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ORIGINAL PAPER

Image Based Techniques for Crack Detection, Classification and Quantification in Asphalt Pavement: A Review

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Abstract Pavement condition information is a significant component in Pavement Management Systems. The labeling and quantification of the type, severity, and extent of surface cracking is a challenging area for weighing the asphalt pavements. This paper presents a widespread review on various platform and image processing approaches for asphalt surface interpretation. The main part of this study presents a comprehensive combination of the state of the art in image processing based on crack interpretation related to asphalt pavements. An attempt is made to study the existing methodologies from different points of views accompanied by extensive comparisons on three stages of methods—distress detection, classification, and quantification to facilitate further research studies. This paper presents a survey of the developed pavement inspection systems up to date. Additionally, emerging and evolution technologies considered to automate the processes are discussed.

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1 Introduction

Visually inspecting the infrastructure and evaluating them by subjective human experts is the simplest method [277]. This approach, however, involves high labor costs and produces unreliable and varying results [87, 203]. Furthermore, it exposes the inspectors to dangerous working conditions on highways. Destructive Testing (DT) and Non-Destructive Testing (NDT) are both costly and time consuming [229, 288]. To overcome the limitations of the subjective visual evaluation process, various attempts have been made to develop semi-automatic and automatic procedures (Montero et al., [77, 114, 169, 191, 203, 285, 286]. Ideally, an automated system could be used as an alternative of the human eye, which could quickly detect and quantify diverse types of cracking and spalling in any size, in rapid collection speed, and different weather conditions [152, 226].

Recently, departments of road maintenance, repair and transportations have become more interested in using automatic systems for pavement assessment. The rate of making and utilization of computer vision methods for pavement engineering applications have been exponentially increased [114].

Recently, massive research attention has been given to developing automated and semi-automated procedures for pavement assessment and evaluation [114, 277]. Non-destructive evaluation techniques, such as Digital Image Processing (DIP) [77], Ground Penetration Radar (GPR) [213, 294], fiber optic sensors [34], laser systems (LS) or Hybrid systems (HS) [77, 213] are emerging procedures for health monitoring [30, 203]. For consistency and uniformity of data collection and promoting the data's quality, cost-effective automated systems and modified algorithms are proposed [2, 87, 277, 295, 296]. Most pavement

cracking analyzer systems use machine vision and image processing models to automate the process and moderate problems [2, 43, 229, 272]. However, due to the irregularities of pavement surfaces, there has been limited success in correctly detecting, classifying, and quantifying cracks. In addition, most systems require complex algorithms with high levels of computing power. While many attempts have been made to automatically collect pavement crack data, better approaches are necessary to evaluate these automated crack measurement systems under various conditions [48, 173, 229, 288, 295, 296]. Implementation costs, processing speed, repeatability, accuracy, objective and accurate detection or evaluation for these cracks and reducing the operation cost are very important tasks in this kind of system [77].

The characteristics of type, severity, and extent of pavement surface cracking are primary features for assessing the condition of asphalt pavements [246, 253]. For nearly all the methods, three groups have to be taken into account, the Image Acquisition Group (IAG), Image Processing Group (IPG) and Image Interpretation Group (IIG).

This paper covers these three groups and presents a survey of the developed semi-automatic and automatic systems for becoming up to date (Figs. 1, 2).

1.1 Image Acquisition Group (IAG)

Previously, Jahanshahi et al. [87], Koch et al. [114] and Chambon and Molirad [30] reviewed automatic distress detection methods and devices. Diverse types of systems have been used to simplify data gaining using equipped vans. Non-contact evaluation techniques classified as the Charge-Coupled Device (CCD) [165], Ground Penetration Radar (GPR), Laser Systems (LS) [109] or Hybrid systems (HS) [77, 149, 158] are innovative procedures for health monitoring [23, 30, 152].

Generally, these systems employ CCD cameras, thermal cameras, laser sensors, Electro-optical sensors [65], three-dimensional (3D) cameras [6, 149, 183] or a mélange of this device [61] like the Kinect sensor [158, 220].

Based on our knowledge, nearly all commercial systems need a powerful illumination system to prepare uniform

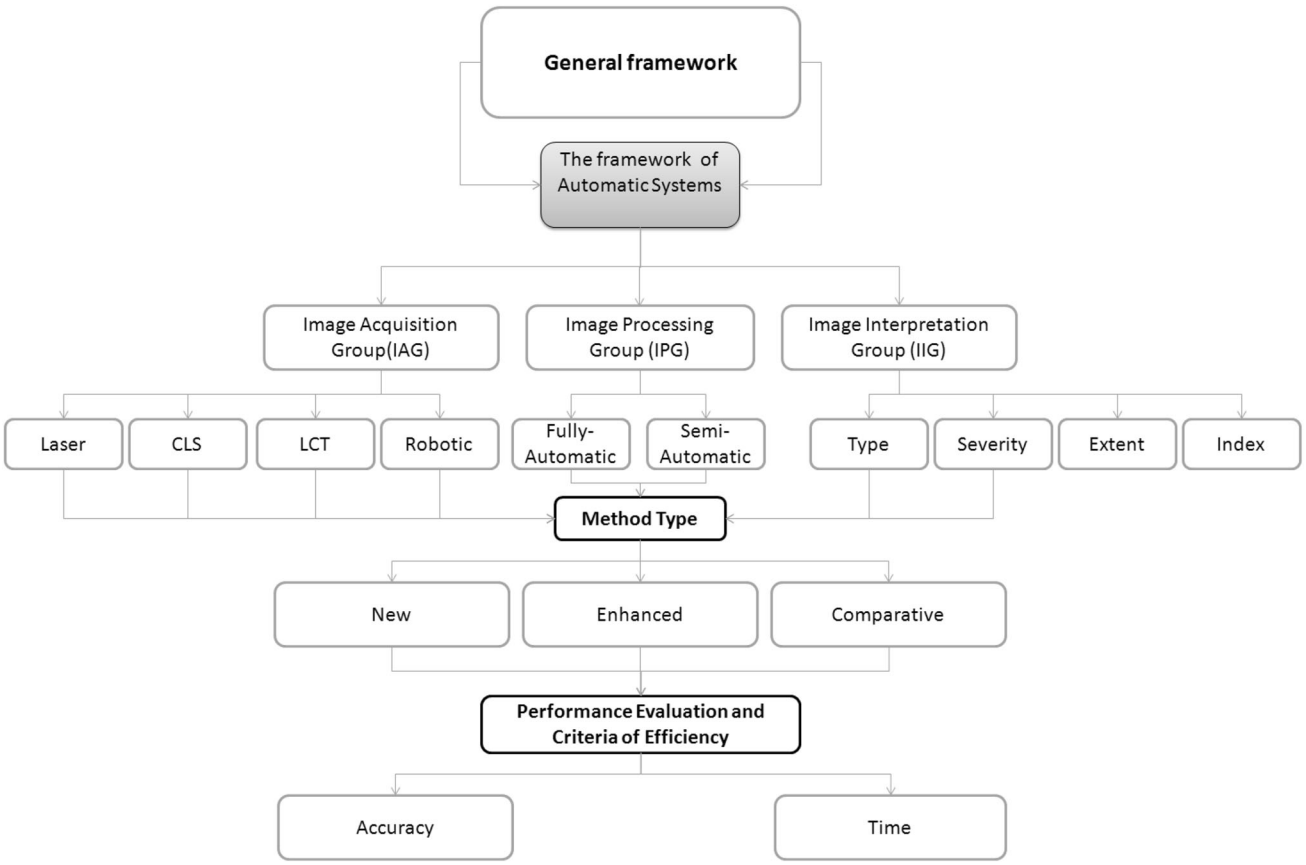


Fig. 1 The framework of automatic systems for pavement distress detection and classification

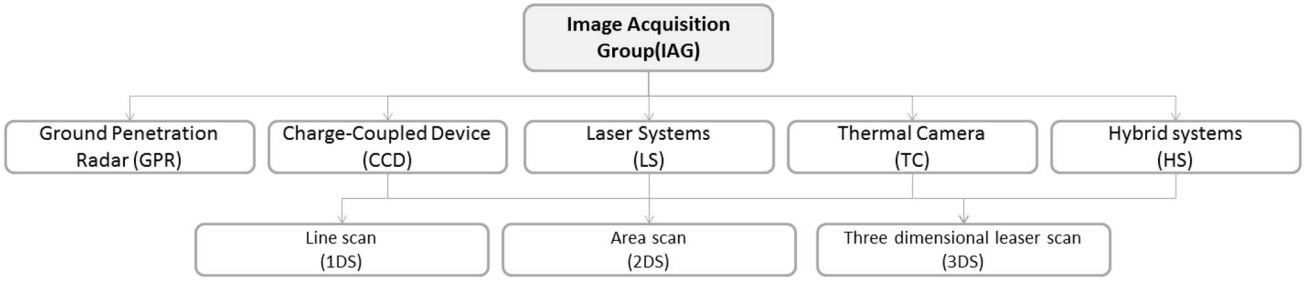


Fig. 2 The framework of IAS for pavement

lighting conditions for capturing images [218]. Automated Road Analyzer (ARAN), Digital Highway Data Vehicle (DHDV), Automated Distress Data Acquisition (ADDA), Automated Crack Monitor (ACM), SIRANO, Highways Agency Road Research Information System (HARRIS), Automated Distress Analyzer (ADA), AIGLE RN, AMAC, Profilograph and laser, Road Excellent Automatic Logging (REAL), Road Crack, ADVantage, PAVUE, CREHOS, RIEGL VMX-450 System [66], SIRANO and GIE are systems for capturing pavement surface images [30]. Manufacturing and supporting this equipment is very expensive and the result of the analysis highly depends on the circumstances and employed sensors [80, 153]. Additionally, images obtained from these systems are very discrete and automatically deciding on the type of distress is a difficult and time consuming task. Therefore, in order to improve the quality of images taken from the pavement, more powerful tools are needed.

Many scientists have developed inspection robots in order to increase safety and convenience during assessments [35, 40, 69, 211, 212]. Various motivations such as the safety, efficiency, and quality have promoted the increased use of robotic systems. The results demonstrate that the UAV is capable of carrying out difficult missions independently [185, 203]. The use of robotics rapidly increased in many fields of civil engineering because of its benefits [44, 100]. Some applications of robotics consists of: making highway material, construction of roads and pavement (including quality control and compaction), pavement maintenance and operations (including inspection and monitoring), and evaluation in unsafe and difficult-to-access locations like tunnels and bridges. However, it is luxurious and expensive. Robotics uses high technology and requires extraordinary facilities. It is sensitive, complicated, and often requires expensive machineries that need special training to operate and maintain.

The robotic systems [242] involve three parts according to Fig. 3: (1) A specially designed car, (2) A robot instrument and control system and (3) A machine vision system (Montero et al., [174, 235, 275, 297].

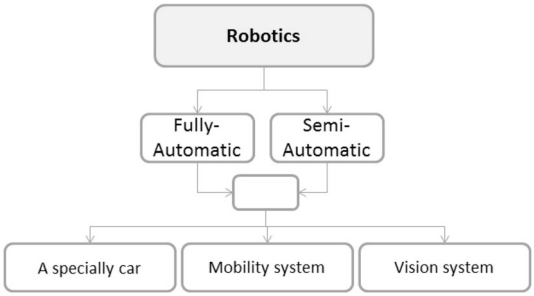


Fig. 3 The general components of robotic systems

Robots have superior flexibility, mobility and movement, are more appropriate and have the capability to moderate the labor required, making them very suitable for surveying responsibilities. Robots can operate without human control which means they are autonomous and independent. Robots can convey several kinds of devices and integrate with different controllers [235].

Recently, scientists have made wide applications in the field of the UAV system for the unmanned aerial vehicle (UAV) for the monitoring of structures and maintenance controls (1999, [19, 155, 185, 195, 280]. The potential of UAV is recognized by modern photogrammetry and remote sensing [46]. The UAV systems provide a new platform for data acquisition [195, 212]. They believed that the experiences with the UAV systems are useful and practical for other applications [19, 84, 212]. These systems are tested in autonomous surveillance, photogrammetric for 3D modeling, remote-sensing, monitoring of bridges and super structures, infrastructures like pipelines, bridges and roads [212]. Recently, Zhang and Elaksher presented a UAV based imaging system for the 3D evaluation of rural roads surface distresses [284]. It was good demonstrating the potential of this sort of system for future practice. This is mainly due to the low cost, fast speed, high maneuverability, and high safety of UAV systems for collecting images. UAVs are already replaced over satellites and manned vehicles. Moreover, they have overcome the disadvantage of low flexibility and high cost of aerial imagery [46]. Quadcopters have distinct advantages compared to other existing UAV approaches. Some of the advantages

are its low cost of manufacturing and maintenance, its flexibility and maneuverability to work in a very hard and complex surveying mission, the controllability in both autonomous and pilot mode, and manageable in abnormal circumstances, like storm, winds, snowy and rainy weather. In this paper, a new attempt has been made to use a Quadcopter UAV instrument to capture pavement images [284]. Table 1 shows a survey vehicle for the collection of data at normal speeds.

The new robotic developed is a Quadcopter Unmanned Aerial Vehicle (QUAV) for pavement inspection. The QUAV was selected because of its low cost and high flexibility to operate in a very complicated mission. The hardware architecture is shown in Fig. 4. The developed system—Rahbin—is assembled with:

Four sets Tarot 4114 320 kV Out runner Brushless Motor, 4 set 40 Amp OPTO Brushless Motor, ESC Speed Controller, Carbon Fiber Quad copter Frame, Main controller, Power Management Unit (PMU), GPS, LED, flight control, telemetry system, GoPro 2Axis Brushless Gimbal All Multi-Rotor, Head Track Video Goggles and LCD for monitoring, 5.8 GHz 8CH FPV Transmitter for sending data, AV Receiver, LCD, and 2 set Radio controller.

Its total size in diameters is 100 cm. The QUAV is able to produce an absolute thrust of 3 kg. Its empty (without battery and camera) and gross weight is 500 and 1000 g, respectively. The flight control system serves both aided and programmed mode. An autopilot software (Grand Station NAZA-M V2) is utilized on the main computer system. The software GUI enables the user to define a mission plan according to Google map and sets the height, speed, rote mission, and resolution of distress. Additionally, 3D MapDisplay, Real-time Flight Monitoring, One Key Takeoff, Joystick/Keyboard Mode, One Key Go Home, Click Go Mode, Waypoints Editing, Automatic Takeoff and Landing, F Channel Controller, General Purpose Servo Action and Photogrammetric Tool can be used. The Gopro Camera has a wide range of resolution (5, 7, 12, 14 Mega pixel). The Flight Control Unit (FCU) is the central part of the QUAV. It is able to apply autonomous inspection based on predefined scenarios. The Inertial Measurement Unit (IMU) is used to identify the additional information data (such as alignment, acceleration, and altitude). The four Brushless set motor controllers receive their orders from the FCU to adjust the rotational speed of the motors. The FCU is connected to a GPS receiver and a compass to increase navigational capabilities.

Since it is very maneuverable—'location hold', 'coming start point', and 'flight according to pre identified waypoints'—it could be useful in all kinds of situations and dangerous positions for surveillance. An expert can generate the new waypoints based on the footprint of regions of interest, for example flying the QUAV in a circle, network, polyhedral, zigzag, curved or other more complex patterns with the ability of staying in the air for 45 min and a distance of nearly 7 km at the speed of 4 m/s. The QUAV used in this work required it to travel above 2000 m with a variable operating altitude in the range of [1–100] m. However, it is not restricted. The pavement surface information of the lane is collected via a transmitter device sent to the host computer, where the proposed method for classification of pavement distress algorithms is implemented. The images that show distress will be detected and saved in the pavement Distress Data Base (DDB). Also, the positioning information indicating where the images are taken that is obtained from a global positing system is saved. Existing systems have shown good performance to collect new forms of pavement surface images.

From Table 1 it can be extracted that the current state-of-the-art Image Acquisition Group (IAG) works well with the mechanization of data collecting. However, there are currently no intelligent platforms available that work autonomously, with low cost and high speed. With the growth of technology, the number of automatic and robotic systems grows quickly. The USA is the greatest user of the system. However, other countries are interested in using this technology seriously. More than any sensor, the two-dimensional (2D) camera is used. Recently, the Robotic Image Acquisition (RIA) system, as an emerging technology over other systems, has been addressed for management and inspection. Smart flying robots will be replaced by experts and automatic/semi-automatic systems in the coming years.

1.2 Image Processing Group (IPG)

Recently, pavement surface image processing played a central role in automatic bridges and pavement assessment systems and scientists have paid more attention to this field [160], 1994, [30, 87]. Champion and Moliard [30] mentioned that image processing is an important step for the success of the automatic road pavement assessment [30]. Based on a review about image processing methods for pavement crack detection and classification, every method can be exploited in six assumptions [30]:

Based on Table 2, assumptions H_{G3}, H_{PGH1} and H_{T1} have a small degree of ambiguity that is also ambiguous. The use of fuzzy theory, especially the Type II, can lead to good results (Figs. 5, 6, 7).

