Table 1: Comparison between PASER, PSCI and EPCI

Section	**Description of condition**	**PASER**	**PSCI**	**Average frame-entropy**	**EPCI**
A	New construction	10	10	5.42	1.00
B	Recent overlay, like new	9	10	5.45	4.54
C	Low-severity raveling	7	8	5.69	32.82
D	Medium-severity longitudinal cracking	6	6	5.72	36.36
E	High-severity transverse cracking, low-severity longitudinal cracking	5	5	5.76	41.07
F	Low-severity patches	5	5	5.8	45.79
G	High-severity raveling, medium-severity patching	4	5	5.98	67.00
H	High-severity patches, high severity longitudinal and transverse cracking, high-severity raveling	3	3	6.08	78.79
I	High-severity alligator cracking	2	2	6.16	88.21
J	Road disintegration of surface. Pavement failure	1	1	6.26	100.00

condition index, as presented below. The entropy values are normalized to a 1-100 scale and used as a condition rating index, while also calibrated against two of the most widespread pavement condition indices, called Pavement Surface Evaluation and Rating (PACER) and Pavement Surface Condition Index (PSCI). The pavement condition indices of PACER and PSCI were selected because: (a) they are currently used by transportation authorities; (b) the way they are used as well as their description for each level of the scale are clear; (c) they consider almost all possible pavement defects of asphalt pavements. The developed index is also divided into severity levels, with each level including possible pavement defect types.

The proposed system was tested by use of videos collected from roads (of approximate total length of 10 km), separated into lane sections of 50 m. The selection of the 50m-lane sections was based on a review of 56 different pavement manuals used by different DOTs, and on interviews of pavement engineers/experts. The entropy value of each frame is calculated using Equation 1, followed by the calculation of the average of entropy values for all images of the 50m-section. The average frame-entropy is then normalized to a scale from 1 to 100 (Equation 2) and compared with the PASER and PSCI indices. Figure 4 shows 10 representative frames collected from 10 different sections. Table 1 presents the defects that exist in these sections, the pavement condition rating by PASER and PSCI, the average frame entropy and its normalized value.

$$x' = a + \frac{(x - A)(b - a)}{(B - A)} \qquad (2)$$

where:

x': normalized value
x: initial value
A: lowest entropy value in the dataset (i.e. 5.42)
B: highest entropy value in the dataset (i.e. 6.26)
a: lowest normalized value (1)
b: highest normalized value (100)

The comparison in Table 1 clearly shows that as the values of PASER and PSCI decrease, the normalized entropy value increases. Thus, the latter can be used as a pavement condition index, with similar results with the other two indices. It also has the advantage of being a continuous variable, compared to the other two indices that are integer and have only ten possible values. After reviewing all collected data, Table 2 was created to divide the entropy-based pavement condition index (EPCI) into levels. Each level characterizes the general pavement condition, while Table 2 also includes the possible pavement defects that might exist in every level, along with their severity level (low (L); medium (M); high (H)). The values of EPCI corresponding to possible defects were defined based on the conducted case study (10 km-length road network). It should be noted that the current paper presents work in progress. Thus, these values need validation, testing the developed system in other road sections.

Table 2: Entropy- based pavement condition index

Entropy-based index	**Pavement defects**	**General pavement condition**
1-32	No defects.	Healthy
33-35	Raveling or bleeding (L). Longitudinal or transverse cracking (L).	Very good
36-40	Raveling or bleeding (M). Longitudinal or transverse cracking (M). Block cracking (L)	Good
41-55	Raveling or bleeding (M). Longitudinal or transverse cracking (H). Block cracking (M). Edge cracking (L). Patching (L)	Fair
56-70	Raveling or bleeding (H). Longitudinal or transverse or block cracking (H). Edge cracking (M). Patching (M). Shoving or rutting or distortion (L).	Fair
71-80	Raveling or bleeding (H). Longitudinal or transverse or block or edge cracking (H). Alligator cracking (L). Patching (H). Shoving or rutting or distortion (M). Potholes (L)	Poor
81-95	Alligator cracking (M or H). Patching (H). Shoving or rutting or distortion (H). Potholes (M or H)	Very poor
95-100	Disintegration of surface	Failed

