Detection of Road Artefacts Using Fuzzy Adaptive Thresholding

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***Abstract*—In this paper the authors are proposing approximate method for road artefacts detection and their location by analyzing acceleration values recorded in the car during driving over the road fragment using the smartphone mounted in the car. The new method called F-THRESH has been introduced, which is adaptively adjusting threshold for road artefacts detection by the fuzzy system means, allowing for outlier detection in chaotic time streams. First, the road quality is being calculated, then the difference between the current data point and mean acceleration is calculated and those two values are used as the input for the fuzzy system, which is calculating threshold to classify data point as an outlier. The proposed method has been compared to the previously implemented method and has an accuracy over 94% with 1.3% of False Positive Rate for the same problem which makes it a great candidate to be implemented in the IoT Edge scenarios, for reducing amount of data being sent to the cloud analyzing system.**

***Index Terms*—fuzzy, thresholding, accelerometer, road artefact, road quality**

I. Introduction

The road network around the world is very dense today – in the example of Poland, there is more than 300 000 kilometers of roads, mostly supervised by territorial government units, where sub-funding is prevalent, so the continuous monitoring of the road state is a very difficult task. To cope with that, to find road artefacts, e.g. potholes, several researchers are proposing usage of crowdsourcing and citizens as data source, especially with the rise of popularity of smartphones and similar devices, using IoT principles. The bases for the pothole detection systems are usually vibration-based methods or visual recognition systems, where the first are based on measuring of acceleration during ride over the potholes, the latter based on visual detection methods.

Road artefacts are hard to describe without mentioning the fuzzy and indeterministic methods, as potholes for example have different, inequal shape, depth, profile and their physical location in the road's axis; every single of them is different, Fig. 1. Difference is also between road users: every car type has a slightly different wheelbase and track, but also a set of all other parameters like wheel diameter, tire pressure and type and finally load and suspension wear. In the authors proposal, exact description of both potholes and other road artefacts, as well as characteristics of the traction of the vehicle, would require too broad number of different decision variables and parameters. Such complex mathematical model will also be hard to apply to aggregated road quality indices understandable for the typical vehicle operator.

In this paper, the authors will describe their own approach for road artefacts detection. Because of fuzzy characteristic of structure and road surface and many uncertainties due to usage of smartphones' sensors, vehicle characteristics and users unique driving type the heterogenous data streams will be used, with a vibration-based information to be the primary source.

Fig. 1. Example of the potholes on a dirt road.

For road anomaly detection using smartphones based on vibration data two main solutions are proposed in the literature: threshold-based, and classification-based [1]. The whole road artefacts detection can be also performed directly on the smartphone, the acquisition device, or in the cloud processing system. If the processing is done in a data center, a large amount of data needs to be transferred for processing, but in the other case — application must use resources of the device, which are also still very limited. To cope with that the authors believe that the best results are the hybrid systems, where rough, approximate algorithm detects road artefacts directly on the acquisition device, and then data is being sent to cloud processing system for final assessment, greatly reducing

Funded by the National Science Centre, Poland under CHIST-ERA programme (Grant no. 2018/28/Z/ST6/00563).

978-1-7281-6932-3/20/$31.00 ©2020 IEEE

amount of data being exchanged with the cloud system.

The goal of the work is to improve existing techniques of road artefacts detection. The proposed F-THRESH method is based on the classification based on adaptive threshold for acceleration data with the fuzzy system means to calculate the threshold value. In a series of numerical experiments, we show its advantages, namely high efficiency and potential to applicability.

The structure of the paper is as follows. In Section II we recall the related literature. In Section III covered is the problem of data acquisition. The novel algorithm of anomaly detection is discussed in Section IV. The results of numerical experiments are presented in Section V. Sections VI is devoted to conclusions while Section VII covers summary and future work directions.

II. Related Works

To build a solution which can be easily implanted directly on the acquisition device, the authors are willing to concentrate on threshold-based methods. Many systems are using custom-designed hardware [2], [3], but since the smartphone spread most of them switched to smartphones and their sensors [4], [5] as the acquisition and pre-processing devices.

