:

- SOP Laser, consisting of 2 laser to 16 kHz LMI SLS5000-200/300 and 2 accelerometers PCB 3711.
- SmartTexture measurement system, consisting of 1 laser 64 kHz LMI Optocator 2008-128 to measure the macro texture of the road;
- LCMS measurement system, uses high speed cameras, featuring dedicated optics and 48 laser line projector to acquire either in 20 images (black and white images) or high resolution 30 profiles, giving three dimensions surface of pavement with millimeter accuracy;
- 2 GPS L2 (DGPS), OM/, /MU, 3 cameras (2 front and 1 rear).

C. Capability of New technologies to identify traditional visual distress

The available software used e.g. by FUGRO® and Pavemetrics® for processing the LCMS provide an automatic detection of distresses on the pavement surface by combining the use of the images and of the 3D analysis of the points generated by LCMS.

The 3D texture of the pavement surface, generated by LCMS, contains enough information for detecting, measure and classify different distress basing on a flexible setting of several parameters that need operator expertise and calibration trials, as well. Looking e.g. to the PCI classification, LCMS can be used for identification and rating of a large amount of the 17 distresses included in the model such as joint reflection cracking, Lane/shoulder Drop off, potholes, rutting, raveling and all the surface and edge cracking. While few distresses need to be classified and rated manually, such as bleeding, patching, polished aggregate. Another set of pavement surface characteristics of PCI is related to unevenness. Those

distresses are: bumps and sags, corrugation, railroad crossing, shoving, swell and depression. As mentioned in the literature review, those irregularities in the pavement surface are not univocally correlated to the IRI automatically calculated from the laser profiles.

Any information was found in the literature on similar studies considering the Italian SITEB manual as reference.

IV. ANALYSIS

A. Data

Data used for the present research work are available in Asset Transport Open Database (AsTrO Database), an open database created in the framework of a research project at the University of Catania.

Pavement data in AsTrO Database contain longitudinal pavement profiles along two wheel paths and LCMS transversal profiles. That rough data were elaborated using dedicated software (e.g. VISION from Fugro, and PROVAL from FHWA) to detect distresses and longitudinal profile indices as reported in Table III.

TABLE III
NEURAL NETWORK SETTING PARAMETERS

Distresses	DATA
Transversal Cracking	LCMS
Longitudinal Cracking	LCMS
Block Cracking	LCMS
Alligator Cracking	LCMS
Edge Cracking	LCMS
Potholes	LCMS
Raveling	LCMS
Joints	LCMS
Dropoffs	LCMS
Rutting	LCMS
Roughness	LCMS/Laser profiler
IRI	Laser profiler
Straight Edge	Laser profiler

The 5.5 km of road lanes composing the dataset were subdivided in fixed interval 5 m long and 4 m wide, resulting in 1108 segments. In each segment, if a distress is present, information about type, extension and severity are provided.

The SITEB manual, like other similar visual inspection procedures (e.g. FHWA, Distress Identification manual [8]), applies a distress classification suitable mainly for manual inspections. Table IV shows the compliance between the two inspection procedures (manual vs. automatic). Specifically, it is possible to identify the SITEB distresses that can be automatic detected and rated by using data collected by the ARAN or other similar systems.

The previous Tables show as distress typologies related to cracking (R/6, R/7, R/8, P/1, P/2), potholes (A/4, P/4) and rutting (R/2) can be automatically identified, measured and rated. As far as, the pavement surface deformations are concerned, some of them are rated by IRI and area of cracking (i.e. R/1, R/3, R/4, R/5), others are related to deformation area (P/3) or depth (P/5).

Even if IRI can be easily calculated from the longitudinal pavement profile, that information is usually related to the mean value of long sections (e.g., 100 m) and it is not able to

discriminate between different distress typologies (R/1, R/3, R/4, R/5). Analogously, for P/3, P/5 that are not classified in the SITEB manual as irregularities, but which are component of the surface deformations.

Therefore, for identifying and classifying those distresses a different approach for the analysis of data collected by automatic system must be defined.

TABLE IV
DISTRESSES IN SITEB MANUAL, PERFORMANCE INDICATOR, AND THE POSSIBILITY OF AUTOMATIC DETECTION.