The Histogram Analysis Methods are widely used methods. These methods are fast and simple in the field of image processing. However, the mathematical morphological tools show better results than HAM's. The next group is learning tools that are not fast and fully automatic methods. The Filter based method is not fully adoptive because the scale, size and width of cracks is not constant

Table 1 The semi-automatic and automatic image acquisition systems based on different IAG, dimension and method type

No.	References	Year	Country	IAG	Dimension	Method	Speed (Km/h)	Use
1	ADDA Jahanshahi et al. [86]	1991	USA	CCD	2DS	SAI	M	P-APR
2	ACM Chambon and Moliard [30]	1991	USA	CCD	2DS	SAI	M	P-APR
3	SIRANO Chambon and Moliard [30], Jahanshahi et al. [86]	1991	France	CCD	2DS	SAI	M	P-APR
4	HARRIS Pynn et al. [187]	1999	UK	LS	1DS + 3DS	AIA	H	N-APR
5	ADA-APSI-4096 Chambon and Moliard [30]	2007	USA	HS	3DS + 2DS	SAI	H (100)	P-APR
6	AIGLE RN Chambon and Moliard [30]	2008	France	CCD	2DS	SAI	M	P-APR
7	AMAC Chambon and Moliard [30], Jahanshahi et al. [86]	2004	France	HS	1DS + 2DS + 3DS	SAI	H	N-P-APR
8	Profilograph and laser Chambon and Moliard [30]	2007	Denmark	LS	3DS	SAI	H	N-APR
9	REAL Chambon and Moliard [30]	1992	Japan	HS	3DS + 2DS	AIA	H	N-P-APR
10	ARAN Jahanshahi et al. [86]	2003	Canada	HS	3DS + 2DS	AIA	H	N-P-APR
11	PAVUE	1999	Sweden	CCD	2DS	AIA	H	P-APR
12	RPDIS Ferguson et al. [56]	2003	Australia	CCD	2DS	AIA	H	N-APR
13	ASDMS	2005	USA	CCD	1DS	LS	H	P-APR
14	VSDT Laurent and Doucet [121]	2005	Canada	LS	1DS	AIA	H	P-APR
15	RoadCrack Chambon and Moliard [30]	1999	Australia	CCD	2DS	AIA	H (105)	P-APR
16	PCDS 长安大学 [300]	2009	China	LS	1DS	AIA	H	P-APR
17	HSPSSPS Reeves [194]	2011	Australia	CCD	2DS	L	H	L-APR
18	APIS	2011	Iran	CCD	2DS	L	M	L-AIA
19	APCA Jahanshahi et al. [86]	2013	USA	HS	3DS	SAI	M	L-P-APR
20	RIEGL VMX-450 Guan et al. [66]	2015	China	HS	3DS + 2DS	AIA	H	P-APR
21	Tadbir gar	2008	Iran	HS	3DS + 2DS	SAI	M	P-N-APR
22	Bostan sanaat	2013	Iran	CCD	2DS	SAI	H	N-APR
23	ACSM Kim et al. [110, 112]	1998	USA	CCD	2DS	RIA	S	P-APR
24	LCSM and 2TLS Velinsky et al. [240], Yoo and Kim [273]	1998	USA	CCD	2DS	RIA	S	P-APR
25	OCCSM Velinsky et al. [240]	2003	USA	CCD	2DS	RIA	S	P-APR
26	ARMM Kim et al. [110, 112], Kim and Haas [111]	1997	Korea	CCD	2DS	RIA	S (1.08)	P-APR
27	ACSTM Yoo and Kim [273]	2015	Korea	CCD	2DS	RIA	S	P-APR
28	PathRunner	1990	USA	HS	3DS	AIA	H	N-APR
30	Samsung		USA	CCD	2DS	RIA	S	P-APR
31	An innovative UAV Zhang and Elaksher [284]	2012	USA	HS	3DS	RIA	H	P-UPR
32	UAV Grandsaert [64]	2015	USA	HS	2DS	RIA	H	L-APR
34	Rahbin: QUAV	2016	Iran	CCD	2DS	RIA	H	L-P-APR

Image acquisition group (IAG)	Dimension	Use	Speed
Ground penetration radar (GPR)	Line scan (1DS)	Laboratory (L)	Low (L)
Charge-coupled/digital device (CCD)	Area scan (2DS)	Project (P)	Medium (M)
Laser systems (LS)	Three dimensional (3DS)	Network (N)	High (H)
Hybrid systems (HS)		Concrete paved road (CPR)	
Method		Asphalt paved road (APR)	
Semi-automatic image acquisition (SAI)		Unpaved road (UPR)	
Automatic image acquisition (AIA)			

Table 1 continued

Image acquisition group (IAG)	Dimension	Use	Speed
Robotic image acquisition (RIA)			

ADDA automated distress data acquisition, *HARRIS* highways agency road research information system, *ACM* automated crack monitor, *APCA* autonomous pavement condition assessment (University Of Southern California), *SPS* stereo pavement scanner, *RPDIS* road pavement deterioration inspection system, *ASDMS* automated surface distress measurement system (The University Of Texas System), *VSDT* vision system and a method for scanning a traveling surface to detect surface defects thereof (Institute National D'optique), *PCDS* pavement crack detection system based on image and the detection method thereof, *ADA* automated distress analyzer, *DHDV* digital highway data vehicle, *APSI-4096* automated pavement surface imaging model 4096, *REAL* road excellent automatic logging system, *HSPSSPS* high speed photometric stereo pavement scanner, *ARMM* automated road maintenance machine, *OCCSM* operator controlled crack sealing machine, *TTLS* transfer tank longational crack sealer, *APCS* automated pavement crack sealer, *APIS* automated pavement inspection system, *ACSTM* automated crack sealer with telescopic manipulator, *ARMM* automated road maintenance machine, *ACSS* automated crack-sealing machine, *LCSM* longitudinal crack sealing machine, *2TLS* transfer tank longitudinal sealer

[126, 208, 232]. Most approaches in the model based methods are based on local/global analysis [30, 80, 114, 173, 226, 229, 246, 247, 279, 288, 295, 296, 298].

1.2.1 Pre-processing (PPS)

The asphalt pavement images are not captured under the same lighting condition (day/night), (sun/cloud) and some of them contain unwanted objects like random particle textures, inhomogeneity [263], non-uniform illumination and irregularities in the surface of the pavement, [289] shadows [282], very noisy environment lines [4, 175], water, tire marks, oil spills [219] and etc. As a result, selecting a uniform threshold is a very challenging issue in the segmentation step, therefore designing an effective pre-processing step is vital for obtaining good results [114, 159, 167, 168]. This step is related to accentuation, or sharpening features like edges, boundaries, or contrast to analysis. Image enhancement covers a wide range of classes including noise reduction, fuzzy edge eliminating, filtering, interpolation, magnification, contrast stretching, histogram modeling, transform operations, false coloring and pseudo coloring. The challenging part of pre-processing is quantifying for enhancement. Nearly all of these approaches are empirical and require an interactive procedure to get the optimum results. In the field of pavement distress analysis, some of the common image enhancement techniques are shown in Fig. 8.

Point operations are zero memory which are mapped into gray level based on transform $v = f(u)$. Contrast stretching, noise clipping and thresholding, gray-level windows slicing, bit extraction, bit removal and range compression are several of these transformations.

Many methods are based on spatial operations performed on local neighborhoods of input pixels. These kinds of enhancement operators convolved with an image called spatial mask. The spatial averaging and low pass filtering, directional smoothing, median filtering, un-sharp mask and crisping, spatial low pass, high-pass, and band-pass filtering, inverse contrast ratio mapping and statistical scaling, magnification and interpolation are some examples of this operator.

Fig. 4 The general components of **a** semi-automatic (SAI) and automatic image acquisition (AIA), **b** kinect sensor [85, 158], **c** RIEGL VMX-450 a system with an inset picture of the laser scanners, cameras, and the navigation system [66, 265], **d** Telemaster UAV [64] and **e** Robotic Image Acquisition (RIA) systems

The next class is the transform operation enhancement method in which zero-memory operators are performed on a transformed image followed by the inverse transformation. Generalized linear filtering, root filtering, generalized spectrum, and homomorphic filtering are several examples of this operator.

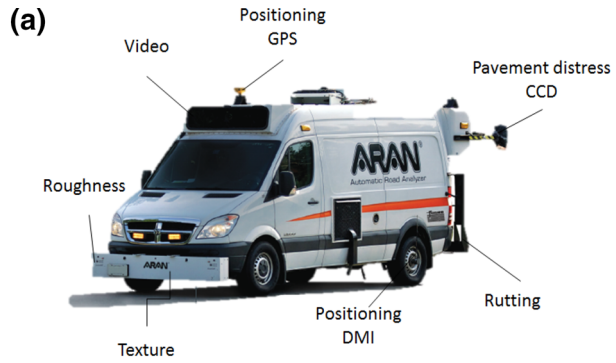
Generally, these methods are application dependent, and the final enhancement algorithm can be obtained by trial and error. Modern approaches employ hybrid or complex functions, which enable the user to enhance the image based on its applications (detection, classification, and quantification).

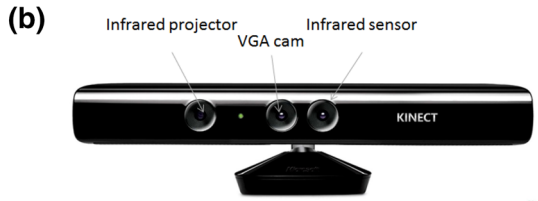
Yao et al. [267] have developed a new imaging system with the ability of scan pavement surface without using any artificial lighting for solving the noise and artifacts in images. The paired images [130] contain balancing details that are employed for making an image in which the shadows effects are moderated [267].

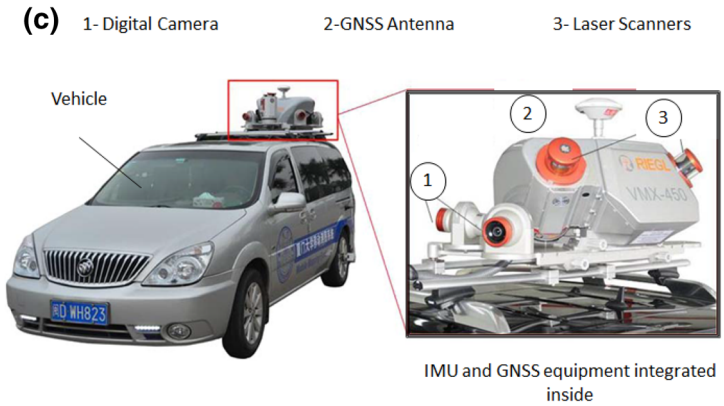
Gavilán et al. [61] proposed an adaptive road crack detection system by pavement classification. The first step was pre-processing that was carried out to both smooth the texture—spatial operation class—and enhance the linear features [61].

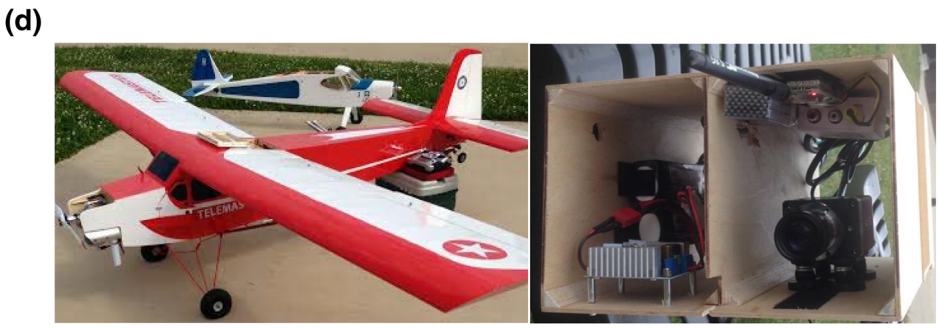
Zhou et al. [293] proposed an illumination invariant image enhancement and segmentation mode, which are crucial for feature extraction and classification. The experimental results show that the method was efficient for the illumination invariant and the irregularities in the surface of asphalt pavement [293].

Jiang et al. [93] used a new crack enhancement algorithm based on the Electromagnetism-like Mechanism


(a)
Positioning
GPS
Video
Pavement distress
CCD
Roughness
ARAN
Rutting
Positioning
DMI
Texture


(b)
Infrared projector
VGA cam
Infrared sensor
KINECT


(c)
1- Digital Camera
2-GNSS Antenna
3- Laser Scanners
Vehicle
1
2
3
RIEGL
VMX-450
IMU and GNSS equipment integrated inside


(d)


(e)
Radio controller
Blades
GPS
Monitor
Cover
RC receiver
Motors
Motors
LED positioning Lightning
FPV
Mount
Radio controller
Frame
Landing gear
Camera
Battery
Landing gear

Table 2 Various Assumptions based on semi-automatic and automatic crack analysis methods

Assumptions	Description	References
H_{P1}	Crack pixels are darker than the background	Chambon and Moliard [30], Amhaz et al. [7]
H_{P2}	Independence in the gray—level distribution	Zou et al. [298], Grandsaert [64]
H_{G1}	Thin continuous object	Oliveira and Correia [179], Tang and Gu [224]
H_{G2}	A set of connected objects	Jahanshahi and Masri [90], Tsai et al. [230]
H_{G3}	Various widths	Oliveira and Correia [179]
H_{PGH1}	Vague character of the points inside the crack	Tang and Gu [224]
H_{T1}	Pattern analysis in transformed domain	Salman et al. [202]

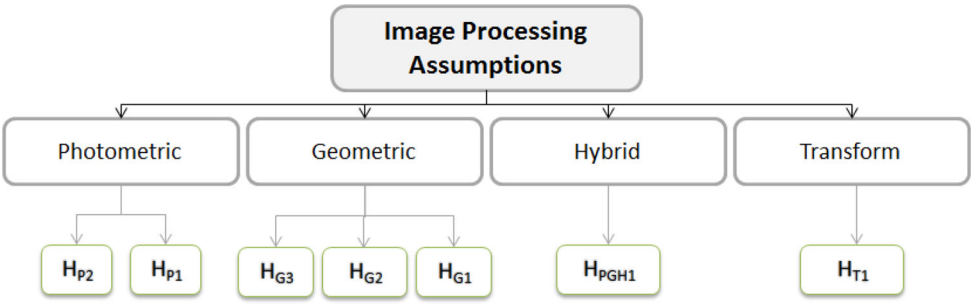


Fig. 5 The general classification of hypotheses of Semi-automatic (SAI) and Automatic image processing (AIP) methods based on visual analysis

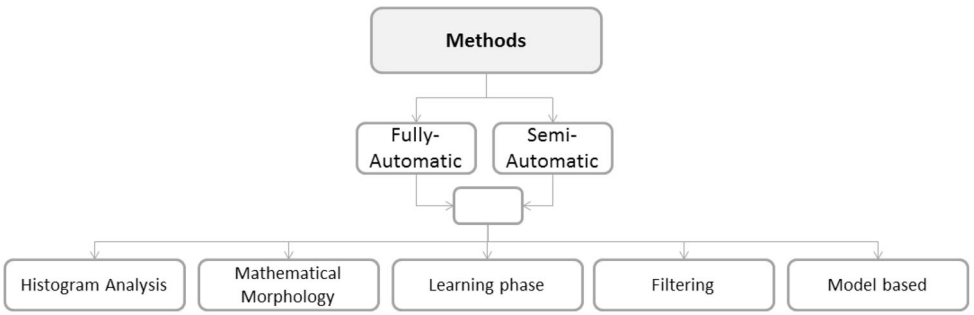


Fig. 6 Five families that are proposed for semi-automatic and automatic methods in the field of image processing distress detection and classification [30]

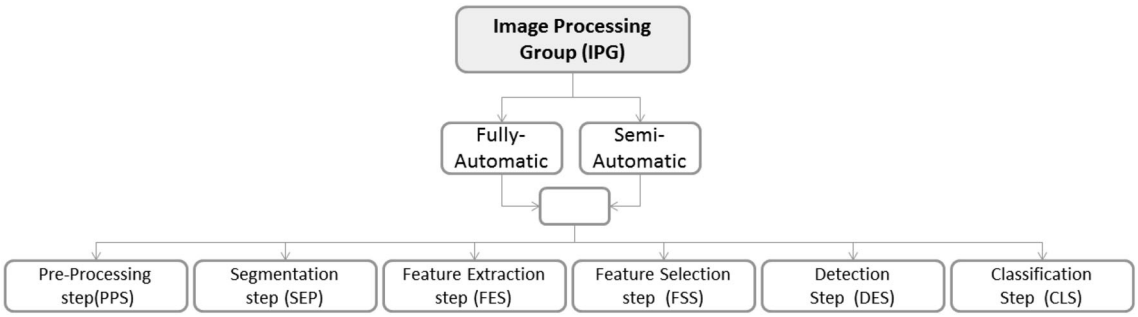


Fig. 7 The framework of IPG for pavement distress detection and classification

(EM) to interpret the crack images. Local neighborhoods of pixels are divided into strong and weak neighborhoods and noise points. The idea of Shuffled Frog-Leaping Algorithm (SFLA) is used in the EM Algorithm for linking global and local information search. Experimental consequences demonstrated that the algorithm proposed is good at crack enhancement and it shows better performance in image segmentation [93].

Li et al. [130] used the grey entropy to the road surface image enhancement to lay a good foundation for the automatic detection of cracks. They applied the grey entropy to characterize the scale of the increase or decrease

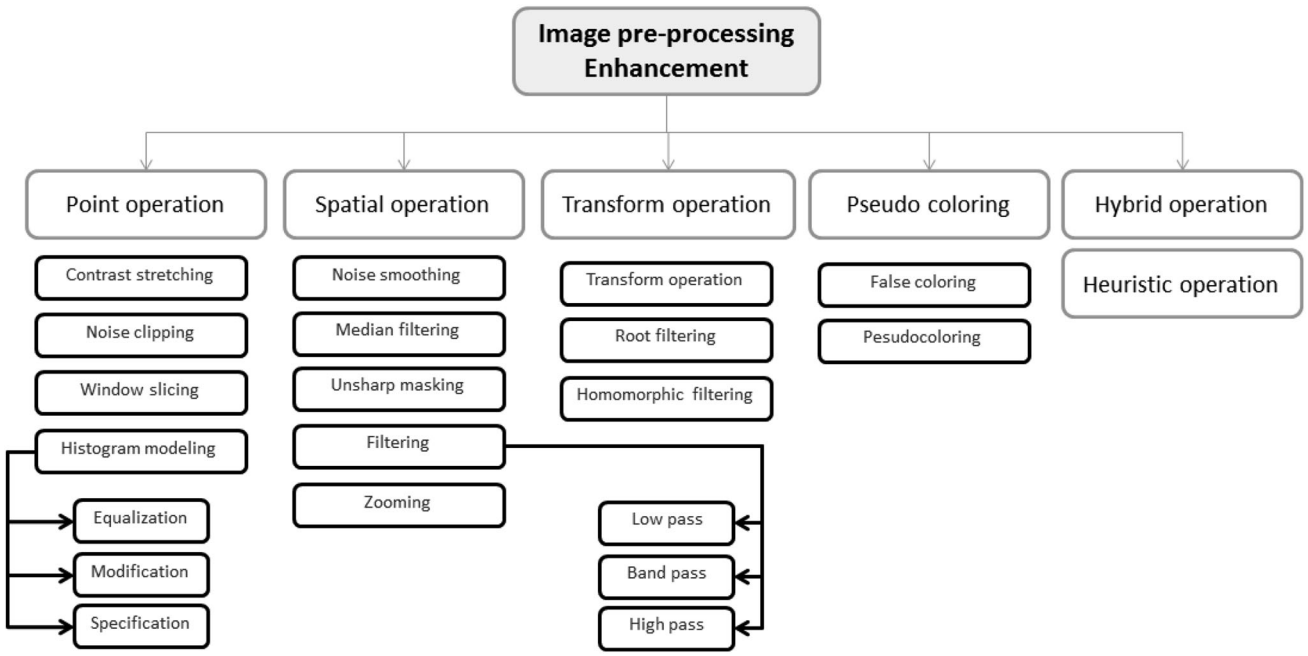


Fig. 8 The framework of common images enhancement methodologies

in the process of image local contrast enhancement. As a final point, simulation results demonstrated that the proposed method is more effective than other traditional algorithms.