The classification-based methods, like Support Vector Machines or k-Nearest Neighbors are not currently feasible for implementation for the low-power IoT devices [6], thus thresholding is a good start. Four algorithms were proposed in [7] for a threshold-based road anomaly detection based on acceleration measured by the smartphone:

- Z-THRESH, where detection occurs when value of z component of acceleration exceeds a specified threshold,
- Z-DIFF, where there is a need for difference between two consecutive values to be greater than threshold to classify as a pothole detection,
- Z-STDDEV, based on the standard deviation in a small sliding window,
- And G-ZERO detecting free fall motion.

In [1] it was proposed a modification to the previous methods by usage of Grubbs test. The authors earlier already implemented a modified version of the Z-THRESH method, called MOD-Z-THRESH [8], where threshold value was calculated relatively to the overall road surface quality in a set of tumbling windows, instead of using strictly defined threshold. Other threshold-based methods include mostly also just Z-axis acceleration [9], but it must be noted that some more complex features extracted from accelerometer signals, for example time domain features, such as mean, median etc. [10], could be used in the described problem.

In [11] the fuzzy system was proposed, where whole uncertainty and noisiness of data was handled by the system itself. The capability of fuzzy systems to converse and make decisions with imprecise data, which is a base for fuzzy logic [12] was also mentioned in [13]. In the fuzzy logic field, the usage of it to perform thresholding is also prevalent [14], however mostly in visual recognition systems and image analysis [15].

Accuracy of the proposed road artefact detection systems differ: Nericell [16] uses thresholding with 5-10% of false positive rate. The SmartPatrolling [17] using Dynamic Time Warping is providing 88.89% and 88.66% of accuracy on speed breakers (speed bumps) and potholes respectively. Another techniques accuracy is ranging from 91.43% in the case of the rough road [18], to 94% when Artificial Neural Networks and similar techniques are used [19]. The authors' own method MOD-Z-THRESH [8] can provide an average accuracy of about 93.2%.

The authors however would like to prepare a hybrid system, where candidates for the detection are found directly on the acquisition device in the real time, where usage of calculation heavy methods is impractical – the overall system accuracy will be higher and allow for usage of heavily computational methods, but the goal of the proposed research is to provide a method possible to be implemented on the acquisition devices itself. Because of this requirement, high accuracy and low number of false positives is required to lower amount of data to be sent to the cloud processing system.

Based on the two above proposals, the authors would like to implement adaptive fuzzy system for road artefacts detection based on acceleration data thresholding, called F-THRESH.

III. Data Acquisition

Because of difference between cars and their parameters, every data can be understood as averaged fuzzy information. The data acquisition procedure was based on the concept already implemented in [8], where smartphone, Lumia 820, was mounted in the car in a stable position, which was the only requirement, and in case of the experiments presented in this paper it was in the central console.

The orientation of the acquisition device in the car was mitigated using the orientation sensor and translation of the data to the global coordinate system [20], see Fig. 2.

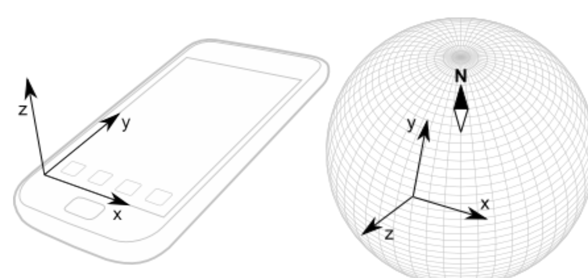

Fig. 2. The global coordinate system [20]

The global coordinate system is based on three axes: magnetic north, magnetic earth, and perpendicular to the Earth's surface (which will be marked Z_2). Reorientation of the data from the sensors is performed using the rotation matrix. Acquisition device was calibrated as described in the previous paper to cope with a slight data oscillation of the accelerometer.

Finally, a set of heterogenous data is being acquired:

- Acceleration in the X, Y, and Z axis of the device, measured in g, unit relative to the Earth's acceleration factor (9.81 m/s^2),
- Acceleration in the global coordinate system: N, E and Z_2,
- Current location from the GNSS (Global Navigation Satellite System),
- Current speed (in m/s), magnetic course and time.

Data are being acquired every 100 milliseconds. However, GNSS system frequency is only about 1 Hz due to smartphone operating system limitations.