DISTRESSES	CODE	INDICATOR	AUTOMATIC
Corrugation	R/1	IRI	yes
Rut	R/2	Mean Rut depth	yes
Bumps & Sags	R/3	Area of Cracking	yes
Depression	R/4	IRI	yes
Unevenness of pavement surface	R/5	IRI	yes
Edge Cracking	R/6	N/D	yes
Block Cracking	R/7	Area of Cracking	yes
Joint Cracking	R/8	N/D	yes
Low Potholes	A/4	Number Standard Potholes	yes
Long. & Trans. Cracking	P/1	Structural Number	yes
Alligator Cracking	P/2	Area of Cracking	yes
Extended Depressions	P/3	Area	no
Deep Potholes	P/4	Number Standard Potholes	yes
Localized Depressions	P/5	Depth	no

To improve the accuracy in the identification of local pavement surface deformations, the IRI was re-calculated by using a reduced base of 5 m, two different values of straight edge were applied (3 and 5 m) calculating the maximum deviation and extension of the area with overall deviation higher than 12.5 mm. The presence of a surface deformation (R/1, R/3, R/4, R/5, P/3, P/5) was manually collected for each of the 1108 segments composing the sample. Table V shows the frequency distribution of the distress manually classified.

TABLE V
DISTRESSES FREQUENCY DISTRIBUTION.

Value	Number	Frequency
No Distress	1029	0.9287
P3	7	0.0063
P5	34	0.0307
R1	4	0.0036
R3	24	0.0217
R4	2	0.0018
R5	8	0.0072

B. Methodology

After same trials for searching a statistical correlation between distress (dependent variable) and straight edge or IRI values (independent variables), that shows very bad results (e.g. largest adjusted R-Squared values of 6%), the classification of distresses was carried out by using a neural network classifier.

The Probabilistic Neural Network Classifier (PNN) implements a nonparametric method for classifying observations into one of g groups (Classification Factor) based on p observed quantitative variables (Input variables). Rather than making any assumption about the nature of the

distribution of the variables within each group, it constructs a nonparametric estimate of each group's density function at a desired location based on neighboring observations from that group. The estimate is constructed using a Parzen window that weights observations from each group according to their distance from the specified location.

Observations are assigned to groups based on the product of three factors:

1. the estimated density function in the neighborhood of the point.
2. the prior probabilities of belonging to each group.
3. the costs of misclassifying cases that belong to a given group.
4. The sphere of influence of the Parzen weighting function may be specified by the user or optimized via jackknifing.

To test the ability of the neural network to identify the distresses, the database was adapted considering a 0-1 code when the distress is not present or present respectively. At the end the distressed analyzed were P/3, R/4, and, R/5.

Input variables: IRI, Straight edge 5 m and 3m.

Classification Factor: categorical variable containing an identifier of each distress (R/1, R/3, R/4, R/5, P/3, P/5).

Validation set: cases, randomly selected, withheld from the training set for validation.

The network consists of four layers:

1. An input layer with p neurons, one for each of the input variables.
2. A pattern layer with n neurons, one for each case that will be used to train the network.
3. A summation layer with g neurons, one for each output class.
4. An output layer, also having one binary neuron for each output class that turns on or off depending on whether or not a case is assigned to the corresponding group.

Conceptually, the input layer provides the information from the p predictor variables by feeding their values to the neurons in the pattern layer. The input values are standardized by subtracting the mean of the n training cases and dividing by the sample standard deviation. The pattern layer passes the values through an activation function, which uses the input values to estimate the probability density function for each group at a given location.

$$g_{ij} = W \left(\frac{X - X_i}{\sigma} \right) \quad (1)$$

If observation i belongs to group j and $g_{ij}=0$ otherwise. σ is a scale parameter that controls how quickly the influence of a point decays as a function of its distance from X. W is the Gaussian function:

$$W = \exp \left(- \frac{\|X - X_i\|^2}{\sigma^2} \right) \quad (2)$$

The spacing parameter σ may be specified by the user, may be iteratively tried to maximize the percentage of observations correctly classified, or may be ignored and an observation at point X always matched to the group corresponding to its nearest neighbor.