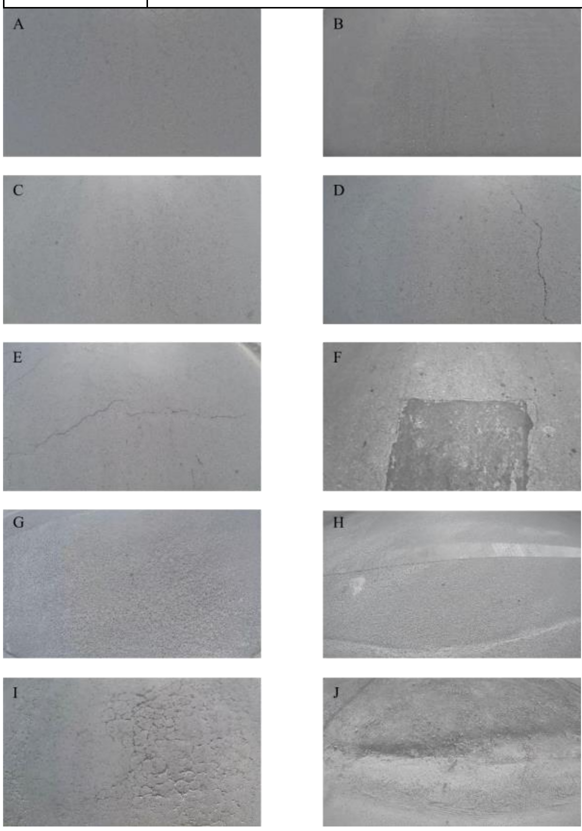

Figure 4: Frames from the examined roadsections

Traffic Volume Index

A vision-based method for traffic monitoring, provides the data needed for the development of a novel traffic volume index (TVI) (Figure 5). An already developed algorithm, called “Detecting Cars Using Gaussian Mixture Models” (The MathWorks, Inc., 2010), included in the Computer Vision System Toolbox of MATLAB, formed the basis of the automated traffic monitoring system. The initial algorithm was modified so that it is able to classify vehicles into three classes (Figure 6) and count the number of vehicles belonging in each class.

Firstly, a video is imported, from which frames are extracted, with the first frames being used to initialize the foreground. Moving objects (foreground) are segmented from the background. The algorithm utilizes the morphological “opening” to remove the noise and to fill gaps in the detected objects. Figure 6 shows the initial foreground mask computed by the detector as well as the improved foreground mask (after the application of morphological opening) for a two-wheeled vehicle, a light vehicle, and a heavy vehicle.

The following step finds the bounding box of every connected element corresponding to a moving vehicle, using the Matlab command “vision.BlobAnalysis” that tracks and computes statistics for a set of connected points in a binary image. Once detected, the vehicles are classified into one of three classes based on the number of connected pixels. The minimum and maximum number of connected pixels, for the examined video resolution (640 x 360), for each class are the following: 4500 and 11000 for two wheeled-vehicles; 11000 and 30000 for light vehicles; and more than 30000 for heavy vehicles, respectively. These numbers were arrived at through a search over the range of 3,000 to 40,000 connected pixels in increments of 100, to identify the best performing district connectivity count based on the performance of the testing set. Finally, the vehicles of each class are counted. This method has an overall recall of 94.07 %.

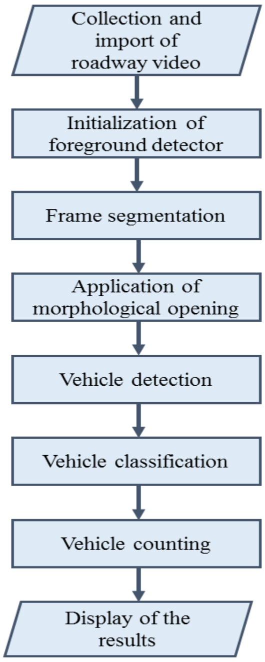

Figure 5: Main stages of the proposed traffic monitoring system

Figure 6: Initial foreground mask and improved foreground mask for: (a) a two-wheeled vehicle; (b) a light vehicle; and (c) a heavy vehicle

Presented herein is the way the counted vehicles are used to estimate the novel TVI. The three different classes of vehicles are transformed into Passenger Car Equivalent (PCE) to estimate traffic flow. Additionally, the daily proportion of PCE/hour is normalized to a scale from 1-100. This value is combined with the EPCI to form the final maintenance prioritization index (MPI).