Data was divided into two sets: primary, which is Z_2 axis (axis perpendicular to the Earth's surface) acceleration value and current GNSS location and secondary – N and E axis acceleration, current speed, course and time.

The dataset presented in Table I is a data taken when the car was driving over a road artefact example - the speed bump, which is visible when data from Z_2 is presented in Fig. 3. The data acquisition frequency for this dataset was 10 Hz for an acceleration values and they are during the drive of the discrete geographical location – due to GNSS system receivers, geographical points have both lower accuracy and much lower sampling rate than acceleration values. However, discrete geographical data points will be used later as a base for calculation of detection of road artefacts in the desired location.

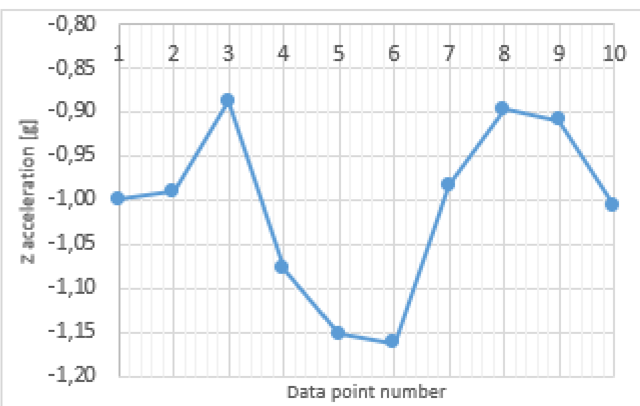

Fig. 3. Z acceleration value when driving over the road artefact.

In the presented case, there is a value rise in the first 3 data points which is a representation of the car going "up"' when driving, then there is going down when acceleration values are greater than -1 g in the absolute value and then up again when the second pair of wheels is meeting the surface of the road artefact.

IV. The Outlier Detection Algorithm

In case of MOD-Z-THRESH, the main concept was based on adapting the threshold based on the current road quality as measured by the average acceleration value. The Z_S value was calculated as the absolute difference between the current Z_2 (Z reoriented to be perpendicular to the Earth's surface) axis acceleration value minus the average acceleration value in that axis, as presented in (1).

$$Z_S = |Z - avg(Z)| \tag{1}$$

The current data point was marked as potential road artefact when Z_S was greater than threshold defined as multiplication of standard deviation for the current road fragment (σ) by a defined factor (t).

$$Z_S > \sigma_Z \cdot t \tag{2}$$

That factor was experimentally validated to get best values when about 4.3 [8].

In the proposed method, the similar approach will be used but the threshold (t) should not be expressed as the static value, but it should be calculated automatically by the fuzzy system, and to perform this, a few solutions have been proposed and validated.

Every calculation for the algorithm is performed based on a tumbling window principle – a set of windows which are not overlapping, which is a basic technique of analyzing data on the fly. Size of the tumbling window may be different, and different options have been tested later.

In the proposed algorithm for the inputs for the fuzzy system two variables will be taken into consideration: road quality, based on the RRUI (Road Relative Unevenness Index) as defined in [8], but expressed as the number instead of a letter scale. RRUI scale classified road quality as an integer from 0 to 7, where 0 is the best quality and 7 is the worst quality.

The proposed system architecture is presented in the Fig. 4. The vertical acceleration signal is derived from the smartphone sensors, which readings are being reoriented by the usage of rotation matrix for calculation of Z_2, acceleration value in the axis perpendicular to the Earth's surface. Then, this value is divided into a set of tumbling windows. For each tumbling window, the average Z_2 is used in calculation of the relative road quality, classified into a numerical value and then for each acceleration value the in a window the fuzzy system is fed with its Z_S value calculated by (1) for current Z_2 value and road quality for currently analyzed window, which is calculating the threshold value. The system is then finding the threshold and if the current data point threshold is met by (2), the current geographical location is marked as possible road artefact. Then, aggregation of the road artefacts in the same geographical position is performed, to group all possible artefacts in the near neighborhood and remove duplicates. In the final version of the system, the notification of the new road artefact should be also presented on the user's screen, but it is not used in the presented research.

A. Road Quality Classification

The road quality classification values were divided into three classes introducing fuzzy numbers by linguistic variables ("good", "mediocre", and "poor") by membership functions presented in the Fig. 5 and Fig. 6.