Adu-Gyamfi et al. [3] used a multi-resolution image enhancement method based on Gaussian pyramids.

1.2.2 Segmentation (SEP)

Image segmentation is a process to extract the region of interest from the image [216]. It is vital for successful classification of pavement cracks [14]. It is an important step in image processing since it conditions the quality of the resulting interpretation [205, 206, 287]. It is important to extract the objects like crack and pothole. Several image segmentation methods have been proposed by scientists [91], and these techniques are classified in Fig. 9. The latest study on image segmentation methods is shown in Fig. 9 which is discussed in the field of pavement distress analysis.

Kan and Ravi [106] conducted a research on Image Segmentation Techniques, and classified segmentation into different groups: Threshold Based, Region Based, Edge Based, Fuzzy Theory Based, ANN Based and PDE (Partial Differential Equations) Based. They concluded that a hybrid method for image segmentation involving two or more methods is the best tactic for analyzing the image segmentation [106].

Basavaprasad and Ravi [15] have introduced a framework for a systematic comparative study on segmentation based on Pixel based, Threshold based, Edge based and Region based segmentation. They conclude that there is no general segmentation technique that can be implemented for all kinds of images. On the other hand, a number of techniques shows better performance by a combination of suitable techniques [15]. The prior knowledge about images enable the user to adopt and select a better method to segment the image [15, 106].

In this section, we summarize a brief review of methods proposed in the literature based on the Fig. 9 classification in the field of pavement distress detection and classification, and then a new method based on hybrid theory will be proposed.

The overall analysis and discussion about segmentation of the surveyed methods will be presented in the current section. In this paper, the entire available segmentation methods new or developed and enhanced for pavement image analysis were discussed and their advantages were investigated. To present a comprehensive viewpoint to the readers for finding essential information about each technique, we have classified the entire methods in six classes. These six categories consist of: Edge based segmentation (EBS); Threshold based segmentation (TBS); Region based segmentation (RBS); Clustering based segmentation (CBS); Matching based segmentation (MBS); and Fuzzy Based Image Segmentation (FBS). Table 2 contains the collected information on the studied methods.

It can be observed that most of the approaches developed for segmentation try to use the Threshold based segmentation (TBS). These methodologies mostly develop

on basic principles of single thresholding. Based on this theory, the entire image pixel intensity value is compared with the selected threshold value. If a pixel value is larger than the threshold value, then those pixels are considered. Thresholding consists of: Global Thresholding and Local Thresholding and each one can be classified into: Simple/Single Thresholding, Multiple Thresholding and Optimal Thresholding [216]. In all methods, thresholding plays an important role in distress detection and classification.

On the other hand, similar methods on segmentation such as Clustering based segmentation (CBS); Matching based segmentation (MBS); and Fuzzy Based Image Segmentation (FBS) are rather scarce. This may be based on the low speed of these approaches. We can see that two major segmentation methods can be found in the literature. From these six categories, two papers present new segmentation methods while the remainder just apply them in pavement cracking cases. Therefore, segmentation has not received much research attention and except one new approach, no new effort has been made on uncertainty bounds of edge and branches of cracking in recent years [298].

Tasi et al. [233] compared six segmentation techniques, regression thresholding, edge detection (Canny), crack seed verification, wavelets, iterative clipping technique, and dynamic optimization-based thresholding to quantitatively evaluate the performance of various image segmentation approaches. Based on the test results, it was determined that the dynamic optimization-based technique shows better performance than the other methods for all of the images [233].

In contrast to Edge based segmentation (EBS), Threshold based segmentation (TBS) methods are increasing more and more. From 2004, when Zhou presented the first thresholding algorithm based on *Wavelet and Radon Transforms*, most multiresolution based approaches were concentrated on *time–frequency* [159, 167, 168] and other representation methods such as edge based Clustering based segmentation (CBS) and Matching based segmentation (MBS) seem to be less attractive to researchers [295, 296]. From the contents of Table 2, it can be concluded that higher simple methods are more practical in pavement distress segmentation.

Ayenu-Prah and Attoh-Okine [14] used bi-dimensional empirical mode decomposition (BEMD) for pavement crack evaluation. The proposed method explores pavement crack detection using BEMD together with the Sobel edge detector. The results are compared with results from the Canny edge detector.

Salari et al. [201] proposed an adaptive approach for pavement distress segmentation based on Genetic Algorithms. An objective function is used to maximize by applying the information theory to select the ideal threshold for segmentation [201].

Salari and Bao [199] use a novel color segmentation method based on a feed forward neural network to separate the road surface from the background. They also use a thresholding approach based on probabilistic relaxation to separate cracking from the pavement surface [199].

Huang and Tasi [79] proposed a fast algorithm based on dynamic programming-based (DP-based) for pavement crack segmentation. The proposed method incorporated the DP and grid cell. Based on this hybrid method, the region-based non-uniform background illumination was removed, and the pre-processed image was divided into grid cells. Experimental results showed that the hybrid method worked three times faster than the single DP-based approach [79].

Genetic programming has been used by Nishikawa et al. [173] for segmentation of distress, removing residual noise, and filtering the subjects in the backgrounds of the cracks to improve the results.

Texture-based features have been used to identify cracks from the asphalt pavement [237]. They used a group of regions pixels of coherent texture by over segmenting the image. The superpixels obtained are then classified by Multiple Instance Learning as either cracked or not cracked [237].

Lokeshwor et al. [141] presented a robust technique for automated segmentation of cracks from the road surface based on imaging systems under natural lighting based on the adaptive thresholding technique and user defined decision logic. To evaluate the performance, three fast image segmentation algorithms—Canny edge detection, iterative clipping and weighted mean based adaptive thresholding—are assessed based on noisy road surface

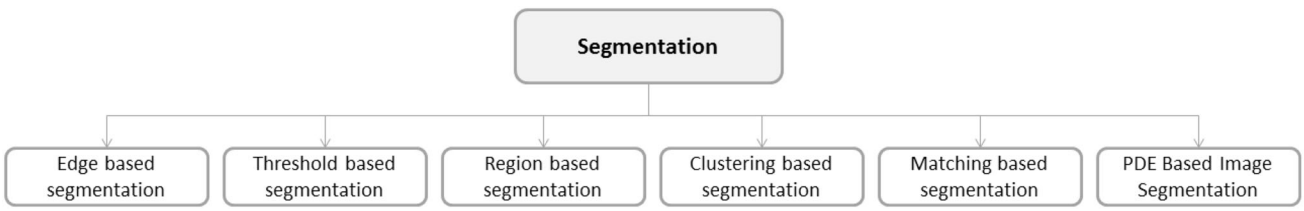


Fig. 9 Image segmentation methods

images. Based on this research, the weighted mean based adaptive thresholding technique shows better performance. The experimental results demonstrated that this method works with accuracy up to 96 % [141].

Guan et al. [67] have proposed the ITV Crack method for segmentation, an ITV-based framework for extracting cracks in road surfaces from MLS point clouds. The ITV Crack worked based on curb based road extraction, GRF image generation and ITV based crack extraction. They believed that one of the limitations is the intensive computation required due to the iterative operations involved in the tensor voting process. Using a multithread scheme, computational performance and time complexity will be greatly reduced [67].

Xu et al. [264] proposed the saliency concept into the challenging work of automatic pavement crack detection. Their method combines and improves the rarity and contrast based saliency measure. The proposed statistical feature extraction and Bayesian estimation method have greatly enhanced the saliency map. This suggests that spatial cracks shall be measured through the feature extraction. The experimental results demonstrated that this method has significantly outperformed several traditional EBS, TBS, PDE and MBS methods [264].

From Table 3 and Fig. 10 it can be concluded that MBS and TBS methods are used more than the others. It also means that FBS and PDE are less discussed. Based on the vague and fuzzy nature of the crack, as mentioned in Sect. 1–2, the FBS method is considered a good research area for future works.

1.2.3 Feature Extraction (FES)

The final purpose in pavement image processing like the other applications is to extract significant features, from which understanding and interpretation of the scene can be provided by the computer [92]. In image analysis, the input image is first preprocessed and then certain features are extracted for segmentation and classification. The segmented image is fed into the understanding system or segmentation system. Image classification draws diverse parts into one or several objects. For instance, in distress classification, all cracks identified as line shapes with branches may be classified as Multiple Crack (MC) and those without branches, as Single Crack (SC). A classification of feature selection methods is shown in Fig. 10.

The spatial feature (SFE) is characterized by its gray levels, their joint probability distribution, and spatial distribution [92]. For example, in pavement images, the amplitude of Radon transform represents the crack, which determines the size and severity of the crack being imaged [159, 167, 168, 295, 296]. Histogram feature extraction (HFE) is based on the histogram of the cracked section. Some of the prevalent histogram features are moments, absolute moments, central moments, absolute central moments, entropy, mean, variance, average energy, skewness, kurtosis, median and modes. The frequency domain contains a useful hidden information in the data that can be extracted by Transform Features (TFE). Generally, the high transform feature, like High amplitude wavelet coefficient (HAWC), High Frequency Energy Percentage (HFEP) and STD in the frequency domain [295, 296] can be used for crack detection and the low frequency can be employed for surface analysis (skid resistance). Also, high pass filter, low pass filter, and bandlimited can be used for decreasing the periodic effect of texture. Different filters in frequency, like Discrete Fourier Transform (DFT), Harr, Hadamard, Daubechies, Coiflet, Sine, cosine, Slant, KLT, Radon Transform, Garbor Filter [279] Beamlet Transform [95, 137, 256, 271], Ridgelet Transform [136, 285, 286], Curvelet Transform [169], contourlet transform [143, 292], Shearlet Transform [258] are also useful for feature extraction [159, 167–169] (Fig. 11).

In the area of transportation infrastructure, image analysis, and specially edge detection (EFE) is a challenging issue. The edge detection method is not an easy task to select or be used because of complexity, diversity of pavement images and pavement distress's weak information [33]. Edge detection is an alternative method in the process crack detection and classification [247]. A wide range of edge detector methods are recommended in image processing. Based on the concept of gradient theory, one edge detection approach is to measure the gradient □ along radius ρ in direction θ, and five classes of edge detection have been proposed: (1) gradient operators (GO), (2) compass operators (CO), (3) Laplace operators (LO), (4) Zero crossing (ZC) and (5) Stochastic gradient (SG).

The first group works by a pair of mask which measures the □ in two orthogonal directions. Several common GO presented in some references are Fast Haar transform (FHT), Fast Fourier Transform, Sobel, and Canny [27], [145], Roberts, Laplacian of Gaussian (Log), Zerocross.

Some classical approaches like Sobel, Prewitt, and Kirsch are simple to detect edges, and their orientations are also fast and easy to operate. However, these procedures are sensitive to noise and are inaccurate. Zero Crossing based on Laplacian and second directional derivative, are responding to some of the existing cracks, and show sensitivity to noise. Laplacian of Gaussian (LoG) is useful for finding the correct places of edges; however, it is not useful for discovering the orientation of edges because of using the Laplacian filter. Other OC methods like Gaussian based Canny and Shen-Castan have complex computations, false zero crossing and are time consuming [145, 205–207]. Stochastic gradient (SG) [207] shows poor performance in noisy images. The general performance of these methods is subject to the adaptable factors like threshold values and standard deviation. Evaluation of the images demonstrated

Table 3 Comparison of different image segmentation techniques

No.	References	Year	Method	Type class	Performance measure	Compared to other methods
1	Ayenu-Prah and Attoh-Okine [14]	2008	BEMD*	EBS	C	Yes
2	Salari and Bao [199], Salari and Ouyang [200]	2011	Fractal + Th	TBS	E	No
3	Huang and Tsai [79]	2011	DP-based	RBS	T–A	Yes
4	Wang et al. [248], [247]	2007	Trous + Wavelet	TBS-EBS	V	Yes
5	Cheng et al. [38], Cai and Zhang [26]	2001	Fuzzy set	FBS	V	Yes
6	Mohajeri and Manning [160]	1991	Directional filter	PDE	V	No
7	Koutsopoulos and Downey [116]	1993	Regression Th.	TBS	A	No
8	Ayenu-Prah and Attoh-Okine [14]	2008	BEMD*	EBS	A	Yes
9	Salari and Yu [201]	2011	GA	RBS	A	No
10	Liu et al. [138]	2008	SE*	TBS	V	No
11	Song et al. [215]	2015	RED*	EBS + TBS	A + V	Yes
12	Jiang et al. [93]	2015	Improved EM*	RBS	V	Yes
13	Golparvar-Fard et al. [63]	2015	STFs*	MBS	V	No
14	Mertz et al. [154], Varadharajan et al. [237]	2014	Superpixels	RBS	A + V + T	Yes
15	Tsai et al. [231]	2014	Multiscale CFE*	MBS	V	No
16	Ying and Salari [272], Ouyang and Wang [182], Ouyang et al. [181]	2014	Beamlet	MBS	A + V	No
17	Lokeshwor et al. [141]	2014	ATT*	TBS	A + V + T	Yes
18	Guan et al. [67]	2014	ITVCrack	EBS + MBS	A + V + T + C + I	Yes
19	Kaul et al. [103, 104], [105], Amhaz et al. [7]	2014/2/0	EMPS*	MBS	A + V	Yes
20	Adu-Gyamfi et al. [3], [4]	2013/4	ACM*	TBS + EBS	V + A + T	Yes
21	Zuo et al. [299]	2013	IFCM*	FBS	V + A	Yes
22	Zhang et al. [282]	2013	MFM*	MBS	V + A	Yes
23	Xu et al. [264]	2013	SSF*	RBS + MBS	V + A	Yes
24	Na and Tao [164], Xu et al. [262, 264]	2013/2	ITSM*	TBS	V	No
25	Tsai et al. [230]	2013	GMPBM*	MBS	V + A	No
26	Tang and Gu [224]	2013	HCDSA*	TBS + EBS	V	No
27	Koutsopoulos et al. [117], Oliveira and Correia [178], Wang and Tang [250, 251], Li [127, 128], Song and Wei [214]	2013	Otsu	TBS	V + A	No
28	Salman et al. [202]	2013	2D Gabor Filter	MBS	V + A	No
29	Oliveira and Correia [179]	2013	Otsu + k-means	TBS + CBS	V + A	No
30	Li [129], Li et al. [130]	2013	ACIGE*	FBS	V	No
31	Zou et al. [298]	2012	TVT*	MBS	V + A	No
32	Zhang and Zhou [289]	2012	Radon + Th	TBS	V + A	No
33	Wu and Liu [259]	2012	DWT* + Th	TBS	V	No
34	Wang and Gao [244]	2012	DT-CWT*	TBS	V + A	Yes
35	Tsai and Li [234]	2012	DOBCS*	RBS	V	No
36	Tsai et al. [232]	2012	AFP* + SPIHT	EBS	V + T	No
37	Ying and Salari [272], Li [127, 128], Ouyang and Wang [182]	2012	Beamlet + Otsu's	TBS + EBS	V	Yes
38	Nishikawa et al. [173]	2012	GP-based*	MBS + RBS	V + A + T	No
39	Ni et al. [172]	2012	BIM*	RBS	V + A + T + C	Yes
40	Li [127, 128]	2012	Contourlet	MBS	V	Yes
41	Jahanshahi et al. [87], Youquan et al. [274], Huang and Zhang [78], Jahanshahi and Masri [89]	2012	MOP* + Otsu's	RBS + MBS	V + A + T	Yes

Table 3 continued

No.	References	Year	Method	Type class	Performance measure	Compared to other methods
42	Moussa and Hussain [163]	2011	GCST*	TBS	V + A	No
43	Salari and Bao [198], Nejad and Zakeri [159]	2011/2010	Wavelets	MBS + TBS	A	Yes
44	Li et al. [135]	2011	FoS*	RBS	V + A + T + C + I	Yes
45	Chambon et al. [29]	2010	AFMMB*	MBS	V	No
46	Salari and Bao [199]	2011	FFNN*	TBS	V	No
47	Chambon et al. [29], Chambon and Moliard [30]	2011	Markovian	MBS	V + A	Yes
48	Zhou et al. [293]	2010	AT	TBS	V	Yes
49	Oliveira et al. [176]	2010	PDE	CBS	V	Yes
50	Kaul et al. [103, 104]	2010	Hausdorff	TBS	V + A	Yes

Performance measure	Method type	Type class
T: Time	N: New	EBS: Edge based segmentation
C: Computational complexity	E: Enhanced	TBS: Threshold based segmentation
I: Iterations	C: Comparative	RBS: Region based segmentation
A: Accuracy		CBS: Clustering based segmentation
V: Visual		MBS: Matching based segmentation
		FBS: Fuzzy based image segmentation
		PDE: Partial differential equations

BEMD bi-dimensional empirical mode decomposition, *SE** segment extending, *RED** ridge edge detection, *EM** electromagnetism-like mechanism, *STFs** semantic texton forests, *CFE** multiscale crack fundamental element, *ATT** adaptive thresholding technique and user defined decision logic, *EMPS** an enhanced minimal path selection (MPS) algorithm, *ACM** active contours or snake method, *IFCM** an improved fuzzy clustering method, *MFM** matched filtering algorithm, *SSF** saliency and statistical features, *ITSM** iterated threshold segmentation method, *GMPBM** geodesic minimal path based method, *HCDSA** hybrid crack detection and segmentation algorithm, *ACIGE** adaptively changing index via grey entropy, *TVT** tensor voting technique, *DT-CWT** the dual-tree complex wavelet transform, *DOBCS** dynamic optimization-based crack segmentation, *DWT** discrete wavelet transform, *AFP** adaptive filter-bank in lower-level sub-bands, *SPIHT** said pearlman set partitioning in hierarchical trees, *AT** adaptive thresholding, *BIM** biological inspired model, *AFMMB** adapted filtering and markov model-based, *MOP** morphological operation procedure, *FFNN** feed forward neural network, *GCST** graph cut segmentation technique, *FoS* F*Seed-growing, *PDE** parzen density estimation

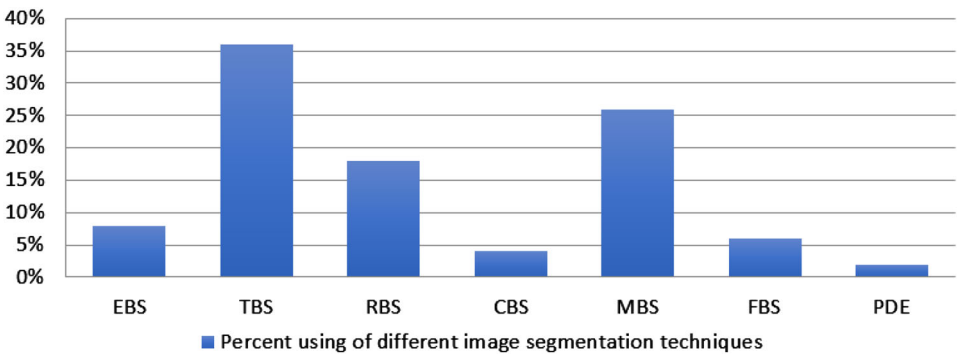


Fig. 10 Comprehensive comparison of methods used by researchers in recent years

that under noisy conditions (like asphalt pavement), Canny, LOG, Sobel, Prewitt, and Roberts's reveal better performance, respectively [145, 207].

