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# Semi-automatic inspection tool of pavement condition from three-dimensional profile scans

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**Abstract**

In the present work the preliminary study on qualitative and quantitative assessment of the road surface condition is presented. The work is motivated by a very actual and important problem of visual inspection of the road network. In general the road managers are obliged to perform a regular, periodic maintenance road testing, also the road constructors and civil engineers in the recent design framework – 'design-build-maintain' are interested in seasonal inspections of their constructions. Therefore the semi- or full-automatic visual testing methods of the road surface condition are under a constant development and in the center of interest of many research groups. Herein the main attention is focus on the automatic quantification of a road surface damage type from the three-dimensional cloud points. The stereo vision system, its intrinsic and extrinsic parameters as well as the correspondence-reconstruction problems are here assumed theoretically, since the practical design of the full methodology is still under the development in the ongoing national project.

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*Keywords:* three-dimensional laser scanning, point cloud, pavement crack detection, road surface condition.

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## 1. Introduction

Many researchers, civil and structural engineers devote their work to develop reliable systems for the monitoring of pavement condition. As the problem has been studied for over two decades, the three approaches seems to dominate in the recent years [1], namely (a) a two-dimensional image processing, (b) a three-dimensional laser scanning and (c) the combination of the two previous techniques. While detection procedures are utilized a different distress type can be monitored [2], e.g. a pothole, a rutting, a macro/micro texture, a shoving, a raveling or a cracking.

Nowadays, the assessment of the road surface using image processing only is considered to be the least reliable method [1], [3], since it's vulnerable to potential artifacts in detection results, such as tire marks, oil spills, shadows and pavement repairs. However, many research groups published interesting papers based on the two-dimensional

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approach, for example [4] shows how to detect potholes in asphalt pavement, basing on pothole shadow, approximated by an ellipse. The achieved accuracy basing on 120 tested pavement images (with different shapes and sizes of potholes) is about 86%. Another instance is presented in the paper [5], where authors describe two different approaches for detecting pavement cracks, namely: edge detection and fuzzy set theory. Presented algorithms are capable to classify four types of cracks: longitudinal, transverse, block and alligator (fatigue) cracking. The comprehensive description of fully automatic road distress assessment given in [6], shows the process based on the line scans and image processing tools. The research introduces detection parameters, which should be correctly adapted for particular type of a pavement in order to reduce false detections which might appear due to bad parameter setting. The similar strategy of setup parameters is also adapted here, more details will be presented in the forthcoming section.

Parallel to the two-dimensional image processing, the methods based on the three-dimensional scans were constantly developed, where the measurement database is usually collected by a laser scanner. For more details in 3D data acquisition technologies used in pavement surveys, the reader is referred to the review article of Mathavan et al. [2]. The instance of the three-dimensional approach is proposed in [7], where a real-time 3D scanning system for tracking the rutting and shoving is presented, the scanned data are preprocessed to create transverse, discrete profile lines. Surface distortions, then, are characterized by computed second-order derivatives of each line. Alternatively, in the work of Sun et al. [3] pavement crack detection is computed from sparse linear representation. It is assumed that the pavement profile signal can be decomposed into a number of components, namely: (a) crack, (b) a main signal, (c) a bump, (d) a rut, (e) a pothole and (e) a noise. In attached example main profile is reconstructed very well, however computations are time consuming. Therefore the implementation of the three-dimensional approach gives good results, however still its performance has to be improved.

Combined methods, both two-dimensional and three-dimensional techniques, are merged together in order to obtain a high detection accuracy. Though the concept is known for almost two decades [8], [9], only recently it turned out to be a current trend in the developing of the pavement condition evaluation tools [4]. In the recent works the several strategies in the road surface inspection are introduced. One of the example is the research initiated in 1997 [8] and continued in 2012 [10], where advance and complete laser crack measurement system (LCMS) was demonstrated. The LCMS uses two-dimensional images called intensity data and a three-dimensional point cloud called range data to merge them into the 3D profiles. The algorithm is able to automatically extract not only pavement defects such as longitudinal, transverse and alligator cracks, but also ruts and raveling. Moreover, the system performance was verified on over 9000 km of road network, what resulted in 95% compliance with the manual classification. Another example of mixed approach of pavement crack detection can be found in the paper [1]. Authors report higher detection accuracy, due to the fusion of the 2D gray-scale image and the 3D laser scanning methods. On the contrary, despite many advantages, the mixed approach requires more instrumentation, merging the two different measurement fields (the color intensity and the 3D point cloud) and more advanced algorithms to handle a complex data.