PCE is a metric used in Transportation Engineering, to evaluate the traffic flow rate on a roadway. A PCE represents the influence that a mode of transport (vehicle type) has on the traffic variables of headway, speed and density, compared to a single car (light-vehicle) (Ahuja, 2007). Various research studies estimated the PCE of different modes of transport. Table 3 represents the PCE values of the three vehicle classes examined by this paper, as introduced by (Webster, 1958), Tiwari et al., (2000), Minh and Sano, (2003), Prasetijo (2007) and Partha et al. (2009). The median PCE value of these studies, for each class, is used for the purpose of this study (last row of Table 3).

Table 3: PCE values, proposed by various research studies and the current work

Study	Two-wheeled vehicles	Light vehicles	Heavy vehicles
Webster (1958)	0.3	1	2.25
Tiwari et al. (2000)	0.4	1	2.4
Minh and Sano (2003)	0.29	1	-
Prasetijo (2007)	0.3	1	3.1
Saha et al. (2009)	-	1	2.16
Proposed system	0.3	1	2.3

After automatically counting all vehicles of each class and calculating the daily proportion of PCE/hour for an examined road lane, a traffic volume index is calculated. Lane capacity varies due to a number of conditions, such as lane width, neighboring lanes, elements next to the road, number of driveways, presence of parking and speed limits. The range of lane capacity is between 1000 and 4800 PCE/hour. Normally lane capacity is between 1500 and 2400 passenger cars per hour (Austroads, 2013).

The aforementioned lane capacity numbers serve as guides for the normalization of the proportion of PCE/hour to a range between 1 and 100 (Equation 2). The maximum number of 4800 PCE/hour is transformed into the value of 100. Additionally, 2400, 1500, and 1000 PCE/hour are converted into the traffic volume index values of 90, 80, and 70, respectively. Everything in between is normalized accordingly. For instance, the values of vehicles/hour between 4800 and 2400 are normalized intro the TVI values between 100 and 90, while the values of vehicles/hour between 2400 and 1500 are normalized intro the TVI values between 90 and 80.

Maintenance prioritization index

This paper proposes the evaluation of pavement condition and traffic, dividing a roadway network into lane sections of 50 m. Every section is rated by the proposed EPCI and TVI. The combination of the two indices provides the final MPI, which also ranges from 1 to 100. The weighted arithmetic mean is utilized for calculating the MPI (Equation 3).

$$\mathrm{MPI} = \frac{\mathrm{w1} * \mathrm{EPCI} + \mathrm{w2} * \mathrm{TVI}}{\mathrm{w1} + \mathrm{w2}} \quad (3)$$

A weighted arithmetic mean is estimated by data points that do not contribute equally to the final average. In case of all weights being equal, then the weighted arithmetic mean equals the arithmetic mean. The current paper proposes an equal contribution of traffic and pavement condition, after advised by pavement experts. However, transportation authorities can utilize the proposed maintenance prioritization method, selecting the weights of EPCI and TVI according to their needs and priorities (pavement condition or traffic volume of a section).

A case study was conducted to test and validate the presented MPI in the roadway network of Nicosia, Cyprus. The EPCI was tested by use of videos acquired from roads of total length of 10 km, with a classification accuracy of 89.2 %. However, the TVI was tested in a portion of these roads (of total length of 1 km), with an overall recall of 94.07 %. Thus, the final MPI, which depends on both EPCI and TVI, was estimated for the common 1 km-length roadways. These roads were divided into 20 equal road sections of 50m-length. Firstly, EPCI, TVI and MPI were calculated for each section, and secondly, sections maintenance was prioritized, with the section with the highest MPI being first in the prioritization list.

Conclusions

Transportation authorities normally have to select the road sections that they will be maintained amongst many sections, due to budget constraints. This paper proposes a maintenance prioritization technique for 50 m-length sections of roadway lanes. Each section is rated by a novel index (MPI), which is a combination of the proposed pavement condition (EPCI) and traffic volume (TVI) indices. The following characteristics summarize the advantages of the proposed method compared to existing maintenance prioritization systems:

- The EPCI is a continuous variable with a range from 1 to 100.
- The MPI considers not only pavement condition but also traffic volume.
- The maintenance prioritization system provides not only the theory on the calculation of the MPI based on the EPCI and TVI, but also the vision-based tools for automated assessment of pavement condition and traffic.

Future work includes the investigation of other factors that might be taken into account for the prioritization, such as maintenance and rehabilitation cost, and road width. The weights given to each considering factor for calculating the weighted arithmetic mean will also be explored. The final proposed solution should be tested and validated by a greater case study in a real road network.

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