Huili et al. [82] proposed an improved Canny edge detection procedure and an edge preservation filtering method for pavement edge detection applications. They used Mallat wavelet transform to reinforce the unclear edges and GA to get a better self-adapting threshold canny algorithm.

Changxia et al. [33] has introduced a method based on FDWT (fractional differential and wavelet transform). This method can effectively enhance high-frequency, medium-frequency signals and non-linearly preserve low-frequency signals. The FDWT is compared with other operators like

Soble, Prewitt and LoG, to demonstrate its performance [179]. The authors concluded that this procedure is effective for different road crack images even in noisy images.

A modified Soble operator is used with bi-dimensional empirical mode decomposition to crack extraction by Ayenu-Prah and Attoh-Okine [14]. Some challenges faced in these sort of approaches for crack detection were false crack edge detection due to the white lane marking, and irregularities in pavement surface, as reported by Oliveria and Correia [179] and Li et al. [135].

Benteli (Bentil and Zhang [11]) presented Multiresolution Information Mining for Pavement Crack Image Analysis. They stated that although some methods or features could have good image edge characteristics, others might show better performance to the special shape and size of objects like crack.

Lokeshwor et al. [140] presents a robust method for automated segmentation of frames with/without distress from road surface video clips based on Canny edge detection. They claimed a method accuracy of up to 96 %.

Tasi et al. [229] stated that the Canny edge detector is the best edge detector among traditional edge detection algorithms. However, the problem is the distress that may seem wider than it actually is and severity of level detection. Therefore, the experimental results show that both accuracy and speed do not meet the requirements.

Mahler et al. [144] used gradient histogram analysis in which the image gradient is highest near an edge of the crack. They employed a sliding mask to calculate the gradient magnitude for each pixel of intensity.

Abdel-Qader et al. [1] presented a comparison of the usefulness of four crack detection methods: Fast Haar Transform (FHT), Fast Fourier Transform, Sobel, and Canny. The outcomes indicated that the FHT was more reliable than the other methods.

The boundary connected the edges to build the shape of an object. They are valuable in the computation of geometry features such as Area, Orientation, Bounding Box, Centerior, Eccentricity, Euler Number, Extent, Extreme, Filled Area, Perimeter, Solidity, Weighted Centerior, and etc.

Connectivity, counter following, edge linking, heuristic graph searching, dynamic programming, and Hough transform are prevalent methods for the analysis of extracted edges. The Hough transform can generalize to detect curves other than straight lines. It can be expressed as Radon transform of a line delta function. One of the functions that can provide local approximations of contours of shape is the B-spline representation function. It is useful in shape synthesis and analysis, graph theory and recognition of parts from boundaries.

Hough transformation is used to detect or classify all cracks in parallel [39]. The experimental results have demonstrated that the cracks are correctly and effectively detected by the proposed method, which will be useful for pavement management.

Nejad and Zakeri [159, 167, 168] presented boundary properties of the peaks to quantify the width and severity of a crack, and the value of a peak to quantify the length and extent of the crack. The volume also covered by the peak is used to serve as a general index for crack quantification (Fig. 12).

The moment's theory provides a useful method to represent the shape of objects as a powerful feature extraction method (MFE). The moments of the region could represent the shape. A crack can be characterized as a point in an N-dimensional vector space. They are useful for shape analysis, and can be used for distress detection, classification, and quantification. Two different types of moments are reported in the references: the nth central moment and nth moment [296]. Zhou et al. [295, 296] reported that when n is 4, the moment could be a good feature for distress detection and isolation. However, it is time consuming and needs a higher speed processor for analysis. When n is 1 it is a good feature for crack detection at the moment. They stated that to detect very small distress it is necessary to choose larger n (1–4) (Fig. 13).

Chou et al. [42] presented a novel approach of applying the theory of fuzzy sets and moment invariants to analyze pavement images. They extracted features based on the theory of fuzzy sets and calculating moment invariants from different types of cracking. They proved the feasibility of using this feature to classify diverse types of pavement cracks.

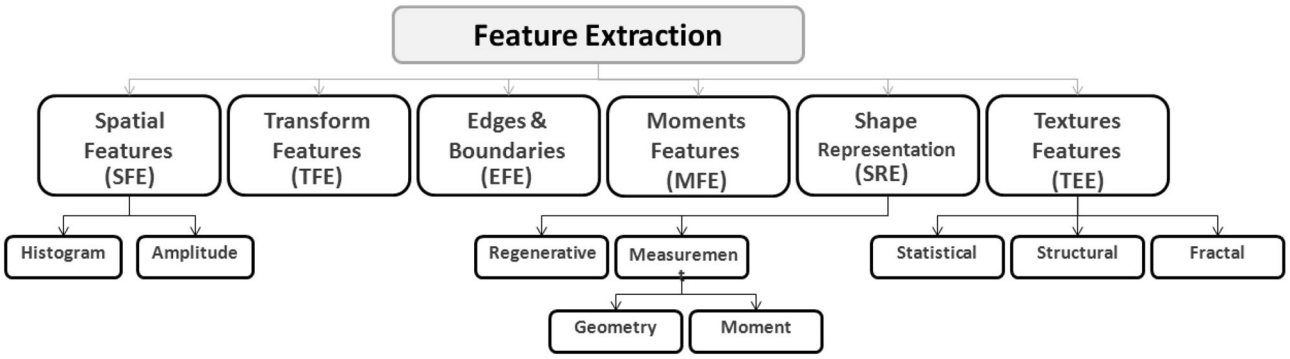


Fig. 11 Image feature extraction methods

In the literature, Rababaah et al. [190] and Hsu et al. used a moment invariant procedure for feature extraction. Feature vectors containing eighteen moments were supplied for classification. Hu, Bamieh, and Zemike moments were some of these moments that were employed for feature generation.

The moments are useful for shape analysis with high speed. A crack can be described by a structure composed of line or curve patterns. Therefore, shape and structure are important for feature extraction. Medial axis transformation, skeleton algorithm, thinning algorithms, morphological processing, and systematic representation are useful for analysis of the structure of cracks [92]. The shape of distress refers to its physical structure. These shapes can be used for crack feature extraction. Several useful shape features are listed in Fig. 10.

In many image based crack analyses, the final goal is to measure certain geometric characteristics based on the shape representation (SRE) of cracks based on previous features, such as: perimeter, area, minimum, and maximum distance, number of hole, Euler number, corners, bending energy, roundness and symmetry.

Many cracks can be represented in terms of moments, such as center of mass, orientation, bounding rectangle, best fit ellipse, and eccentricity. These features are suitable for crack recognition.

The pavement surface as a background of distress is generally random, and it may be coarse, fine, smooth, granulated, rippled, regular, irregular with additional intensified objects like oil, water or shadow. The properties can be changed during the day time and subjected to light and materials. Several statistics that are presented in the references for surface analysis are: the auto colorant function, image transforms, edge density histogram features consisting of [Inertia, mean attribution, variance, and spread distribution] and random texture model (TEE). LeBlanc et al. [122] used the basic fractal characterizations, including the fractal dimension, of some forms of pavement distress.

Pavement images are characterized by a vector of extracted features. These features are then used for the segmentation, detection, or classification steps [298].

The system proposed by Adu-gymfi et al. [4] has three different algorithms for feature extraction: (1) Bi-dimensional empirical mode decomposition (BEMD) and principal component pursuit (PCP), (2) Adaptive thresholding and (3) Active contour models. They combined the BEMD with a crack information mining technique called PCP [2]. The goal was to extract crack information from the different levels or modes of resolution using the BEMD. They concluded that intermediate modes or levels of BEMD hold important crack information.

Traditional pavement detection systems extract crack features by the use of edge detectors and thresholding algorithms which generally work by setting the grey value of each pixel in the image to a value that is dependent on the magnitude of the gradient of the grey level at the corresponding point in the original image. The processing from this class of systems is purely local. They believed that such systems may be unsuccessful in difficult conditions like rough textures and oil stains [3, 4]. An edge detector method, however does not clearly have the proficiency of recognizing the spreading of the gradients [4].

Since the pavement image texture is very rough, the pavement image surface has foreign objects such as oil stains and paint markings and the image contains a mixture of distress types, and it is difficult to use edge detection or thresholding for feature extraction [4]. The snake method is strong in difficult conditions because of its unique understanding of the edge detection concept. They defined snakes as energy minimizing deformable splines, subjective by limitation and image forces that attract it towards object outlines or borders [4]. These methods are classified into two main classes: the parametric and the geometric active contour models. Parametric models characterize the active contours as parameterized curves. In geometric models, however, they are symbolized as level sets of a two-dimensional function that evolves in an Eulerian framework [3].

Tasi et al. [230] proposed the minimal path method based on the computation of the geodesic distance map U (x) that searches to minimize the weighted distance between two points p1 and x.

The snake model was also employed by Tang and Gu [224] as a set of discrete points to capture crack borders by diminishing the energy function. In the snake model, the external forces are significant. The general gradient vector flow (GGVF) as the external forces is used, can be obtained by minimizing the following energy function.

The higher order statistics method proposed by Song and Wei [214] is based on the non-homogeneousness illumination improvement technique, which improves the image feature considerably. The proposed method is based on the fact that local sections of pavement images have similar geometric texture, and then the probability distribution of image pixel values (PDIPV) in local regions is also similar. This is based on the statement that the feature vector is built by the joint pixel value and the characteristic values of statistical correlation.

Three parametric and three non-parametric supervised classification strategies were presented by Oliveira and Correia [177]. The cracks were then classified to longitudinal, traversal and combined by reconnoitering the 2D feature space [202].

A one-class clustering, using Parzen density estimation, is applied to select cracks, exploiting a simple two dimensional feature space [176]. These features consist of the mean and standard deviation from non-overlapping image blocks.

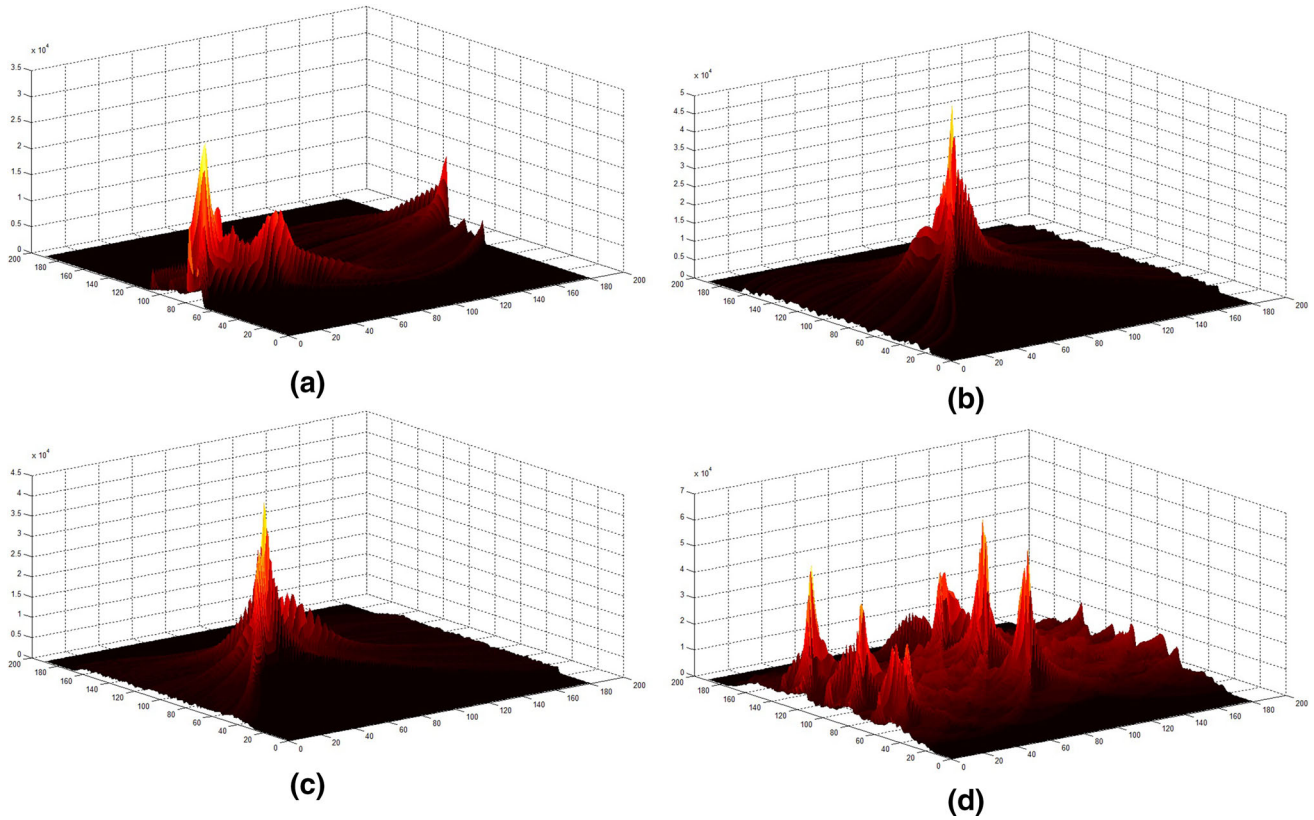


Fig. 12 Three dimensional radon transform (3DRT) reconstruction images, **a** horizontal and vertical cracking, **b** horizontal, vertical and diagonal cracking, **c** block cracking, and **d** alligator cracking [159, 167, 168]

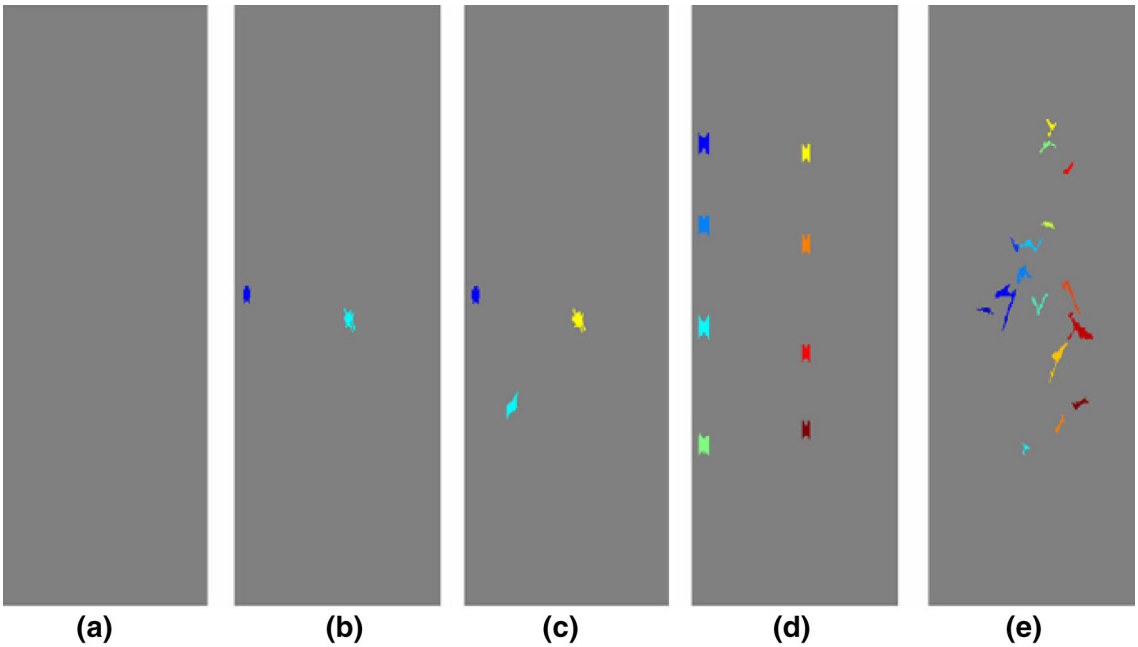


Fig. 13 Binarization of 3DRT and pattern extraction: **a** without cracking, **b** horizontal and vertical cracking, **c** horizontal, vertical and diagonal cracking, **d** block cracking, and **e** alligator cracking [159, 167, 168]

As shown in Fig. 14, among the stated methods, the EFE class is most widely used. According to the study, the frequency of the two TEF and SRE groups in total, is equivalent to using the SEF. According to Fig. 14, more than 50 % of the total approached are EFE and SFE. Also about 23 % of the current approaches are new while the remaining are mostly comparative or enhanced versions of other methods.

According to the above analysis, 57 % of the existing feature extraction techniques are totally used for edges & boundaries extraction and spatial feature extraction. Similar comparisons have also been performed on the originality of feature extraction methods. These comparisons are provided in Fig. 15.

Also about 53 % of the existing approaches are compared with other methods while the remaining 47 % of the methods are not, as shown in Fig. 16.

1.2.4 Feature Selection (FSS)

Although there is inadequate theory to guide in the selection of the best features for crack detection, classification and quantification, it can be stated that some necessary attributes of features are in hand for crack interpretation; and the features should be invariant with translation, scale, and light conditions [163].

The adequacy of feature selection approaches exist in the literature that can be categorized into three groups based on the searching strategy, namely complete search, heuristic search and random search. Feature selection approaches are significant due to dropping computation time, improving the accuracy, decreasing the noise and a better interpretation of the images [31]. Noise and error can be generated using dependent variables and no extra facts, information, and knowledge can be extracted. Reducing the dependent variables can lead to moderating the error and increasing the accuracy in the classification. An appropriate ranking measure is employed to weigh the features and a threshold is selected to reject low weight features [31, 45] (Fig. 17).