In this communication a slightly different approach is proposed, namely a stepwise global search of surface distress of any type, its further classification and final quantification. The starting point in the proposed procedure is a 3D representation of a road surface. Details on the remaining parts of a full system, namely: (a) acquisition, (b) stereo vision setup and (c) correspondence-reconstruction procedures are omitted here for brevity. The detection procedure bases on smoothen lines (both in longitudinal and transversal directions) and their first-order derivatives.

## 2. Methodology

### 2.1. Acquisition and simplification of database

In general a stereo vision refers to the ability to infer information on the 3D structure and distance of a scene from a series of images taken from different viewpoints. In the herein presented design and methodology the two cameras at fixed position and distance from the observed surface are utilized together with a linear scanning system. Both provide a mutually complementary measurement data which after an algorithmic preprocessing allows to perform proper and precise projection to a 3D cloud of points. Since all optical, photometric and geometric parameters as well as intrinsic (e.g. focal length, frame and pixels coordinate, geometric distortion) and extrinsic (e.g. cameras positions and their arrangement) parameters of the stereo system are known, there is no need to use the standard correlation procedure and therefore the further algorithmic steps are much simpler.

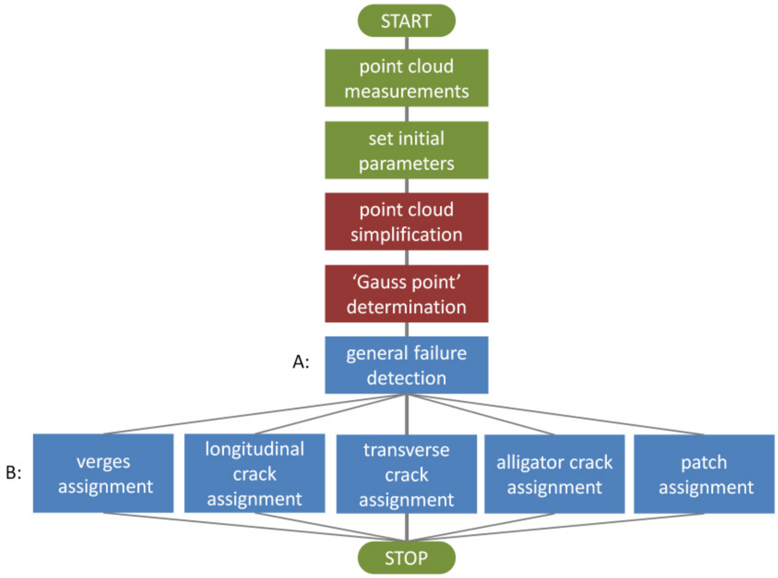

Fig. 1. Framework of pavement failure detection system.

From a computational standpoint, a stereo system must solve two problems. The first, known as correspondence, consists in determining which item in the left camera image corresponds to which item in the right camera image. This involves two decisions: (1) which image element to match, and (2) which similarity measure to adopt. The correspondence algorithms can be roughly divided in two classes, correlation-based and feature-based methods. Although almost indistinguishable from a conceptual point of view, the two classes lead to quite different implementations: for instance, correlation-based methods apply to the totality of image points, which correspond to the family of algorithms widely used in digital image correlation (DIC) techniques [11], [12] and [13]. On the other hand the feature-based methods attempt to establish a correspondence between sparse sets of image features (numerical and/or symbolic properties of features, available from feature descriptors).

The second problem that a stereo system must solve is reconstruction – the interpretation of the computed difference in retinal position, named disparity, between corresponding items. The disparities of all the image points form the so-called disparity map, which can be displayed as an image. The 3D reconstruction that can be obtained depends on the amount of a priori knowledge available on the parameters of the stereo system. In our case both intrinsic and extrinsic parameters are known (due to fixed position and setup of both cameras), therefore the reconstruction problem can be unambiguously solved by a triangulation.