TABLE I
EXAMPLE DATASET

X	Y	Z	N	E	Z2	Latitude	Longitude	Time
0.05537	0.00898	-0.9998	0.01728	0.0473	-1.00011	51.27294	22.54432	2015-01-24 09:29:13;854
-0.03643	-0.02422	-0.99492	-0.07287	0.06645	-0.99099	51.27294	22.54432	2015-01-24 09:29:13;952
0.05732	-0.04961	-0.88555	0.00227	-0.01717	-0.88862	51.27294	22.54432	2015-01-24 09:29:14;048
0.15107	-0.02227	-1.07305	0.09636	-0.04815	-1.07849	51.27294	22.54432	2015-01-24 09:29:14;159
0.03975	0.05781	-1.15313	0.04665	0.06677	-1.15238	51.27294	22.54432	2015-01-24 09:29:14;251
-0.05205	0.04512	-1.16484	-0.03391	0.09776	-1.16228	51.27294	22.54432	2015-01-24 09:29:14;348
-0.02373	-0.01348	-0.98516	-0.04081	0.03077	-0.98421	51.27294	22.54432	2015-01-24 09:29:14;449
0.07393	0.08613	-0.89727	0.09052	0.06121	-0.89779	51.27294	22.54432	2015-01-24 09:29:14;549
0.196	-0.08184	-0.90215	0.10269	-0.1417	-0.91014	51.27294	22.54432	2015-01-24 09:29:14;651

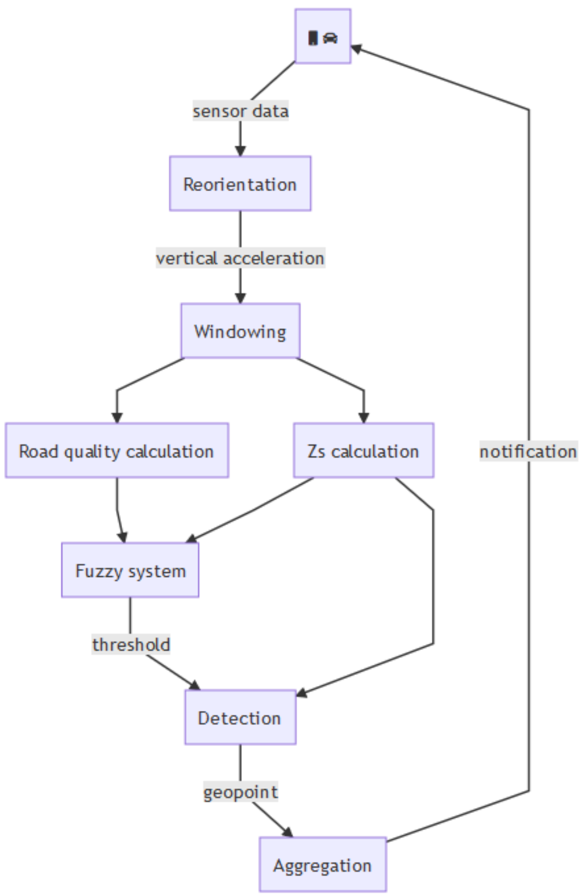

Fig. 4. The proposed system architecture.

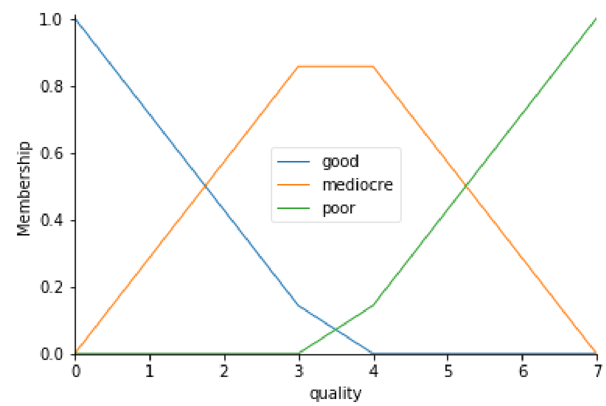

Fig. 5. Membership function for the road quality indicator (variant 1).