Supervised

The effectiveness of features, especially inter feature correlation, is an important criterion to rank a series of features [71, 107, 269]. Ranking methods can be classified into two methods: Correlation criteria, which shows the correlation ranking between variable and goal and Mutual Information, which is an index for measuring the dependency between two variables [16, 31]. Chandrashekar and Sahin [31] classified two ranking techniques as Correlation criteria and Mutual Information to explore the relevance and dependency of a set of features. Various features can be extracted for Pavement distress detection and classification from images. Thus, it can be considered as a

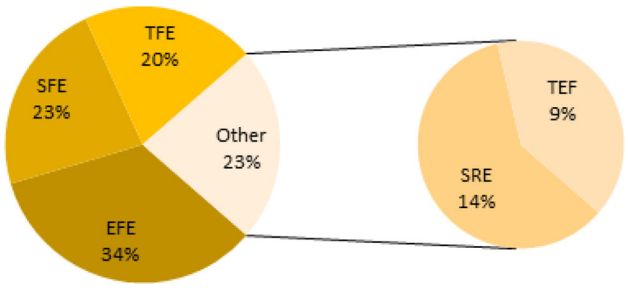


Fig. 14 Comprehensive comparison of methods used by researchers in recent years

multiple variable task. Various methods exist and are proposed by researches for feature selection based on mutual information [12, 24, 49, 75, 97, 139, 217, 254]. Lee and Kim [124] proposed the Mutual Information-based multi-label feature selection method based on interaction information by a measure of dependencies of multiple variables. As a consequence, the proposed method shows good performance for feature selection. A novel feature redundancy index based on mutual information was suggested by Wang et al. [254]. New procedures are proposed to learn feature/kernel weights and NMF parameters by Wang et al. [245]. Jin et al. [97] have used a nonlinear factor for the evaluation function of the feature selection approach. The wrapper procedure shows better performance when the sample size is sufficient.

Hybrid methods (filter-wrapper) show better performance in accuracy and the number of features selected [18, 59, 74, 236]. A hybrid method using the mutual information criterion and a wrapper approach searches in the space for the selection of the candidate feature proposed by Foithong et al. [59]. Huang et al. [76] have proposed a hybrid genetic algorithm to find a subset of features based on two stages consisting of global and local search by using wrapper and filter manners. Zhang and Hu [283] proposed a hybrid feature selection method based on ant colony optimization (ACO) and mutual information. They stated that it can be useful to reduce the dimensionality of the variable, increase the speed of the training and acquire better accuracy. They believed that the hybrid

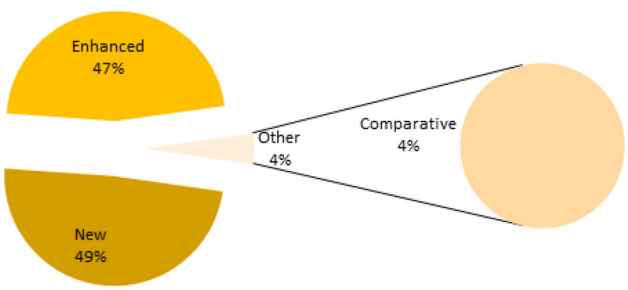


Fig. 15 Categorizing the feature extraction methods based on their originality

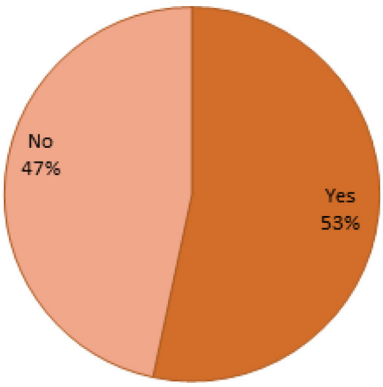


Fig. 16 Classifying the feature extraction methods based on their comparison with other approaches

method shows better performance in both parsimonious feature selection and classification accuracy [18, 54, 59, 74, 76, 283].

Gavilán et al. [61] proposed the best feature vector including diverse texture-based features. The method that they used for feature selection based on the output was provided by the classifier-SVM.

Zhao et al. [290] classified feature selection and extraction techniques into three categories: Fisher score, Principal Component Analysis (PCA), and Laplacian score. Between these three classes, the first one is the supervised method. Based on this method, the score is computed for each discrete feature, and then the highest scores are criteria for selecting those features [290].

Unsupervised

Due to the lack of class labels, unsupervised methods [53, 249, 276] are useful to find an optimal feature vector for data classification (Han et al., [25, 52, 157]. They mined the feature weight matrix and by using pseudo labels, mapped the original data into a low dimensional space. The majority of existing unsupervised feature selection techniques requires prior knowledge of the data and minority work automatically without need for prior knowledge [119, 266]. PCA and Laplacian score are unsupervised methods that worked by unlabeled data [290].

Maldonado et al.(Maldonado et al.) present an unsupervised method-Kernel K-means—that picks out the most related features, at the same time minimizing the damage of the initial cluster structure and penalizing the use of features via scaling factors (Maldonado et al.).

Previous studies of feature selection are mostly dedicated to supervised and unsupervised approaches. Semi–supervised feature selection is rarely addressed in references. The knowledge from unlabeled and labeled [8] data at the same time exploit using this approach [73, 94, 114, 209]. None of the two methods can take advantage of both labeled and unlabeled points [290]. Supervised and unsupervised feature selection methods need to measure feature weight, however in different ways [291]. Zhao et al. [290] presented a semi-supervised feature selection procedure, which used both labeled and unlabeled data.

Cong et al. [47] used Forward Selection (FS), Backward Selection (BS), Genetic Algorithm (GA) and Principal Component Analysis (PCA) for road distress feature selection. They concluded that PCA is the best method for feature selection when the number of features is larger than 5 [47] and FS is the finest when the number of features is larger than 2 and smaller than 6.

Gavilán et al. [61] stated that the main drawback of methods used for pavement analysis is in the supervised learning group which needs a great amount of data to show good performance [61]. The feature vector included a combination of dissimilar texture-based features. The contour area, bounding box area, fitted bounding box area, contour orientation and the aspect ratio. The idea was to detect blobs with high rectangularity and a wide area inside the bounding box. The AdaBoost algorithm has been employed for choosing Gabor features for the classification of images [279].

Nejad and Zakeri [159, 167, 168] employed the classification accuracies of the dynamic neural network (DNN)

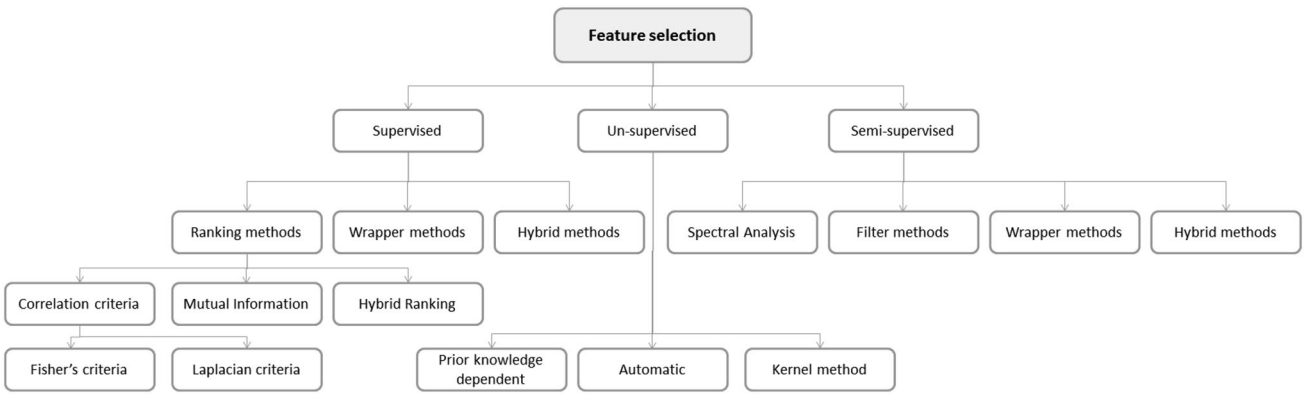


Fig. 17 Feature selection methods

classifier and static neural network (SNN) classifier, as indexes for feature selection.

Table 4 contains the collected information on the studied approaches in the feature selection area. It can be observed that most of the approaches used for feature selection FSs try to use the supervised approaches. These methods mostly develop on basic principles of the error reduction algorithm. On the other hand, similar works on unsupervised feature selection such as Prior knowledge dependent and the Kernel method are rather scarce. This may be based on low accuracy, complexity, and the time of these approaches. We can see that three types of methods based on the concept of ranking methods can be found in the literature. From these three approaches, Hybrid Ranking shows better performance. Therefore, unsupervised and semi-supervised have not received much research attention and except for one new approach, no new work has been done on unsupervised feature selection in recent years. In contrast to unsupervised feature selection, the use of supervised methods is increasing. A portion of these classes among the entire reviewed methods is depicted in Fig. 18.

The pie charts illustrate the feature selection methods based on their originality. They are divided into three parts. 41 % of the total methods are new for feature selection. Also, about 53 % of the existing methods are enhanced while the remaining (6 %) are comparative. In conclusion, we can see that the majority of methods have had positive developments for feature selection.

1.2.5 Detection (DES)

In order to provide good results for automatic systems, it is important to employ objective criteria for distress detection [295, 296]. The first step is the ability to sort images with distress or without defects and then identify distress classes [48].

Various methods have been presented for detecting an isolation of different kinds of distress in pavement surface images [114]. Based on Cord and Chambon [48], research on two major types of tactics have been suggested in the literature for pavement distress detection: (1) Unsupervised methods [175, 179] and (2) Supervised methods [179, 180]. Recently, the semi-supervised method is proposed for using labeled and non-labeled data. The first ones work based on pixels and the second work on classification [48]. In all three supervised, unsupervised and semi-supervised methods, five various approaches can be employed to isolate the images with distress: (1) Statistical Method Based (PMB), (2) Physical Method Based (PMB), Filtering Method Based (FMB), Model-Method Based (MMB), Hybrid Method Based (HMB). In Fig. 13, the various groups based on different methods are illustrated in three levels.

The Statistical Method Based (SMB) can work based on a wide range of methods like histogram analysis [113, 144], adaptive thresholding [61, 99, 140], thresholding based on fuzzy logic [42], fractal thresholding [200], Gaussian modeling [116, 131, 179], sparse representation [219] kernel tracker [191] Hausdorff distance [233] and invariant moments. These methods are simple but not very efficient because they do not analyze the geometry of cracks [48].

The Physical Method Based (PMB) use morphological tools or contour detection [82, 95, 114, 122, 135]. CrackTree [298] and Contourlet transform and multi-direction morphological structuring elements [127, 128] are several examples of this class. These methods consider the constant width and scale for cracking and it is not truthful [48].

The Filtering Method Based (FMB) provides a multi scale platform. Several examples of these methods are the wavelet based method [47, 126, 159, 167–169, 247, 270, 295, 296], Beamlet method [95, 137, 271], contourlet transform [143, 208, 292], shearlet transform [258], ridgelet [285, 286], multi resolution methods [2, 4, 159, 167, 168, 231], filtering based [126, 219–221, 279, 288], average filtering [219–221], Matched filtering [282], adaptive filter-bank [232] or partially different equations, and multi-features [263].

The Model- Method Based (MMB) [48] employed some assumptions related to the geometrics of crack for detection and classification. Some texture decomposition, pattern based, Markova modeling, texture anisotropy measure methods like intra-regional and inter-regional connectivity [263], radon transform [289], minimal paths and dynamic programming [13], Gradient Vector Flow (GVF) [147], Dempster-shafer theory [77] can be considered in this category [135].

The Hybrid Method Based (HMB) is using two or more methods to make a better model for detection and isolation [169, 179, 227, 277, 278].

Cord and Chambon [48] stated that rare classification methods are based on local analysis while local methods are a motivating technique for pavement surface digresses isolation. They proposed an AdaBoost classifier on the multiple descriptor based on PMB and MMB to improve the classification performance [48] (Table 5).

Table 6 The five classes are summarized and researches are cited in the stage of pavement distress detection and isolation.

Zhou et al. stated that all detection methods can be classified into two major classes: edge detection and thresholding. These two categories detect distress in the space domain. However, it is difficult to find a certain

Table 4 Comparison of different feature extraction techniques

No.	References	Year	Method	Type class	Number of features	Method type compared
1	Adu-Gyamfi et al. [4]	2014	BEMD* + ACM* + AT*	EFE	3	N-Yes-[threshold]-(#2)-U
2	Ayenu-Prah and Attoh-Okine [14]	2008	BEMD* + Sobel + Canny	EFE	–	C-Yes-(#2 method)
3	Salari and Bao [199], Salari and Ouyang [200]	2011	Radon + Th + Factal	TFE	2	E-No-[SVM]-S
4	Wang et al. [248], [247]	2007	Holes algorithm	EFE	–	N-Yes
5	Cheng et al. [38], Cai and Zhang [26]	2001	Fuzzy set	EFE	4	N-Yes-[reasoning]-S
6	Salari and Yu [201]	2011	GA	SRE	4	E-No-[NN]-S
7	Song et al. [215]	2015	RED*	SFE	8	N-Yes-[reasoning]-(#1)-S
8	Jiang et al. [93]	2015	Improved EM*	TEF	2	E-Yes –[SFEA]-(#4)-U
9	Golparvar-Fard et al. [63]	2015	STFs*	SRE	2	N–No-[STFC] -S
10	Tsai et al. [231]	2014	Multiscale CFE*	EFE	5	N–No-[reasoning]-U
11	Ying and Salari [272], Ouyang and Wang [182], Ouyang et al. [181]	2014	Beamlet	TFE	3	E-No-[reasoning]-S
12	Lokeshwor et al. [141]	2014	ATT*	EFE	1	E-Yes-[logic]-(#2)-S
13	Guan et al. [67]	2014	IGRF*	EFE	5	E-Yes-[threshold]-(#2 Method)-S
14	Adu-Gyamfi et al. [3], [4]	2014	BEMD* + PCP* + AT* + ACM*	TFE	–	E-Yes-[]-(#2)-U
15	Tsai et al. [230]	2013	GMPBM*	SFE	3	N–No-[]-(#0)-U
15	Tang and Gu [224]	2013	HCDSA*	SFE + MFE	4	E-Yes-[threshold]-(#1)-S
16	Koutsopoulos et al. [117], Oliveira and Correia [178], Wang and Tang [250, 251], Li et al. [131, 132], Song and Wei [214]	2013	INCP*	TFE	3	N-Yes-[SVM]-(#1)-S
17	Salman et al. [202]	2013	2D Gabor Filter	TFE	6	N–No-[logic]-(#0)-S
18	Oliveira and Correia [179]	2013	Otsu + k-means	SFE	2	N–No-[threshold]-(#0)-U
19	Zou et al. [298]	2012	TVT*	SRE	4	N-Yes-[threshold]-(#4)-S
20	Zhang and Zhou [289]	2012	MFA*	SRE	–	E-No-[logic]-(#0)-S
21	Wang and Gao [244], Wu and Liu [259]	2012	DT-CWT*	TFE	3	E-Yes-[threshold]-(#1)-S
22	Tsai and Li [234]	2012	DOBCS*	SFE	–	N–No-[threshold]-(#0)-S
23	Tsai et al. [232]	2012	AFP* + SPIHT	TEF	3	N–No-[threshold]-(#0)-US

Table 4 continued

No.	References	Year	Method	Type class	Number of features	Method type compared
24	Ying and Salari [272], Li [127, 128], Ouyang and Wang [182]	2012	Beamlet +Otsu's	TFE	3	N-Yes-[threshold]-(#3)-S
25	Nishikawa et al. [173]	2012	GP-based*	TFE	4	E-No-[threshold]-(#1)-S
26	Ni et al. [172]	2012	BIM*	SFE	4	E-No-[adaboost]-(#1)-S
27	Li [127, 128]	2012	Contourlet	EFE	2	E-Yes-[threshold]-(#3)-S
28	Jahanshahi et al. [87], Youquan et al. [274], Huang and Zhang [78], Jahanshahi and Masri [89]	2012	MOP* + Otsu's + Cany	EFE	5	C-Yes-[NN, SVM, Ne-neighbor]-(#3)-S,U
29	Moussa and Hussain [163]	2011	GCST*	SFE	7	N–No-[SVM]-(#0)-S
30	Nejad and Zakeri [159]	2011	Multi-resolution	TFE	7	E-Yes-[NN]-(#2)-S
31	Salari and Bao [198], Nejad and Zakeri [159]	2011	Wavelets	SFE	2	N–No-[logic]-(#0)-S
32	Li et al. [135]	2011	FoS*	EFE	2	N–No-[logic]-(#3)-U
33	Salari and Bao [199]	2011	FFNN*	SFE	–	E-No-[NN]-(#0)-U
34	Chambon et al. [29]	2010	AFMMB*	EFE	–	N-Yes-[Markov]-(#3)-U
35	Song et al. [215]	2015	RED*	EFE	6	N–No-[threshold]-(#0)-U
36	Varadharajan et al. [237]	2014	Superpixels	TEF	138	N–No-[SVM]-(#0)-U
37	Guan et al. [67], [66]	2014	ITVCrack + GRF*	SRE	2	E-Yes-[logic]-(#3)-S
38	Amhaz et al. [7]	2014	EMPS*	EFE	2	E-Yes-[]-(#4)-U
39	Zuo et al. [299]	2013	IFCM*	SRE	2	E-Yes-[FCM]-(#2)-U
40	Xu et al. [264]	2013	SSF*	SFE	2	E-Yes-[bayesian]-(#6)-U
41	Na and Tao [164], Xu et al. [262, 264]	2013/2	ITSM*	EFE	2	E-No-[logic]-(#0)-S
42	Song and Wei [214]	2013	Statistics Properties	TEF	8	E-Yes-[SVM]-(#1)-S
43	Li et al. [130]	2013	Gray Entropy	EFE		N–No-[]-(#0)-U

Performance measure	Feature extraction techniques
T: Time	SFE: Spatial features extraction
C: Computational	TFE: Transform features extraction
Complexity	EFE: Edges and boundaries extraction
I: Iterations	MFE: Moments features extraction
A: Accuracy	SRE: Shape representation extraction

Table 4 continued

Performance measure	Feature extraction techniques
V: Visual	TEF: Textures features extraction
Method type	
N: New	
E: Enhanced	
C: Comparative	

*SFLA** shuffled frog-leaping algorithm, *GRF** geo-referenced feature, *BEMD** bi-dimensional empirical mode decomposition, *PCP** principal component pursuit, *AT** adaptive thresholding, *ACM** active contour model, *INCP** illumination non-uniformity correction principle, *MFA** matched filtering algorithm, *GRF** geo-referenced feature, *EMPS** an enhanced minimal path selection (MPS) algorithm

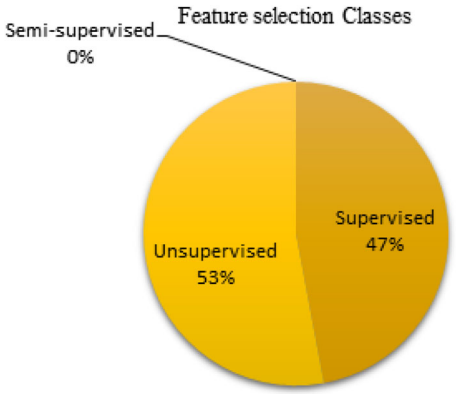


Fig. 18 Ratio of feature selection classes (supervised, unsupervised and semi-supervised)

threshold to detect a distress for these methods. They use wavelet domain instead of using the space domain for distress detection. Several criteria including the High-Amplitude Wavelet Coefficient Percentage (HAWCP), the High Frequency Energy Percentage (HFEP), the Standard Deviation (STD) and moments of wavelet coefficient (MWC) were used based on wavelet coefficient in the high-frequency-sub bands of the wavelet domain [295, 296]. These quantities were meaningful and effective for pavement fault detection and isolation.