Once the 3D reconstruction of the road surface as a cloud of points is computed, the data compression procedure has to be applied. Here the averaging algorithm, which provides a line representation of longitudinal and transversal strips of a certain width is utilized. In order to ensure an optimal compromise between the data reduction and retain precision the amount of pixels used for averaging process should be in a range from 5 to 15 pixels. After the compression process the simplified 3D surface is represented by the orthogonal grid lines which are spaced in a certain distance, optimally from 10 to 20 pixels. Finally in each grid node of the orthogonal net the specific characteristic of joint line segments (i.e. four segments with a half the distance between nodes) are computed. The last stage is essential in a correct quantification of pavement deterioration.

### *2.2. Pavement failure detection*

Algorithms incorporated here for the condition inspection of pavement surface require holistic approach where small zone of the system is analyzed in a reference to a larger region of a road surface. For instance, the rapid change of the profile in the transverse direction could be a curb or a pothole. In order to exclude unsuccessful (wrong) classification, neighborhood of a zone of interest (ZOI) should be also considered while decision making process. Presented here the pavement failure detection system (PFDS), is a part of a FEMat Road package (UDPhoto toolbox) [14], which consist of multiple easily extendible procedures for: (a) a road side detection, (b) a longitudinal, (c) a transverse, (d) an alligator cracking detection, (e) patch area estimation and (f) longitudinal and transversal evenness. A part of the package (not presented here) consists of correspondence-reconstruction procedures, which are used to create the 3D representation of a road surface from a 2D stereo system and/or laser scanning. After a preprocessing and reduction phase, an inspection in three essential stages is performed: (A) first the general condition is identified, then (B) a failure is classified (based on a surrounding area), finally (C) each type of damage is quantified. The block diagram in **Error! Reference source not found.** demonstrates procedure framework. Failures which were reconstructed in the first stage (**Error! Reference source not found.**A) are later classified and quantified (**Error! Reference source not found.**B) to one of the possible type of failure by individual sub-procedures.

The field measurement of a point cloud, apart from pavement surface, includes also inadequate areas which should be excluded from the detection process. The major representative of the group is the verge – road side. The PFDS initially qualifies verge as a failure (**Error! Reference source not found.**A). However, in the second stage (**Error! Reference source not found.**B), before other failures assignment, road sides are characterized and deleted from identified domain of failures. We assume that a verge is parallel to a side edge and would cover significant part of the longitudinal profile, in contrast to other failure types. The user determines the threshold *V*, which reads a ratio between summed lengths of identified road failure in longitudinal profile to entire length of measured road section. Moreover, we assume that verge is ended when first encountered longitudinal profile does not satisfy the condition (i.e. algorithm breaks while searching for verges). In other words, if the particular longitudinal profile ratio is larger than the ratio provided by the user the profile is assigned to the verge type and excluded from the general failure domain.

The procedure is also able to track separately longitudinal and transverse cracks. The identification method bases on a micro-pattern search technique. The algorithm loop (over general failures) checks closest area of each pixel. Two pixel setups are analyzed for a purpose of finding the longitudinal (Fig. 2A.1) and transverse (Fig. 2B.1) cracks (*a-b-c-d-e* pixels for the longitudinal and *f-a-b-d-e* pixels for transverse). Each time four neighbors are analyzed (plus pixel of interest – the one qualified as general failure). In the Fig. 2A.2 and Fig. 2B.2 used micro-patterns are presented, black cell represents pixel which was detected as the failure area of pavement. If one of the micro-pattern in Fig. 2A.2 or Fig. 2B.2 is actual then pixel of interest (pixel *a* in the Fig. 2) is qualified as no longitudinal/transverse crack. If one of presented micro-patterns is not found, then failure is identified as linear crack (longitudinal or transverse) and further, evaluation of alligator crack type is performed.