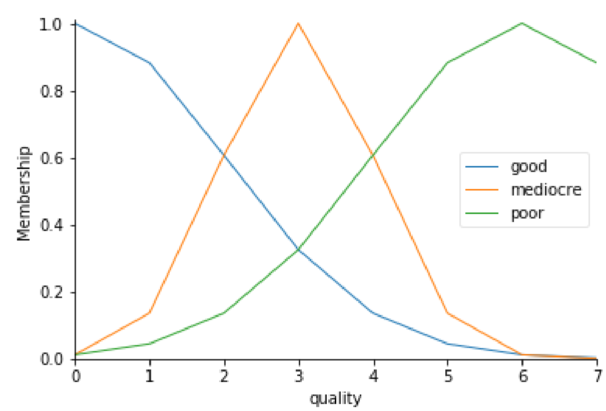

Fig. 6. Membership function for the road quality indicator (variant 2).

On the other hand, a difference between current reading and average value of acceleration in Z axis will be classified into two classes: “low” and “high”, by simple membership function as presented in the Fig. 7.

The system will be calculating output parameter, the threshold value, by the means of fuzzy system, based on the membership functions dividing values into three classes: “low”, “medium” and “high”.

The system set of rules was defined by two simple rules:

- IF quality is poor or reading is high, THEN threshold will be high,
- IF quality is good or reading is low, THEN threshold will be low.

Defuzzification operation was implemented using the standard centroid method. The threshold value was calculated for every datapoint and if the current Z axis acceleration was greater than current threshold, that data point was classified as a possible road artefact.

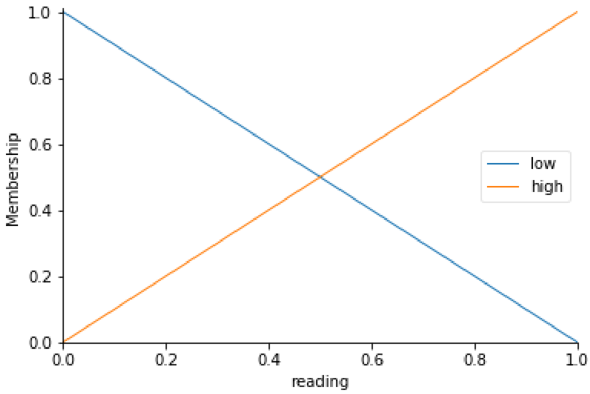

Fig. 7. Membership function for the difference between reading and average value of the acceleration in the current window.

B. Threshold calculation

Several variants of the membership functions for the output parameter were proposed, as presented in the Fig. 8–11. First one is a simple function based on three triangular functions, the second is a combination of triangular functions and gaussian function. Variants 3 and 4 are using three gaussian functions where medium value in both cases is based over mean of 4.3 and deviations of 0.3 and 0.5, respectively.

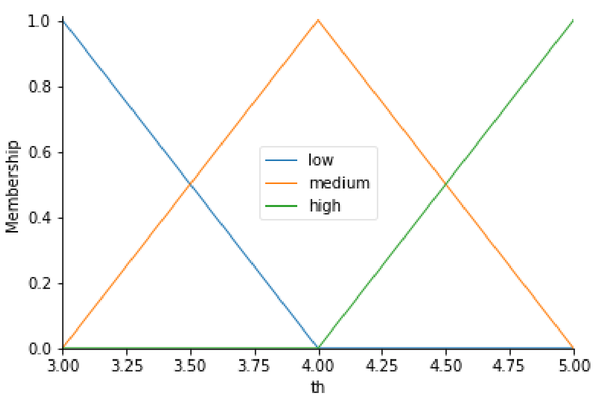

Fig. 8. Membership function for the calculated threshold (variant 1).

C. Possible road artefacts aggregation

A crucial final step is also the possible data points aggregation to remove possible duplicates. There is a possibility for detection of one road artefact as a several ones. For example, based on a data from Table I, there is a possibility for the algorithm that detection will be true for datapoints number 3, 5 and 8 – but they are all in the same location. Aggregation of the points which are in the geographical neighborhood may be performed dynamically, based on current GNSS system accuracy or based on the static neighborhood size.