Changxia et al. [33]. proposed a new approach of pavement cracks isolation based on fractional differential and wavelet transform (FDWT). Fractional differential can effectively enhance various frequencies. Then wavelet transform is applied in order to strain noise. Experimental results proved that the proposed detection was a valid method for the different road crack images even if no noise exists.

Gavilán et al. [61] used a seed-based approach for crack detection, combining Multiple Directional Non-Minimum Suppression (MDNMS) with a symmetry check which is classified in MMB crack detection methods. Several parameters are used to adjust the method. Seeds are linked by computing the paths with the lowest cost that meet the symmetry restrictions. For the entire detection, they statured it to get optimal results without manual intervention and correct setting played an important role [61] (Figs. 19, 20).

Overall, as it can be seen from Fig. 21, unsupervised and supervised types were the main approaches of distress detection and isolation, whereas the semi-supervised type was not used in this regard.

According to the above analysis, 55 % of the approaches are designed for SMB and FMB, and the remaining are proposed in PMB, MMB and HMB. Similar comparisons have also been made for the reader in the realm of detection and isolation. These comparisons are provided in Figs. 22 and 23.

1.2.6 Classification (CLS)

Machine learning methods are frequently used for pavement distress segmentation and classifications [114, 152, 159, 167, 168, 190, 200, 208, 219, 229, 247, 250, 251, 271, 272, 277, 288]. These procedures distinguish the variances between crack and non-crack regions, and also different types of distress, severities and extent. Diverse classification approaches have been proposed for different applications [114, 161]. Very few studies have been carried out to evaluate diverse classification methods [161]. On the other hand, limited approaches have been used for detection of pavement cracks from images and classifying the type, severity and extent which can be categorized based on Fig. 14: Artificial neural networks (ANN), [13, 21, 39, 41, 101, 102, 123, 171, 189, 197, 229, 260, 261], Fuzzy and adaptive neuro-fuzzy inference system (ANFIS) [20, 36–38, 225], Support Vector Machine (SVM) [61, 88, 134, 136, 148, 164, 200, 222], decision trees [159, 167, 168, 295], Chain code [243], k-nearest neighbors [91, 101], Parzen windows [177], Fisher's Least Square Linear classifiers [177], Genetic algorithm [201], Multiple Instance Learning [237], AdaBoost [48], Metaheuristic methods [172], and Bayes [32].

Table 5 Comparison of different distress detection and isolation techniques

No.	References	Year	Method	Type class	Descriptor	Compared to other methods
1	Jiang et al. [93]	2015	Unsupervised	TEF	Global	Yes
2	Song et al. [215]	2015	Unsupervised	HMB	Global	No
3	Adu-Gyamfi et al. [3], [4]	2014	Unsupervised	HMB	Global	Yes
4	Lokeshwor et al. [141]	2014	Unsupervised	PMB	Global	Yes
5	Guan et al. [67]	2014	Supervised	HMB	Global	Yes
6	Varadharajan et al. [237]	2014	Unsupervised	HMB	Global	Yes
7	Amhaz et al. [7]	2014	Unsupervised	PMB	Local	Yes
8	[4]	2008	Supervised	PMB	Local	Yes
9	Changxia et al. [33]	2009	Supervised	FMB	Global	No
10	Gavilán et al. [61]	2011	Unsupervised	MMB	Global	Yes
11	Moussa and Hussain [163]	2011	Supervised	SMB	Global	No
12	Salari and Bao [198]	2010	Supervised	SMB	Global	No
13	Nejad and Zakeri [159]	2011	Supervised	SMB	Global	Yes
14	Li et al. [135]	2011	Unsupervised	FMB	Global	Yes
15	Chambon et al. [29]	2010	Unsupervised	FMB	Global	Yes
16	Zuo et al. [299]	2013	Unsupervised	MMB	Global	Yes
17	Xu et al. [264]	2013	Unsupervised	SMB	Global	Yes
18	Na and Tao [164], Xu et al. [262, 264]	2013/2	Supervised	SMB	Global	No
19	Tsai et al. [230]	2013	Unsupervised	PMB	Local	No
20	Tang and Gu [224]	2013	Supervised	HMB	Local	No
21	Song and Wei [214]	2013	Supervised	SMB	Local	Yes
22	Salman et al. [202]	2013	Unsupervised	FMB	Global	No
23	Song and Wei [214]	2013	Supervised	SMB	Local	Yes
24	Oliveira and Correia [179]	2013	Unsupervised	SMB	Global	Yes
25	Li [129], Li et al. [130]	2013	Unsupervised	FMB	Local	No
26	Zuo et al. [299]	2013	Unsupervised	SMB	Local	Yes
27	Zou et al. [298]	2012	Unsupervised	HMB	Local	Yes
28	Zhang and Zhou [289]	2012	Unsupervised	FMB	Global	No
29	Wang and Gao [244]	2012	Supervised	FMB	Local	Yes
30	Tsai and Li [234]	2012	Supervised	PMB	Global	No
31	Tsai et al. [232]	2012	Unsupervised	FMB	Global	No
32	Ouyang and Wang [182]	2012	Supervised	FMB	Local	Yes
33	Nishikawa et al. [173]	2012	Supervised	FMB	Local	No
34	Ni et al. [172]	2012	Supervised	MMB	Global	Yes
35	Li [127, 128]	2012	Supervised	FMB	Local	Yes
36	Jahanshahi and Masri [89]	2012	Supervised	MMB	Local	Yes

Descriptor	Method type	Type class
Local	Supervised	SMB: Statistical method based
Global	Unsupervised	PMB: Physical method based
	Semi-supervised	FMB: Filtering method based
		MMB: Model-method based
		HMB: Hybrid method based

Table 6 Comparison of different classification techniques for pavement distress classification

No.	References	Year	Method	Type class	Descriptor	Compared to other methods
1	Jiang et al. [93]	2015	USL	NI	–	Yes
2	Song et al. [215]	2015	USL	DT	–	No
3	Adu-Gyamfi et al. [4]	2014	USL	LC	–	Yes
4	Guan et al. [67]	2014	SL	LC	–	No
5	Lokeshwor et al. [141]	2014	USL	DT	Logic	No
6	Varadharajan et al. [237]	2014	USL	SVM-MIL	LIBSVM	Yes
7	Amhaz et al. [7]	2014	USL	LC	–	Yes
8	Nguyen et al. [171]	2009	SL	NN	BP	No
9	Oliveira and Correia [179]	2013	USL	LC-DT-HC	–	Yes
10	Lee and Lee [123], Ceylan et al. [28]	2004, 2014	SL	NN	–	No
11	Zhou et al. Zhou et al. [295], [296]	2003, 2005, 2006	SL	DT	CART	No
12	Salari and Ouyang [200]	2012	SL	SVM-DT	–	No
13	Avila et al. [13]	2014	USL	LC	DP	No
14	Bray et al. [21]	2006	SL	NN	BEMD	No
15	Tsai et al. [231]	2014	USL	DT	–	No
16	Ouyang et al. [181]	2014	SL	DT-LC	CIT	No
17	Zakeri et al. [277]	2013	SL	NN-DT	–	No
18	Oliveira and Correia [179]	2013	USL	LV	–	No
19	Wang and Gao [244]	2012	SL	LC	–	Yes
20	Gavilán et al. [61], Na and Tao [164]	2012	SL	SVM	PSVM	No
21	Wang and Feng [252]	2012	SL	DT	–	No
22	Salari and Yu [201]	2012	SL	NN	–	No
23	Nejad and Zakeri [159, 167, 168]	2011	SL	NN	DNN	Yes
24	Gavilán et al. [61]	2011	SL	SVM	LSVM	No
25	Moussa and Hussain [163]	2012	SL	SVM	Kernel	No
26	Salari and Bao [198]	2010	SL	LC	LV	No
27	Nejad and Zakeri [159]	2011	SL	DT	–	No
28	Li et al. [135]	2011	USL	–	–	Yes
29	Salari and Bao [199]	2011	SL	NN	–	No
30	Chambon et al. [29]	2010	USL	BC	–	Yes
31	Zuo et al. [299]	2013	USL	FC	Logic	Yes
32	Xu et al. [264]	2013	USL	BC	Bayesian	Yes
33	Na and Tao [164], Xu et al. [262, 264]	2013/2	SL	LV	Interpolation	No
34	Tsai et al. [230]	2013	USL	DT	Logic	No
35	Tang and Gu [224]	2013	SL	DT	–	Yes
36	Koutsopoulos et al. [117], Oliveira and Correia [178], Wang and Tang [250, 251], Li et al. [131, 132], Song and Wei [214]	2013	SL	SVM	Kernel	No
37	Salman et al. [202]	2013	USL	DT	–	No
38	Oliveira and Correia [179]	2013	SL	LC	Logic	No
39	Li [129], Li et al. [130]	2013	USL	FC	–	
40	Zou et al. [298]	2012	USL	DT	MST*	Yes
41	Zhang and Zhou [289]	2012	SL	DT	PC	No
42	Tsai and Li [234]	2012	SL	DT	DO*	No
43	Tsai et al. [232]	2012	USL	LC	–	No

Table 6 continued

No.	References	Year	Method	Type class	Descriptor	Compared to other methods
44	Ouyang and Wang [182]	2012	SL	–	–	No
45	Nishikawa et al. [173]	2012	SL	–	–	No
46	Ni et al. [172]	2012	SL	BC	Adaboost	No
47	Li [127, 128]	2012	SL	–	–	Yes
48	Jahanshahi and Masri [89]	2012	SL	SVM/LC/NN	SVM/NN	Yes

Method	Type class	ID3: Iterative Dichotomiser 3
SL: Supervised learning	SVM: Support vector machines	C4.5: Successor of ID3
USL: Unsupervised learning	LC: Linear classifiers	CART: Classification and regression tree
SSL: Semi-supervised learning	KE: Kernel estimation	CHAID: CHi squared automatic interaction detector
RL: Reinforcement learning	BC: Boosting classifier	MARS: Extends decision trees to handle numerical data better
DL: Deep learning	NN: Neural networks	CIT: Conditional inference trees
HL: Heuristic learning	LV: Learning vector quantization	FLI: Fisher's linear discriminate
	DT: Decision trees	LR: Logistic regression
	QC: Quadratic classifiers	NBC: Naive Bayes classifier
	FC: Fuzzy clustering	PC: Perception
		LSSVM: Least squares support vector machines
		KNN: k-nearest neighbor
		RF: Random forests
		DP: Dynamic programming
		BEMD: Bidimensional empirical mode decomposition
		PSVM: Proximal support vector machine
		DNN: Dynamic neural network
		LSVM: Linear SVM
		MST: Minimum spanning trees
		DO: Dynamic-optimization
		MIL: Multiple instance learning

A comparison of these methods and using the most predictive classifier is very important and difficult. Each of the methods shows diverse effectiveness and correctness based on the kind of datasets. The criteria for evaluation will be discussed in Sect. 1.3.

This section briefly reviews the various classification approaches used in order to categorize the pavement surface images into various distress, severities and extent.

An unsupervised two-step pattern recognition method is presented in [179]. Based on the unsupervised procedure, six clustering methods consisting of hierarchical, k-means and hybrid (two Gaussians) were considered for training. The outcome was the image blocks without crack pixels or with crack pixels [179]. Also, the crack type characterization rules are used for classification of longitudinal (L), transversal (T) and miscellaneous (M) cracks. They reported that all detected cracks were correctly classified as three types of L, T, and M. The best overall performance was 93.5 % for F-measure, recall was 95.5 % and the best global error rate was 0.6 %.

Chou et al. [41, 42] proposed the theory of fuzzy sets and used moment invariants from different types of distress for pavement distress detection and classification. Then, a back-propagation neural network was used as a classifier.

The BP is employed by Nguyen et al. [171] for automatic detection and classification of defects on road pavement using anisotropy measures.

In order to classify crack types of digital pavement images, Lee et al. [123] proposed an integrated neural network-based crack imaging system. The proposed system is used as three neural networks: image-based neural network, histogram-based neural network, and proximity-based neural network. Integrated NNs are used to classify

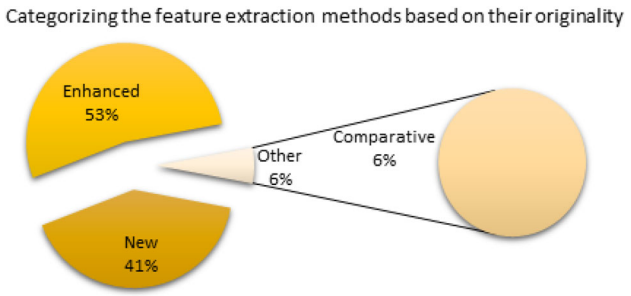


Fig. 19 Categorizing the feature selection methods based on their originality

various crack types based on the tiles. The proximity-based neural network effectively searches the patterns of various crack types. The accuracy of 95.2 % is reported for pavement distress classification.

Zhou et al. [295, 296] used a two-step transformation method by wavelet and radon transform to determine the type of the crack. According to this method, several statistical criteria are developed in distress detection and isolation, which include the High-Amplitude Wavelet Coefficient Percentage (HAWCP), the High-Frequency Energy Percentage (HFEP), and the Standard Deviation (STD). These criteria are tested on hundreds of pavement images differing by type, severity, and extent of distress. Experimental results demonstrate that the proposed criteria are reliable for distress detection and isolation and that real-time distress detection and screening is feasible based on supervised DT learning [296]. However, the proposed method still suffers from (1) the effects of noise which are generated by the asphalt concrete surface and low quality of cracks (which is lower than 2 % information), (2) thresholding method (crisp) and (3) classification procedure. Therefore, these three areas have become the scope of work for many researchers in recent years.

Hsu et al. [74] described a moment invariant technique for feature extraction and a NN for crack classification. The moment invariant technique reduces a two dimensional image pattern into feature vectors that characterize the image such as: translation, scale, and rotation of an object in an image. Then the neural network in which back-propagation learning was used in its training, classifying this feature, attempted to produce the desired output. However, the back-propagation neural network [159, 167, 168, 295, 296] may be used to provide fitness against noise. The results that they reported showed that moment invariant and the neural network can be considered as a robust technique for accurate classification in various types of airport pavement distress [48, 85].

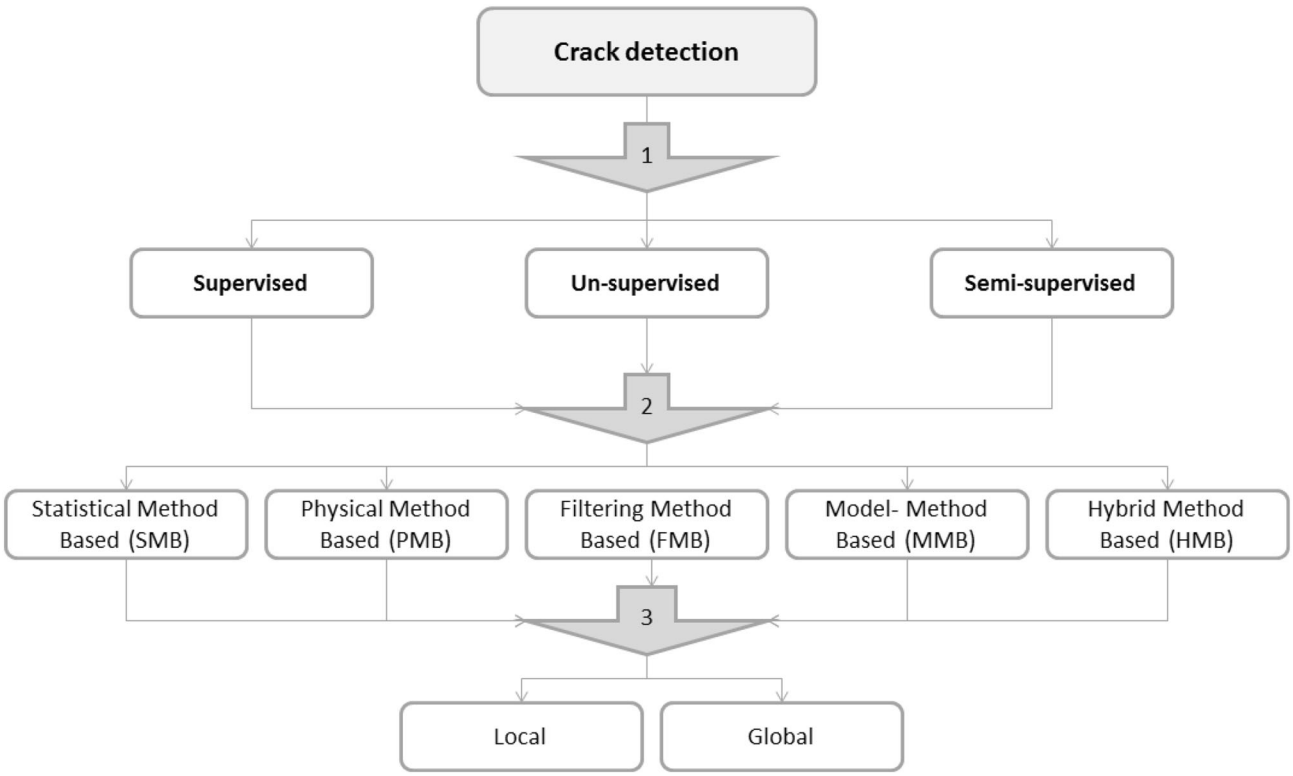


Fig. 20 Classification of crack detection methods based on: *1* supervised, unsupervised and semi-supervised, *2* statistical method based (SMB), physical method based (PMB), filtering method based (FMB), model-method based (MMB), hybrid method based (HMB), *3* local and global [48, 250, 251]

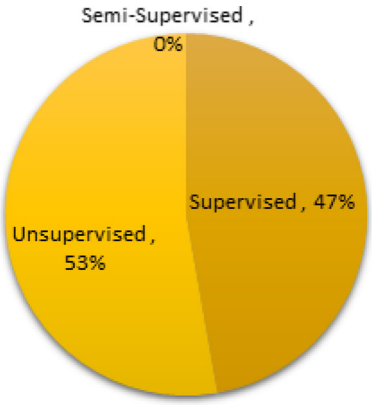


Fig. 21 Comparison of different distress detection and isolation methods

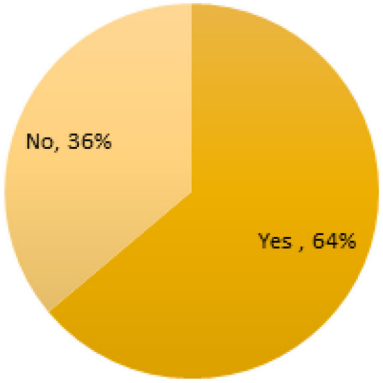


Fig. 23 Ratio of distress detection and isolation compared techniques

Salari and Ouyang [200] used a three step method for distress classification based on SVM. In the first step, they employed a Support Vector Machine to classify the image. Then they used fractal thresholding in order to isolate the cracks. Finally, to classify the cracks they used Radon Transform based on DT to classify the specific crack type [200]. To train the classifier, a total of 40 samples are used. The successful rate of the proposed approach is about 95 for segmentation and over 90 % for classification [200].