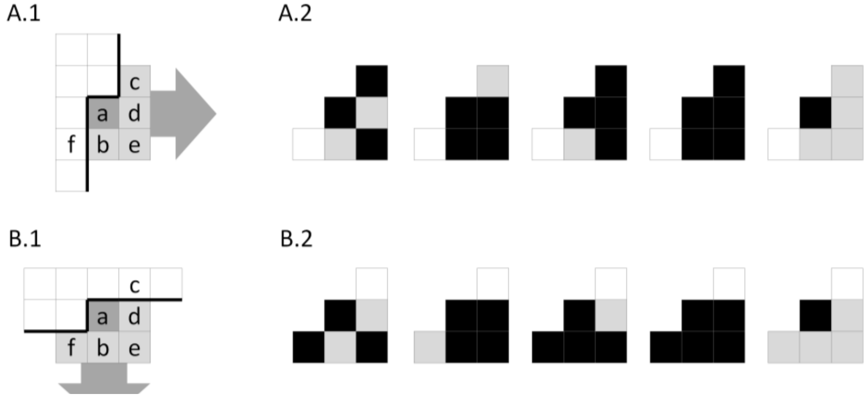

Fig. 2. Line crack detectors, considered pixels in longitudinal (A.1) and transverse (B.1) crack directions; micropatterns for longitudinal (A.2) and transverse (B.2) crack determination.

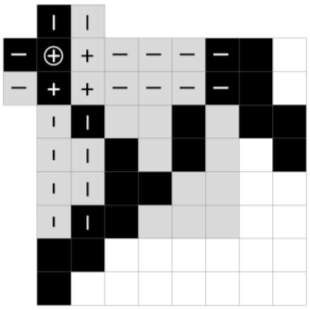

Fig. 3. Example of alligator crack detection, black represents distress pavement, white represents intact surface and grey represents region of interest.

One of the major asphalt pavement distresses is crack with alligator (or crocodile) skin pattern, called briefly alligator cracking. The distress is characterized by interconnected cracks, which form group of polygonal shapes. After linear crack qualification, the program checks if surrounding region of interest contains ‘failure pixels’, if so the rectangular region of interest is qualified as the alligator crack area. Checking is performed in two directions, longitudinal and transverse. Two pixel bands are verified at each direction (pixel of interest and subsequent pixel band). The length of the longitudinal and transverse bands (number of pixels) depends on the determined parameters of *W* and *H*. The idea of alligator detection scheme is presented in **Error! Reference source not found.**, the pixel of interest is marked with "O". Pixels filled with "–" are used for horizontal inspection, pixels filled with "|" are used for vertical inspection, while "+" pixels are used in both directions. Similar, like in Fig. 2B.2 and Fig. 2A.2, a black cell represents the distress area of a road surface, while white one represents an intact pavement. Moreover, by a gray cell the region of interest is marked. In provided example (**Error! Reference source not found.**) parameter *W*, as well as *H*, equals 5.

During the failure identification the procedure can also detect the meaningful repair patches. In order to exclude a characterization of patches’ boundaries as cracks the PFDS checks a surface elevation on the both sides of potential border line (longitudinal or transversal). If the difference is greater than the user threshold *D* then the line is qualified as the patch boundary. It should be noted that the threshold *D* is set a priori before submitting the computations.

After the completion of failure classification, pixels assigned to alligator crack are summed and, therefore, its area can be specified. Similar summation is adapted for computation of a total length of longitudinal and transverse cracks.

## 3. Pseudo-experimental examples

Several important issues must be taken into account in order to create a reliable tool for the pavement inspection. Major points concern (a) processing a large amount of data, (b) an optimal parameter setup and (c) a reliable failure classification. Therefore presented procedure performance was verified on the series of pseudo-experimental tests and examples.

The automatic computations of a pavement condition (instead of visual inspection) are undoubtedly a step forward to improve a road network management quality, raising its efficiency and effectiveness. On the other hand this implies of dealing with very large amounts of digital data. For instance in several meters of a road lane a few millimeters crack should be evidenced, what enforces a high resolution data storage used along thousands of kilometers of the road network. Clearly, for personal computer computations a large dataset must be simplified. Here a set of orthogonal lines for data reduction and simplification purposes is proposed to replace a full 3D data. Example of the simplification on 50x70 mm pavement area is illustrated in **Error! Reference source not found.**, where in **Error! Reference source not found.**A the full 3D data is shown and in **Error! Reference source not found.**B its simplified representation is plotted. The qualitative character of the small road region is preserved, while at the same time matrix of essential data in simplified case is decreased 5 times (in **Error! Reference source not found.**A: the amount of data is 50x70 =

3500; in **Error! Reference source not found.**B: the amount of data is 5x70 + 7x50 = 700 if, like here, the averaging procedure is applied to every tenth line strip in both directions).