V. Experimental Results

The algorithm was implemented in Python using scikit-fuzzy package, every experiment was performed using 64-

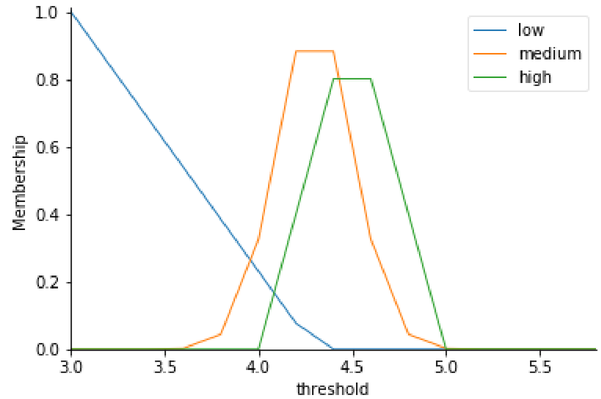

Fig. 9. Membership function for the calculated threshold (variant 2).

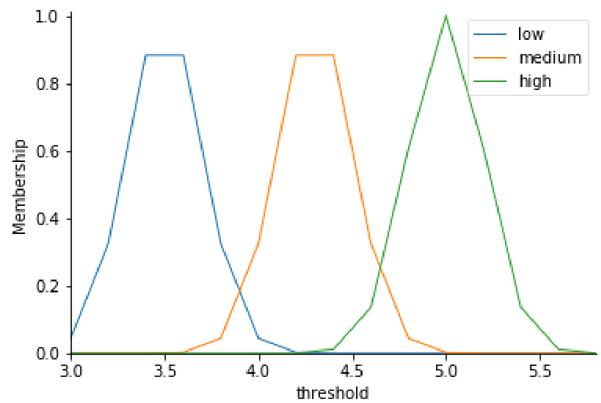

Fig. 10. Membership function for the calculated threshold (variant 3).

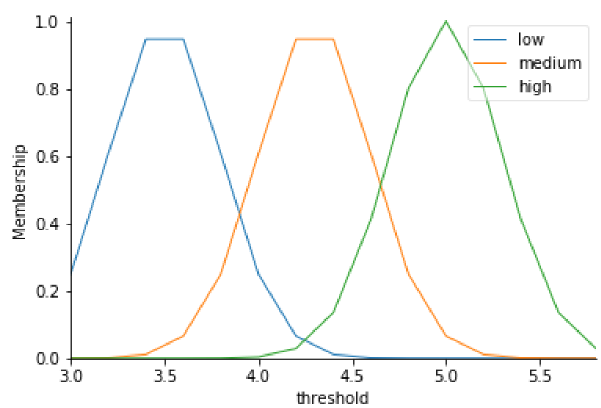

Fig. 11. Membership function for the calculated threshold (variant 4).

bit Python 3.8.0 under Windows 10. From every possible artefact being detected by the tested algorithms only GNSS coordinates were extracted. Because detecting location of the road artefact is the most crucial element of the experimental validation, grouping the artefacts was performed, where every road artefact in the range of 20 meters was combined into one.

Proposed algorithms were compared to the previously implemented methods by the basis of counting number of True Positives (detected position of a road artefact and there is an artefact in that position), False Positives (detected position of road artefact, but there is no artefact in that position), False Negatives (not detected road artefact in the position, but there is one) and True Negatives (not detected road artefact and there is no artefact in the position).

For every algorithm, the same set of experimental data were used for validation, consisted of data recorded during the preliminary experiments in 2015 and 2016. Experimental dataset was divided into 13 parts. Each of them has a slightly different overall road quality and different types of road artefacts to be detected, however in the same class (potholes, speed bumps). Number of separate geographical positions were ranging from 100 to 640, number of road artefacts in the dataset were ranging from 2 to 13. The dataset has been published at [21].

Two parameters were chosen as the base for the comparison: Accuracy (ACC), defined as the number of True Positives and True Negatives divided by the sum of TP, TN, FP and FN. Second one was False Positive Rate (FPR), number of False Positives by the sum of False Positives and True Negatives. Accuracy should be highest, while False Positive Rate should be as low as possible.