Avila et al. [13] proposed a new technique for crack segmentation based on finding the minimal path passing on each pixel of the image. They propose a dynamic programming implementation in real conditions. The results demonstrated the ability of the proposed method for isolation cracks as small as 2 mm [13].

Bray et al. [21] also proposed a classification method based on NN for automatic classification of road cracks. The NN works according to features that are extracted from density and histogram. The features are passed to a NN for the classification. The next NN is employed for the classification of a crack type.

Nejad and Zakeri [159, 167, 168] used a method for Optimum Feature Extraction Based on Wavelet–Radon Transform and Dynamic Neural Network for Pavement Distress Classification. This research demonstrated that the WR + DNN method can be used efficiently for fast automatic pavement distress detection and classification. Dynamic Neural Network (DNN) Threshold selection is used for accuracy of the proposed method. A two-dimensional (2D) extension of EMD is used for pavement distress images. A bi-dimensional intrinsic mode function (BIMF) is employed and the authors reconstruct a composite image by selecting salient information from coarse and fine resolution BIMFs useful for accurate extraction of linear patterns in a pavement distress image. The methodology used in this paper reported better results [2].

Tasi et al. [231] presented a novel crack fundamental element (CFE) approach based on a multiscale topological crack representation. The proposed multiscale CFE model makes available properties of crack that can be employed to develop new crack classification approaches to describe cracks and create a flexibly model for crack classifications [231].

Ouyang et al. [181] proposed the Beamlet algorithm to analyze the pavement crack images and classify the four different cracks based on direction. The Beamlet algorithm has a good robustness for the reason that its line detection was suitable for crack detection and classification algorithm. The proposed method can detect the transverse crack

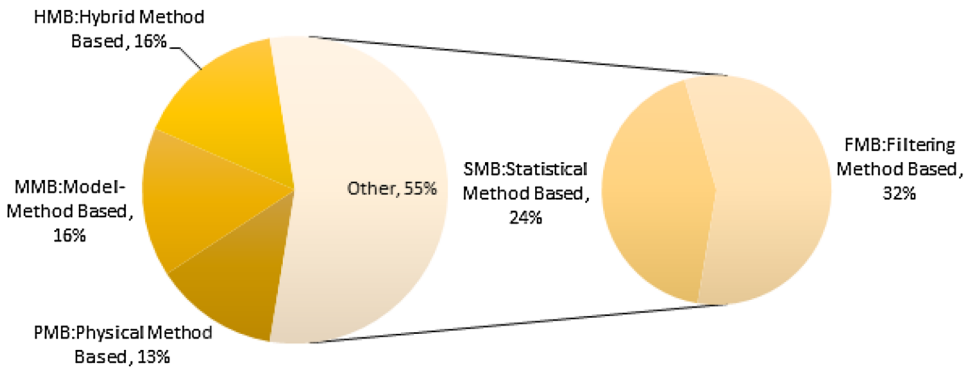


Fig. 22 Comparison type classes of different distress detection and isolation techniques

and longitudinal crack by 100 %, and alligator crack and block crack by above 85 % [181].

Zakeri et al. [277] presented a multi-stage expert system for pavement cracking isolation and classification. The Combination of Wavelet modulus and 3D Radon Transform are employed for knowledge generation. Finally, an NN is used for classification of distress [277].

Nejad and Zakeri developed an automatic diagnosis system for isolation and classification of pavement cracks based on Wavelet–Radon Transform (WR) and Dynamic Neural Network (DNN) threshold selection. The algorithm of the proposed system consists of a combination of feature extraction using WR and classification using the neural network technique. The proposed WR + DNN system performance is compared with the static neural network (SNN) [159, 167, 168].

Two classifiers are used for detection and classification by Olivera et al. [179] for crack detection and then classification which is based on learning from the samples paradigm, unsupervised training. Also, a new procedure for crack severity levels evaluation is presented [179].

Wanng and Goa [244] presented dual-tree complex wavelet transform (DT-CWT) for pavement distress identification. It used a multi-scale and multi-resolution approach to decompose a pavement image into multi-level sub-bands, with high frequency sub-bands containing distress [244]. The experimental study outcomes established its performance enhancement over Discrete Wavelet Transform (DWT) [244].

Na and Tao [164] proposed an approach for automatic classification of pavement surface images. The proximal support vector machine (PSVM)—enhanced classifier—is employed for pavement distress classification, which is more efficient and easier to be implemented than the traditional support vector machine. The experimental results prove that the computation efficiency and classification performance both show better results. The standard PSVM, a variant of SVM, is established based on the optimization concept by Mangasarian, etc. Related with SVM, the method not only improves the computation efficiency but also improves the classification performance. They reported that the classification accuracy rate of the PSVM was 91.15 %. [164].

Wang and Feng [252] proposed the shearlet frame for filtering the pavement images. In the classification of operation, they used the classification rules extracted from Radon transform for crack and angle detection and used scattering distance to verify the result of classification by the texture feature of pavement distress images [252].

Salari et al. [201] used a three-layer feed-forward neural network for a type classification. Based on their method, the vertical and horizontal distress measures along with the total number of distress tiles are then used in NN [201]. The author also used a neural network based pavement distress classifier using the geometrical parameters obtained from the distresses. Simulation results are given to show that the proposed method is both effective and reliable on a variety of pavement images [199].

Figure 24 compares the classification methods for three categories namely Supervised learning (SL), Unsupervised learning (USL) and Semi-supervised learning (SSL). It is clear that the largest proportion of methods went to SL. On the other hand, Semi-supervised (SSL) has the lowest percentage in the chart. A portion of these categories compared to other classifiers is depicted in Fig. 25. According to the above analysis, 69 % of the existing classification methods are not compared with other procedures.

1.3 Image Interpretation Group (IIG)

The number of published papers dealing with crack detection and classification of pavement distress rapidly increased in the previous years. The majority of methods with respect to automatic asphalt pavement evaluation, is concentrated on detection and classification of distress. There is no general and robust automatic method at hand to determine the severity and extent of the level of visual cracking. There are rare indications or quantities in methods assigned to the severity and extent of detected and classified pavement distress.

In [179], a new method is proposed for assigning the severity level of each type of cracks. This method works based on the subset of distress type and width of the crack. Since the calculation of the width of a crack is a difficult task for various widths and directions, the average width of a crack is used to quantify the severity levels. The average width of the cracks can be estimated based on the total number of pixels in a crack to the total number of pixels in the cracks skeleton [179]. However, this method is not excellent at severity assigning for very thin cracks (<2 mm width).

Zhou et al. [296] developed three statistical criteria for distress detection and isolation, which include HAWCP, HFEP and STD, based on wavelet analysis. A norm form cracking quantification based on HAWCP and HFEP was proposed and the usefulness of the proposed indexes is demonstrated. According to this research, the HAWCP parameter for the wavelet at the first level is a high-quality measure for the extent of cracking representation. HFEP, as a good index for severity, is defined as the energy of high-frequency segmented image over the total energy of a pavement image. Also, they believed that one of the best methods to quantify the severity of the cracking section based on wavelet coefficients is to quantify the energy of the coefficients. Distresses are transformed into high-

frequency sub-bands, and the high—amplitude wavelet coefficient has more energy than low—amplitude [296]. The spread of the wavelet coefficients shows the worse pavement conditions. Zhou proposed several simple statistical parameters that facilitate explaining and analyzing the histogram. Finally, pavement distress quantification (PDQ) was proposed as a general index combined of severity and extent and defined PQD = HAWP*HFEP. Based on their research, HAWCP, HFEP and STD proved to be effective criteria for real-time distress detection and quantifying [159, 167, 168, 295, 296].

Additionally, Zhou et al. [295, 296] found relationships between the pattern of peaks and properties of cracks (type, severity and extent). Based on their research, the number of peaks can be used to determine the type of cracks as single or multiple cracks [295]. Based on the RT rules, the position of RT is related to the orientation and position of cracks. The areas of peaks are related to the width of cracks and can be used to determine the severity of cracks. The peak value shows a good relationship between the value of RT and the extent of cracking distress [295].

The pattern of peaks are used for training the neural network to classify the type of crack and the factors of the peaks are employed to quantify the severity and extent of the crack [159, 167, 168]. Under some circumstances, the intensity of the background may be close to the distress, and sometimes there can be some tiny, thin cracks. To solve this problem, a new approach is proposed. For a peak in RT number, position, area, value and volumes are used for knowledge extraction. Nejad and Zakeri used an area of the peaks to quantify the width and severity of a crack, and the value of a peak to quantify the length and extent of the crack. Also, they used the volume of the segmented area as a general index for crack quantification. As a conclusion, they found that some statistical parameters are independent measures for the extent and severity of distress and some of them are subjective. The area of a peak can be selected to quantify the width and severity of a crack and the value of the peak can be used to measure the length and extent of the crack. For the block or alligator cracks, the entire area of the pavement affected by the cracking can be representative of the severity level. The Cumulative Radon Transform (CRT) and Dynamic thresholding are proposed for quantification.

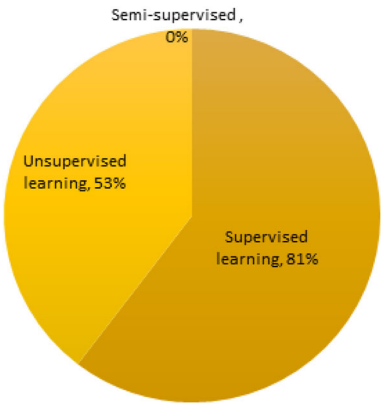


Fig. 24 Comparison of different classification techniques for pavement distress classification based on Supervised learning (SL), Unsupervised learning (USL) and Semi-supervised (SSL)

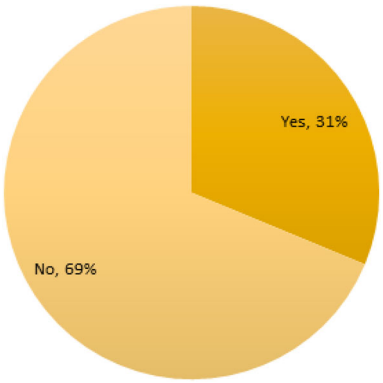


Fig. 25 Compared to other methods

2 Performance Evaluations

To determine the overall performance of a method, a wide variety of well-known metrics for evaluation purposes have been used in the last two decades. The current inspection activity of the pavement surface depends mainly upon the inspectors, technologies, soft computing method, visual inspection, and feeling with distress. This inspection activity could be very subjective and highly dependent on expert opinion.

The reliability and effectiveness of automatic systems are difficult to evaluate especially for different conditions. There are many indexes such as mean square error (MSE), mean absolute error (MAE), entropy, index of fuzziness, mean square error, and peak signal to noise ratio to evaluate the performance. However, accuracy is not a reliable and robust index for the real evaluation of the classifier, because it will yield misleading results if the data set is unbalanced (that is, when the number of samples in different classes vary greatly).

In this section, we classified statistics methods into four classes: General statistics, basic ratios, ratios of ratios, and Additional statistics. From the confusion matrix Accuracy, Error, Probability of detection, Selectivity, Reproducibility, Negative Predicted Value (NPV), False Positive Rate (FPR), False Negative Rate (FNR), False Discovery Rate (FDR), False Omission Rate (FOR), Likelihood Ratio for

Positive Tests (LRPT), Likelihood Ratio for Negative Tests (LRNT), Likelihood Ratio for Positive Subjects (LRPS), Likelihood Ratio for Negative Subjects (LRNS) are computed. Additional statistics like F-measure, balanced accuracy, Matthews Correlation Coefficient (MCC), Chisq: χ^2, Difference between Automatic and Manual classification, Dissimilarity Index of Bray Curtis are used to compare the results. The general performance has been evaluated according to the vector measures extracted from the confusion matrix.

$$\text{Accuracy} = \frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{TN}+\text{FP}+\text{FN})}$$

$$\text{Error} = 1 - \text{Accuracy} = 1 - \frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{TN}+\text{FP}+\text{FN})}$$

$$\text{TPR} = \text{Recall} = 1 - \text{FNR} = \frac{\text{TP}}{\text{TP}+\text{FN}}$$

$$\text{TNR} = \text{Specificity} = 1 - \text{FPR} = \frac{\text{TN}}{\text{TN}+\text{FP}}$$

$$\text{PPV} = \text{Precision} = 1 - \text{FDR} = \frac{\text{TP}}{\text{TP}+\text{FP}}$$

$$\text{NPV} = 1 - \text{FOR} = \frac{\text{TN}}{\text{TN}+\text{FN}}$$

$$\text{FPR} = 1 - \text{Specificity} = \frac{\text{FP}}{\text{FP}+\text{TN}} = \text{Type I error}$$

$$\text{FNR} = 1 - \text{Recall} = \frac{\text{FN}}{\text{TP}+\text{FN}} = \text{Type II error}$$

$$\text{FDR} = 1 - \text{Precision} = \frac{\text{FP}}{\text{TP}+\text{FP}} = \text{q} - \text{Value}$$

$$\text{FOR} = 1 - \text{NPV} = \frac{\text{FN}}{\text{FN}+\text{TN}}$$

$$\text{LRPT} = \frac{\frac{\text{TP}}{\text{TP}+\text{FN}}}{\frac{\text{FP}}{\text{FP}+\text{TN}}} = \frac{\text{Recall}}{1-\text{Specificity}} = \frac{\text{Recall}}{\text{FPR}}$$

$$\text{LRNT} = \frac{\frac{\text{FN}}{\text{FN}+\text{TP}}}{\frac{\text{TN}}{\text{TN}+\text{FP}}} = \frac{(1-\text{Recall})}{\text{Specificity}} = \frac{\text{FNR}}{\text{Specificity}}$$

$$\text{LRPS} = \frac{\frac{\text{TP}}{\text{TP}+\text{FP}}}{\frac{\text{FN}}{\text{FN}+\text{TN}}} = \frac{\text{Precision}}{(1-\text{NPV})} = \frac{\text{Precision}}{\text{FOR}}$$

$$\text{LRNS} = \frac{\frac{\text{FP}}{\text{FP}+\text{TP}}}{\frac{\text{TN}}{\text{TN}+\text{FN}}} = \frac{(1-\text{Precision})}{(1-\text{FOR})} = \frac{\text{FDR}}{\text{NPV}}$$

$$\text{Fmes} = \text{F} - \text{measure} = \text{F1} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall}\ )}$$

$$\text{BalAcc} = \frac{(\text{Recall} + (1-\text{FPR}))}{2} = \frac{(\text{Recall} + \text{Specificity})}{2}$$

$$\text{MCC} = \frac{(\text{TP} * \text{TN}) - (\text{FP} * \text{FN})}{((\text{TP}+\text{FP}) * (\text{TP}+\text{FN}) * (\text{TN}+\text{FP}) * (\text{TN}+\text{FN}))^{0.5}}$$

$$\text{Significance} = \text{Chisq} : \chi^2 = \frac{[(\text{TP} * \text{TN}) - (\text{FP} * \text{FN})]^2 * (\text{TP}+\text{TN}+\text{FP}+\text{FN})}{(\text{TP}+\text{FP}) * (\text{TP}+\text{FN}) * (\text{TN}+\text{FP}) * (\text{TN}+\text{FN})}$$

$$\text{Auto}_{\text{Manu}} = (\text{TP}+\text{FP}) - (\text{TP}+\text{FN})$$

$$\text{Dissimilarity Index of Bray Curtis} = \frac{|(\text{Auto}_{\text{Manu}})|}{\sum(\text{TP}+\text{FP}) + \sum(\text{TP}+\text{FN})}$$

In contrast to FPR = (1 − Specificity), the True Positive Rate (1 − FNR) provides meaningful knowledge about the relevant correctly identified samples. Recall is also sometimes called sensitivity. A test with a high recall and specificity has low type II and type I error rates. The F1-Score or harmonic mean of precision is a hybrid index made of both Precision and Recall. Sensitivity shows the potential of positive recovery rate and complementarity, and the specificity measures the potential of negative recovery rate. The MCC is a powerful index with a range of 1 for perfect correlation and −1 for negative correlation and value 0 for a random prediction. Balanced Accuracy (BalAcc) is a more robust index to compare results of the in balanced data set.

The performance of repeatability or reproducibility enables us to evaluate the performance by the Positive Predicted Value (PPV).

An additional analysis of performance, based on Ratios of Ratios and Additional statistics, can be used for performance evaluation of the methods. The following measures were calculated: Likelihood Ratio for Positive Tests, Likelihood Ratio for Negative Tests, Likelihood Ratio for Positive Subjects, Likelihood Ratio for Negative Subjects, F-measure, Balanced Accuracy, Matthews Correlation Coefficient, and Difference between automatic and manual classification, Dissimilarity Index of Bray Curtis, Discriminate Power, Youdens Index.

Also, Receiver Operating Characteristics (ROC) graphs have been used for checking and visualizing the performance of the methods [55]. This method is able to create a better measure for evaluation of a method than the scalar method such as Type BR, ROR or AS metrics.

A Scoring Measure (ScM) index is proposed based on the Hausdorff distance metric to estimate the crack detection algorithm ability. It has a value between 0 and 100, with ScM of 100 points to the most precise outcomes.