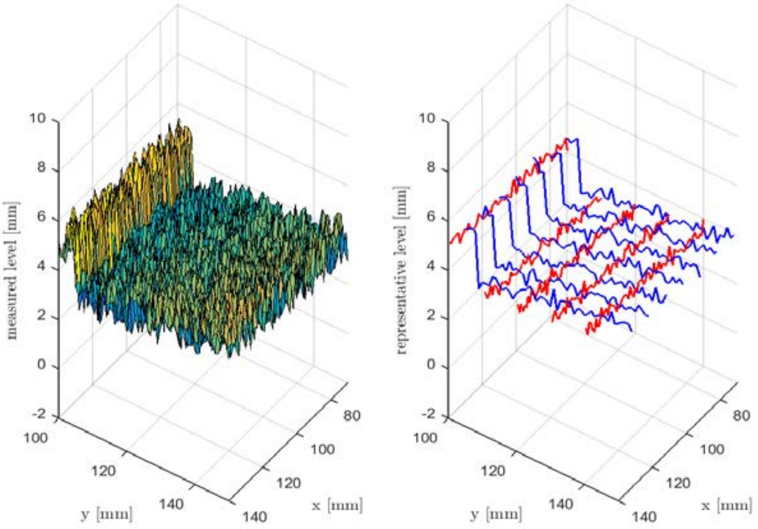

Fig. 4. Raw pseudo-experimental pavement surface (A) and simplified line representation of the same pavement area computed by UDPhoto Toolbox (B).

As mentioned previously the procedure performance strongly depends on the predetermined processing parameters. This approach allows adjusting its efficiency to wider range of an input data and increases a final accuracy, however requires a reasonable parameter setup. Two parameters are studied here in order to find out the best approach for setting the size of an area detector, expressed by the two parameters: pixel width $W$ and pixel height $H$. The results are presented in Fig. 5 (for the pavement demonstrated in Fig. 6A) where a road lane single photo has width of 3 m and length of 5 m. The $Z$ values show how for the different $W$ and $H$ calculated area by the UDPhoto toolbox of alligator cracks is different from the exact value (red plane in Fig. 5). The exact value $A_e$ was calculated manually and equals 2,05 m$^2$. The $Z$ values are expressed by the formula

$$Z(W,H) = (A(W,H) - A_e) \cdot 100\%$$

$$5 \leq W \leq 15 \qquad 5 \leq H \leq 15$$

where $A(W,H)$ is computed by UDPhoto toolbox. For clarity the additional two-dimensional projections of the three-dimensional plots are attached on the right-hand side of Fig. 5. The values $Z_{min}$ = –35% and $Z_{max}$ = 17%, for detector size pairs: $W_{min}/H_{min}$ = 5/5 pixels and $W_{max}/H_{max}$ = 15/15 pixels, respectively. Best parameter setup is denoted by $W$ and $H$ pairs where surface cuts the red plane ($Z$ equals zero), e.g. $W$ = 10 and $H$ = 11.

An adequate inspection parameters' setup allows obtaining a fully automated road surface assessment. The example of a final outcome of the procedure is presented in Fig. 6, where in Fig. 6A orthogonal simplification lines and in Fig. 6B corresponding automatically derived pavement assessment are shown. In Fig. 6B by yellow color the alligator crack are labeled, by magenta – longitudinal crack and by blue – transverse cracks. Deepen road side along the right edge of the road lane – verge (Fig. 6A) is currently not included in procedure of automatic classification (Fig. 6B). The qualitative comparison between Fig. 6A and Fig. 6B gives very satisfactory results of pavement inspection. The vast majority of the longitudinal and transverse cracks are properly identified. Computed alligator cracks coincide with the true area cracks, however some regions, where linear cracks intersects, are wrongly classified. To decrease overestimated areas with alligator cracks the input parameters (*W* and *H*) should be decreased.

For the presented case the calculation time was evaluated. Currently the detection computations of presented (Fig. 6A) single-lane road area (3x5 m) last approximately 10 seconds (on personal computer), therefore for 1km of two-lane road time would increase to over an 1 hour.