The algorithm was tested over a set of different tumbling window size -– 50, 100 and 200 samples. These sizes, with an acquisition data frequency of 10 Hz will represent 5, 10 and 20 seconds of driving, which, assuming average road traffic speed of 10 m/s, is relative to the vehicle size, two times the vehicle size and 4 times the vehicle size. Longer windows were used to analyze the possibility of further aggregation of longer road segments quality indices. All possible variants for F-THRESH algorithm – usage of variant 1 and 2 of the road quality indicator membership functions, usage of every variant of the threshold membership functions, usage of different window sizes - are presented in Table III.

The important element to mention is that all proposed algorithms were strictly deterministic, that means for the same dataset always the same road artefacts were detected or undetected, removing necessity for multiple trials for every possible combination of algorithm, data window size and membership functions variants.

The best results in terms of accuracy and false positive rate are presented in the Table II, compared to the authors' previous method, the MOD-Z-THRESH, on the same test cases.

In the Fig. 12, there is a presentation of the values of threshold in relation to calculated Z_S values, showing how adaptive system is working:

- the grey values are the pure Z_S values,
- green are thresholds, calculated by MOD-Z-THRESH with factor 4.3
- blue are thresholds, calculated using new F-THRESH
- with 50 samples window, quality function 2 and threshold function 3,
- yellow is standard deviation of Z_2.

It may be noticed, that for two presented data windows (data points 1-50 and 50-100, respectively), the standard deviation differs. The most important conclusion may be however seen in the difference between thresholds calculated by the new method (blue) and the old one (green) – the new thresholds are changing more dynamically, respecting changes in the overall road quality faster. Because of more accurate calculation of threshold, there is a possibility to find a road artefact

TABLE II
COMPARISON OF ALGORITHMS' ACCURACY AND FALSE POSITIVE RATE

Algorithm	ACC	FPR
MOD-Z-THRESH with 4.3 threshold factor	93.26%	3.51%
F-THRESH with 50-samples window, road quality function 2, threshold function 3	94.21%	1.41%
F-THRESH with 50-samples window, road quality function 2, threshold function 4	94.16%	1.33%
F-THRESH with 50-samples window, road quality function 1, threshold function 3	94.15%	1.39%

TABLE III
COMPARISON OF F-THRESH'S ACCURACY AND FALSE POSITIVE RATE

Window Size	Road Quality Membership	Threshold Membership	ACC	FPR
50	1	1	93.86%	2.20%
100	1	1	93%	3.85%
200	1	1	92.45%	4.39%
50	2	1	93.81%	2.25%
100	2	1	93%	3.85%
200	2	1	92.32%	4.52%
50	1	2	93.90%	2.15%
100	1	2	92.96%	3.89%
200	1	2	92.45%	4.39%
50	2	2	93.86%	2.24%
100	2	2	92.96%	3.89%
200	2	2	92.33%	4.52%
50	1	3	94.15%	1.39%
100	1	3	93.93%	2.53%
200	1	3	93.35%	3.35%
50	2	3	94.21%	1.41%
100	2	3	93.93%	2.53%
200	2	3	93.33%	3.25%
50	1	4	94.14%	1.33%
100	1	4	93.99%	2.39%
200	1	4	93.56%	3.01%
50	2	4	94.16%	1.33%
100	2	4	93.99%	2.39%
200	2	4	93.52%	3.06%