Table 7 Comparison of different indexes to evaluate the performance

No.	References	Year	Method	Speed	Types performance evaluations		
					BR	ROR	AS
1	Jiang et al. [93]	2015	UM	R	–	–	–
2	Grandsaert [64]	2015	SM	R	TPR, PPV	–	Fmes
3	Song et al. [215]	2015	SM	R	Acc, FDR, FOR	–	–
4	Varadharajan et al. [237]	2014	ROC	R	PPV, TPR	–	–
6	Lokeshwor et al. [141]	2014	SM	R	Acc, PPV, TPR, Error	–	–
7	Guan et al. [67], Guan et al. [66]	2014	SM	S	Acc	–	–
8	Amhaz et al. [7]	2014	SM	S	–	–	Fmes
9	Adu-Gyamfi et al. [4]	2014	SM	S	–	–	Fmes
10	Oliveira and Correia [179]	2013	SM	S	PPV, Acc, FOR, Error, Acc	LRPT, LRNT, LRPS and LRNS	Fmes
11	Salari and Ouyang [200]	2012	SM	S	TPR, Acc	LRNT, LRNS	–
12	Ouyang et al. [181]	2014	SM	R	TPR, Acc	–	–
13	Jahanshahi and Masri [89]	2012	SM	S	Acc, TPR, TNR, PPV	–	–
14	Moussa and Hussain [163]	2011	SM	S	ACC	–	–
15	Salari and Bao [198]	2010	SM	R	ACC	–	–
16	Nejad and Zakeri [159]	2011	SM	R	Acc, TPR, TNR, PPV	–	–
17	Li et al. [135]	2011	SM	S	PPV, TPR	–	Fmes
18	Chambon et al. [29]	2010	SM	NI	TPR, TNR	–	Fmes
20	Zuo et al. [299]	2013	SM	S	Acc		–
21	Xu et al. [264]	2013	ROC	NI	PPV, TPR, Error	–	Fmes
22	Na and Tao [164], Xu et al. [262, 264]	2012	SM	NI	Error	–	–
23	Tsai et al. [230]	2013	SM	R	PPV, TPR, Error	–	
24	Tang and Gu [224]	2013	SM	NI	FOM*	–	–
25	Koutsopoulos et al. [117], Oliveira and Correia [178], Wang and Tang [250, 251], Li et al. [131, 132], Song and Wei [214]	2013	SM	NI	Acc, Error	–	–
26	Salman et al. [202]	2013	SM	NI	TPR, PPV	–	–
27	Li [129], Li et al. [130]	2013	SM	NI	–	–	–
28	Golparvar-Fard et al. [63]	2015	SM	NI	Acc	–	–
29	Tsai et al. [231]	2014	SM	NI	Acc, PPV	–	–
30	Zou et al. [298]	2012	SM	S	TPR, PPV	–	Fmes
31	Zhang and Zhou [289]	2012	SM	NI	Acc	–	–
32	Wang and Gao [244]	2012	GS (PSNR)	NI	–	–	–
33	Tsai and Li [234]	2012	GS (PSNR&ScM)	R	–	–	–
34	Tsai et al. [232]	2012	GS (PSNR&SM)	R	–	–	–
35	Ouyang and Wang [182]	2012	GS (SNR), SM	NI	Acc	–	–
36	Nishikawa et al. [173]	2012	SM	NI	Error	–	–
37	Ni et al. [172]	2012	SM	R	Acc	–	–
38	Li [127, 128]	2012	GS (PSNR), SM	NI	Acc	–	–

Method

ROC: Receiver operating characteristics

SM: Statistics metrics

Type performance evaluations

Speed

S: Slow

R: Real-time

NI: No information

Table 7 continued

Method	Speed
GS: General statistics	
BR: Basic ratios	
ROR: Ratios of ratios	
AS: Additional statistics	
Type BR	
Acc: Accuracy	
Error = 1 − Acc	
TPR: True positive rate	
TNR: True negative rate	
PPV: Positive predicted value	
NPV: Negative predicted value	
FDR: False discovery rate	
FOR: False omission rate	
Type ROR	
LRPT: Likelihood ratio for positive tests	
LRNT: Likelihood ratio for negative tests	
LRPS: Likelihood ratio for positive subjects	
LRNS: Likelihood ratio for negative subjects	
Type AS	
F-measure (Fmes)	
Balanced accuracy (BalAcc)	
Matthews correlation coefficient (MCC)	
Chisq (χ^2) or significance	
Difference between automatic and manual classification (AutoManu)	
Dissimilarity index of bray curtis (DIBC)	
Discriminate power ((DIP), 1 ≈ Poor, 3 ≈ Good, Fair ≈ Otherwise)	
Youdens index (YOI)	

$$\mathrm{ScM} = \left(100 - \left(\frac{\mathrm{BH}(x_i, y_i)}{w}\right)\right) \times 100$$

where the BH (x_i, y_i) is the distance between two sections, and w is the recommended 0.2*width of the image [234] (Table 7).

The following pie chart shows the amount of assessment from different categories of performance evaluations. As is observed from the given data, the Basic Ratios (BR) made remarkable progress in performance evaluations over Table 8 (Figs. 26, 27).

At first glance, it is clear for BR that the biggest slice of the pie chart is devoted to Table 8 which is 74 % (Fig. 28). However, less effort was spent on ROR that was 5 %.

Overall, it can be deduced that fewer studies were accounted for ROR by researchers. Moving to a further description, it is vivid that more researches are needed for quality control and assurance of methods.

Figure 29 illustrates the results of the presented survey about the speed and time of the methods. It is clear that based on the survey results, most of the methods have no information about time analysis and the complexity of algorithms.

2.1 Protocols

A computerization-oriented protocol for conditions of asphalt surface pavements was developed in 1996 by FHWA [70]. The standards of ASTM and AASHTO revealed principles for pavement condition evaluation [70]. (AASHTO R 55 and AASHTO PP 67 and AASHTO PP 68). The severity of cracking was overestimated based on the AASHTO standard protocol [193]. Various indexes are proposed to assess the asphalt pavement condition [81, 246, 253].

3 Emerging and Evolution Technologies and Future Works

The prior sections have given a general review on automatic asphalt pavement surface distress evaluation under the title of three groups: Image Acquisition Group (IAG), Image Processing Group (IPG) and Image Interpretation Group (IIG), for the latest.

Table 8 List of of different future and emerging technologies in the field of asphalt pavement distress detection, classification and evaluation

Number	Research and development	Status	Potential application	Related article
1	Satellite	R and E and P	Remote sensing, less expensive, very fast, and cover wider areas	Jin and Davis [98], Zarrinpanjeh et al. [281], Li et al. [133], Paraforos et al. [184]
2	QUAV	H and R and D and E and P	Remote sensing, high resolution, near real-time imagery less expensive, more consistent, fast, and cover wide section, careful inspection, programmable assessment, flexible, maneuverable	Montero et al. Metni and Hamel [155], Leong et al. [125], Zhang and Elaksher [284], Colomina and Molina [46], Michaelsen and Meidow [156], Siebert and Teizer [212], Vasuki et al. [239], Grandsaert [64], Schnebele et al. [203]
3	BCI, neuro prosthetics, Neuromorphic	H and R	Rapid pavement assessing, expert knowledge extraction, Control judgment in the assessment	Gerson et al. [62], Luo et al. [142], Gao et al. [60], Iacoviello et al. [83], McCane et al. [150], Nguyen et al. [170], Rouillard et al. [196], Wirkner et al. [257], Asensio-Cubero et al. [9], Atkinson and Campos [10], Files and Marathe [58], Rai and Deshpande [192]
4	Behavior-based robots (BBR) and Artificial brain	H	Expert decision simulation, analysis based on meta-knowledge, transfer knowledge to intelligent agent and robots, need no programming	Burattini et al. [22], Kupferberg et al. [120], Fernandez-Leon et al. [57]
5	Swarm robotics (cloud robotics)	H and E	Autonomous audit, pavement distress detection, classification and quantification, knowledge generation and learn from each other agents	Guenard and Ciarletta [68], Tong et al. [228], Jiménez-González et al. [96], Natalizio et al. [166], Tan and Zheng [223], Wei et al. [255], McCune and Madey [151], Qureshi and Koubâa [188], Varela et al. [238], Aghaeeyan et al. [5], Kostavelis and Gasteratos [115], Kruglova et al. [118], Yao et al. [266–268], Bayindir [17], Senanayake et al. [204], Shukla and Karki [211], Shukla and Karki [211]
6	Hybrid (FPV and UAV and BCI)	H	Autonomous inspection, pavement distress recognition, quantifies distress, knowledge generation and learns from experts brain signals	Kim et al. [108]
7	Nanorobotics	H	could be employed to inspect, repair and healing cracks	Verma and Chauhan [241]
8	Kirilan photography (Aura)	H	Detection of vital energy of pavement, prediction to propagate surface distress	Duerden [50, 51], Hubacher [81], Prakash et al. [186]

R research, *D* development and diffusion, *E* experiments, *P* prototypes, *H* hypothetical

In this section, research opportunities with an emphasis on emerging technologies and innovative approaches are discussed. In real environments with regards to different characteristics of asphalt pavement, the use of existing systems that cannot work properly are costly and time consuming. In addition, the parameter of engineering judgment is not considered for existing automatic systems and the knowledge generation by these systems is impossible.

One possible solution for solving the problem could be the use of a satellite or UAV platform as a remote sensing technology for data collection and automatic inspection of the pavement surface.

Images taken from the satellites platform, make available the largest spatial coverage of roads and are used in a wide range of applications. Due to this low spatial resolution, they are still not suitable for road studies. However, it is predicted that in the near future they are equipped with high resolutions and make them a great platform for automatic pavement assessment.

Quadcopter Unmanned Aerial Vehicles (QUAV) are a good platform for making high quality imagery with more maneuverability than both manned aerial platforms (MAP) and unmanned aerial vehicles (UAV). Their short time to answer extraordinary movements, and dynamic resolutions make them a great platform for pavement inspection missions.

These platforms create a new chance to cover large areas in little time. These technologies will create an occasion to decrease the sections number and size depending on the visits.

With the advent of tiny robot inspection, assessment and repair of the pavement could be changed in the near future.

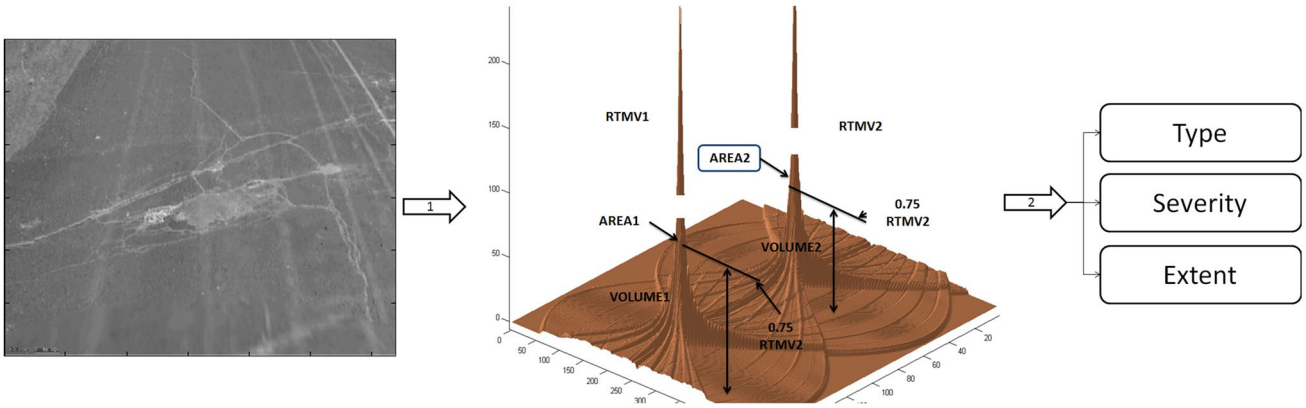


Fig. 26 A peak in radon domain and its parameters [159, 167, 168, 295]

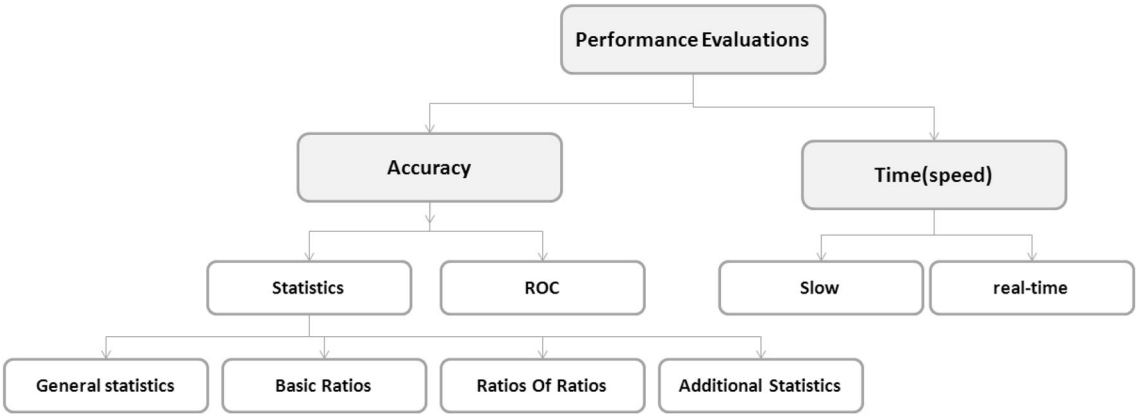


Fig. 27 Classification of metrics for evaluation purpose of pavement distress detection and classification consists of: accuracy and time. The accuracy split in two groups of statistics (general statistics, basic ratios, ratios of ratios, and additional statistics) and receiver operating characteristics (ROC)

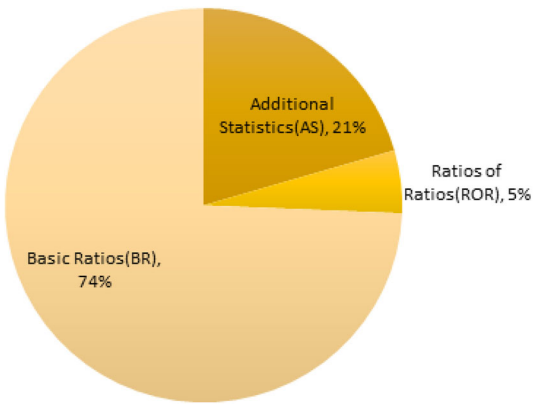


Fig. 28 Categorizing the types of performance evaluations based on their indexes

Nanorobotics are considered as the emerging automatons in the scale of ≤10–9 m [241]. One of the valuable applications of Nano machines might be inspection of pavement. For instance, repairs-nano robots could be employed to inspect, repair and heal cracks.

A stimulating topic for future field studies is represented by transferring the swarm robotics discipline to the micro and nano-scale. Swarms of tiny robots can be employed for pavement network management through the inspection and assessment of distress, maximizing the frequency and accuracy of inspection and minimizing the cost for pavement repairing aims. Several challenges for starting and using these tools are presented in [17].

It is demonstrated that computer vision systems and image processing procedures have to be less successful

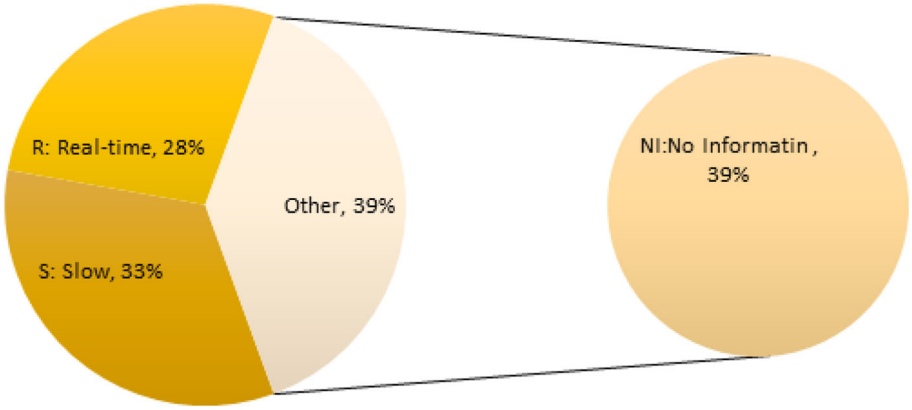


Fig. 29 Determination of different methods in terms of speed

than human visual interpretation [62]. An encouraging topic for future inspection and assessment is brain computer interface "BCI" as an emerging NDT technology. It does not require different sensors or complex algorithms. An electroencephalography (EEG) system capable of identifying neural signatures of visual recognition events was evoked during rapid serial visual presentation (RSVP).

Since the BCI and RSVP method enables inspectors to rapidly analyze facts and figures over a wide section, it has come to be an interesting technique for evaluating distress in infrastructure and pavements. Using BCI for the analysis of infrastructure is a novel and different exploration agenda.

An automatic remote assessment of pavement using an intelligent Quadcopter agent (QUAV) with a low cost electroencephalogram (EEG) headset, like Emotic Epoc, is our mission for the next decade.

4 Summary

It is significant to assess and quantify distress at a regular period. Usually, such evaluations are accomplished as visual, semi-automatic, and automatic approaches. Recently, automated and semi-automated pavement assessment and evaluation has received more and more attention. The appearances of type, severity, and extent of pavement surface cracking are the main features to evaluate the condition of asphalt pavements. The condition assessment results are used to predict future conditions, to support investment planning, and to allocate limited maintenance and repair resources.

This research has studied the current efforts of evaluating the automatic/semi-automatic asphalt pavement distress detection and classification under the headings of: Image Acquisition Group (IAG), Image Processing Group (IPG) and Image Interpretation Group (IIG).

In the first part of this paper, diverse types of automatic/semi-automatic systems are reviewed. Industrialization of thesis platforms are very costly and the quality of consequences are extremely subject to employed sensors. Therefore, in order to improve the quality of images taken from the pavement, more powerful (intelligent, high quality and low cost) tools are required. It is concluded that nearly all commercial systems need a powerful illumination system to prepare uniform lighting conditions for capturing images. Therefore, in order to improve the quality of images taken from the pavement, a more powerful device is needed. The use of robotics quickly increased in many fields of civil engineering because of its benefits (safety, efficiency, and quality).

The second part of the paper has concentrated more on a comprehensive synthesis of the state of the art in the Image Processing Group (IPG). A framework has been proposed for pavement distress detection and classification. Several methods have been categorized, and literature on Pre-Processing (PPS), Segmentation (SEP), Feature Extraction (FES), Feature Selection (FSS), Detection (DES), Classification (CLS) and Image Interpretation Group (IIG) have been presented.

The third part of this paper has focused on parameters and indexes to evaluate the overall performance of a method. There are many methods used to evaluate the performance. However, the current inspection activity of the pavement surface depends on many parameters. A universal synthesis of the cutting-edge in parameters and indices to evaluate models has been summarized in this part.

Finally, future and evolution technologies have been introduced to enhance both the platform and the analysis for future research.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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