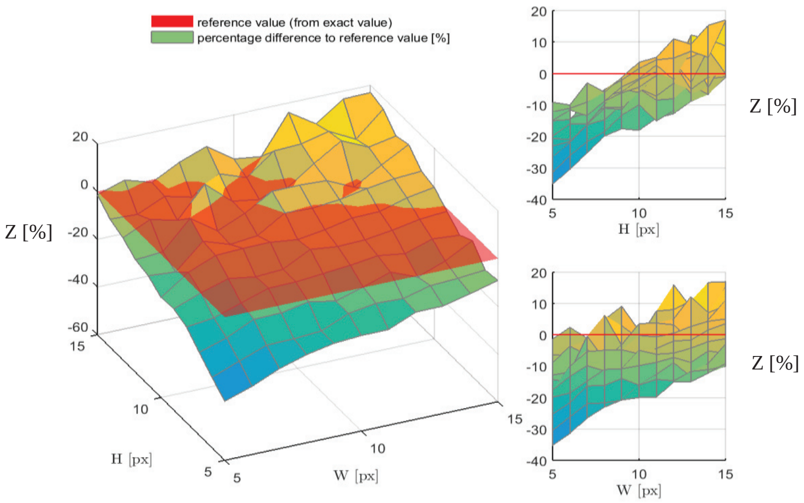

Fig. 6. Study of detector size of alligator crack, three-dimensional (left-hand column) and two-dimensional projections (right-hand column); percentage difference of crack area computed by UDP Toolbox depending on input detector size (values of *W* and *H*) to reference value and reference surface (red) where crack area was computed manually.

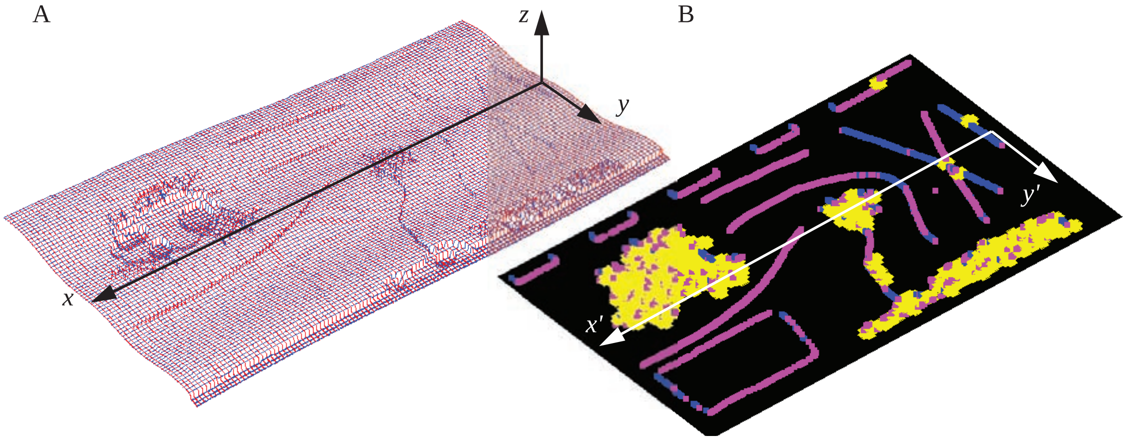

Fig. 5. Example of 3D simplification of pseudo-experimental pavement surface (A) and corresponding computed pavement inspection (B); classified area marked by colours: longitudinal (magenta), transverse (blue) and alligator (yellow) cracks, undamaged surfaces marked by black; axis *x* and *x′* represents longitudinal direction of road lane, *y* and *y′* reflects transverse direction and *z* expresses pavement level.

## 4. Conclusions

The constantly increasing awareness of road managers, civil engineers and constructors in the field of a high quality full-automatic road monitoring triggers a rapid development of visual and nondestructive testing methods. Among many semi- or full-automatic methods available on the market the digital inspections using a stereo vision system or laser scanning seem to be the most popular. In the present communication the novel visual inspection procedure is proposed. The method uses a high quality 3D reconstruction of pavement surface for a full-automatic inspection of a road deterioration type and its quantity. The achieved satisfactory accuracy of the detection procedures encourage for further development on algorithmic precision and speed.

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