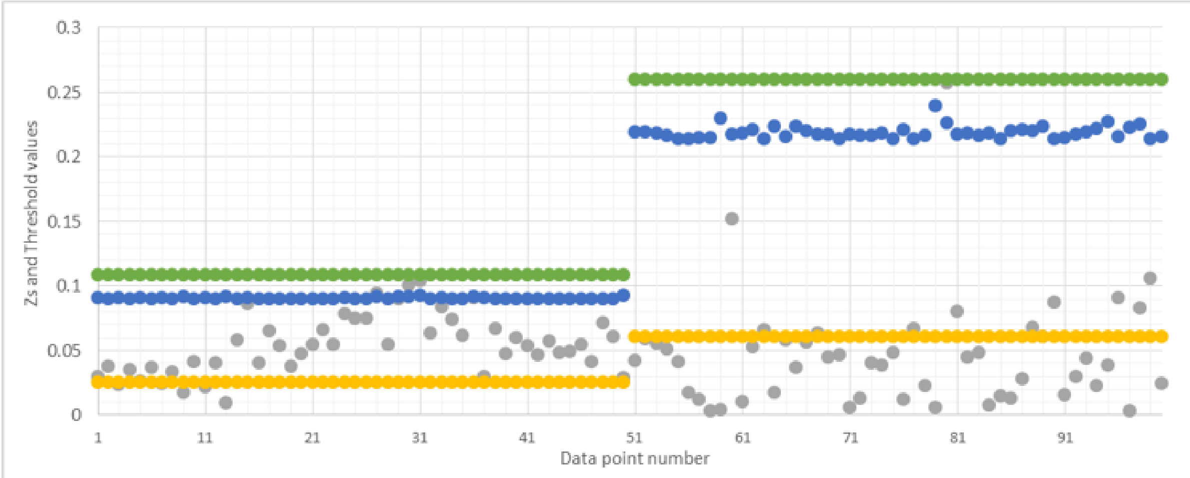

Fig. 12. Z_S values (gray), calculated threshold by F-THRESH (blue), calculated threshold by MOD-Z-THRESH (green), standard deviation of Z_2 (yellow) and detected road artefacts over two data windows analyzed.

not detected by the previous method, as is presented in the Fig. 12 near data point number 31, where grey Z_S values are exceeding threshold value for F-THRESH (blue) but not the threshold value for the previous method, MOD-Z-THRESH (green).

VI. Conclusions

The proposed method of fuzzy adaptive thresholding is connecting both overall road quality in a specified windows size and real-time vibrations. Uncertainty of data is handled by the fuzzy system, allowing for increased accuracy and lower false positive rate than in methods based on thresholding with a given-factor threshold. The proposed method is also one of the best methods when compared to the related works – there is also a possibility of implementation of this method directly in the IoT Edge scenarios, as it is not as computationally complex as ANN for example.

The presented results are allowing us to form the following conclusions:

- F-THRESH method is better in terms both of accuracy and false positive rate than previously proposed MOD-Z-THRESH method in 16 out of 24 overall cases (66%),
- The best results are achieved for smaller window sizes — the longer the tumbling window size, the differences in the road quality are detected worse,
- In the terms of accuracy, the difference between the proposed method and MOD-Z-THRESH method is better by 0.95 percentage point for the best scenario (quality function 2, threshold function 3),
- In the terms of false positive rate, the difference between the proposed method and MOD-Z-THRESH is 2.18 percentage point for the best-case scenario (membership function 2, threshold function 4),
- For the best accuracy scenario, the false positive rate also dropped by 2.1 percentage point, which is 40% drop rate, thus the authors believe that the best method could be described as: road quality membership function variant 2 (Fig. 6) and threshold membership function variant 3 (Fig. 10).

Finally, implementation of the fuzzy logic system improved accuracy and false positive rate for the thresholding method in the case of road artefacts detection.

VII. Summary and Future Works

Fuzzy threshold algorithm to detect anomalies in an on-the-fly, adaptive fashion without a priori knowledge of the underlying data has been proposed and tested in comparison to the previous method, allowing for improvements in terms both of accuracy which rose by about 1%, but mostly for the false positives, which dropped by 40%.

Such interesting results will be applied in the real-world prototype implemented directly on the smartphone, allowing for “stretch-of-road” continuous road quality control, additionally allowing that that acquisition software will only send to the server data which may hold the real road artefacts, without sending “noise”, allowing for further reduction of data usage for a such system.

In the proposed method, no implementation of driver’s own driving style has been taken into account, as well as no information about braking and avoiding the potholes – that means the system will take into the account only the potholes or other road artefacts the driver already “found”. This is a serious limitation to the proposed method, as driving just over the artefacts is finally not a desirable behavior. Trying to detect possible road artefacts from only the car behavior similar to pothole avoidance will be a goal of the author’s next work.

Finally, an interesting future work direction is to consider an application of other fuzzy-set or Granular Computing-based methods to find the anomalies in the road and transport information such as Fuzzy Set-Based Isolation Forest [22] or others enabled to work with spatio-temporal datasets containing categorical information.

ACKNOWLEDGMENT

Funded by the National Science Centre, Poland under CHIST-ERA programme (Grant no. 2018/28/Z/ST6/00563).

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