The density estimates are then passed to the summation layer, which combines the information from the n training cases with prior probabilities and misclassification costs to derive a score for each group. The scores are then used to turn on the binary neuron in the output layer corresponding to the group with the largest score and turn off all other output neurons.

C. Results and discussion

The neural network (Fig. 2) was trained under certain conditions, summarized in the following Table VI and results validated on a part of the dataset not used for training.

TABLE VI
NEURAL NETWORK SETTING PARAMETERS

	Prior Probability	Error Cost
No Distress (code: 0)	0.9000	1.0
Distress (code: 1)	0.1000	10.0
training set: 600 - validation set: 508		
Spacing parameter: $\sigma=0.2$		

The different prior Probability, reflects the actual distribution between sections with and without distresss under consideration. The different Errors costs were selected to give more weight to the wrong identification of distresses (faulse negative) for reducing the chance to missing sections with distress.

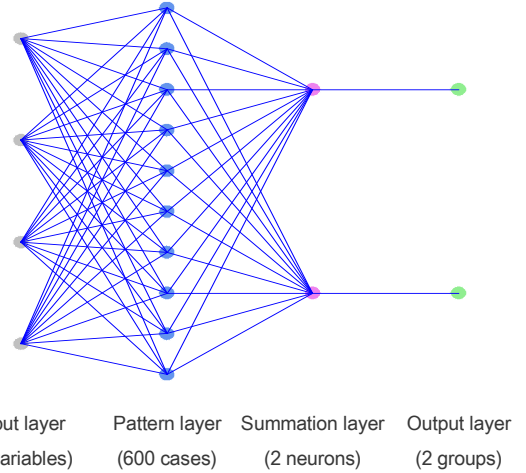


Fig. 2. Neural network structure

The input variables are, alternatively, the Straight Edge (SE) parameters (extension, maximum deviation) or the 5 m IRI for the right and left wheel paths. Output layer include two groups for the classification of the presence or not of the distress.

From Table VII reports the results of the neural network calibration, either the training and the validation set for SE of 5 and 3m and IRI.

TABLE VII
ALL DISTRESS IDENTIFICATION

Training Set			Validation Set	
Straight Edge 5 m				
<i>Distress</i>	<i>Members</i>	<i>Classified [%]</i>	<i>Members</i>	<i>Classified [%]</i>
0	554	90.4	479	90.7
1	46	52.2	29	39.4
Total	600	87.5	508	87.4
Straight Edge 3 m				
0	558	94.5	475	92.5
1	42	32.0	33	17.2
Total	600	89.3	508	88.2
IRI				
0	550	84.7	483	83.3
1	50	48.7	25	52.5
Total	600	83.3	508	80.9

Results demonstrate as the PNN classifier improved noticeably the significance of the statistical relationship between unevenness parameters and visual inspection distresses. While the regression analysis was able to explain only 6% of the variance in the dependent variable, PNN classified about 90% of the sections without distress and 50% of the sections with a distress. Moreover, from the comparison of results, using as input variable different unevenness parameters, 5 m Straight Edge figures out the best results, previous mentioned.

V. CONCLUSION

Despite the increasing development and implementation of automatic systems for detection of road pavement surface characteristics, manual/visual distress classification remains of interest because of the equipment costs and as historical database for development of deterioration models.

Therefore, transferability of results from automatic systems to manual ones is still an open issue. Moreover, international studies, showing uncertain results, are not always applicable to different national systems. In that framework, the present research work, with reference to the SITEB manual for pavement maintenance, showed as 12 of the 14 distress measures can be automatically calculated by using high quality data provided by LCMS and Laser profilometers. Nevertheless, 2 types, depth of localized depressions (P/5) and area of extended depressions (P/3), cannot be automatically measured and unevenness typologies (R1, R3, R4, R5) can be measured by IRI as requested, but not precisely positioned inside long segments.

The application of a Neural Network classifier improved considerably the capability to identify surface deformations within very short section (e.g. 5 m) by using the 5 m Straight Edge extension and deflection parameters derived from the laser profile. Due to the limited number of sections characterized by the presence of surface deformations, it was not possible to classify separately each distress typology. Nevertheless, results are promising for future developments with larger dataset and for the identification of the 5 m SE as the best profile parameter to be used in that effort.

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