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Driving support by type-2 fuzzy logic control model ☆

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ABSTRACT

Advanced models of Artificial Intelligence enable systems of IoT to work with great flexibility to the needs of users. In this article we present our developed IoT system for driving support by the use of type-2 fuzzy logic control module. We have developed the IoT system to collect the data about driving conditions and evaluate them adjusting to the needs of user. Applied module of fuzzy logic of the second type was used in analysis of accelerometers signals to flexibly adjust to uncertainty of evaluation of driving expectations of each driver. Our developed system was tested in different cars by driving on various roads and results show excellent efficiency.

1. Introduction

Development of real-time Internet of Things (IoT) applications improves technological advances in intelligent transportation and car diagnostic systems. We can read about recent ideas which make Cyber–Physical Systems (CPS) not only supportive to humans but also predictive in potential malfunctions of appliances that we all use in our daily routine. In smart car IoT systems are developed by using sensors and devoted smart technologies to compose innovative control processing.

IoT systems for cars can work with many different features used in control and diagnostics to autonomous driving aspects. In Cao et al. (2020) was presented a model for smart front detection by using Singular Spectrum Decomposition (SSD) model. Model explained in Luque-Vega, Michel-Torres, Lopez-Neri, Carlos-Mancilla, and González-Jiménez (2020) was using SPIN-V sensors to improve procedure of safe parking. We can also implement models which will prevent collisions and help to maintain elements of car engine and suspension in good conditions. Idea presented in Krishnan (2018) was based on readings from ultrasonic sensor which measured distances to objects and helped in managing of safe drive. Very important for smart cars is also design of software. In practice we can use operating system in smartphones and just implement apps to connect to car sensors, i.e. Minnetti et al. (2020) proposed a smartphone based flush measurement to improve car body assembly procedure. System presented in Saeliw, Hualkasin, Puttinaovarat, and Khaimook (2019) was developed as mobile app to support parking procedure by using rfid infrastructure. In Xu et al. (2020) was presented an interesting discussion on networking, communication and applicable wireless technologies which serve as data transfers for smart cars. The model presented in Olivares-Rojas, Reyes-Archundia, Gutiérrez-Gnecchi, González-Murueta, and Cerda-Jacobo (2020) used 5G internet infrastructure to improve smart metering of multi-tire objects. A spectrum of control solutions in car development was presented in Gupta, Benson, Patwa, and Sandhu (2019). Future aspects and perspective possibilities for car technologies were discussed in Ooi (2019).

The vast majority of publications on testing the road surface quality concern the use of accelerometers built into smartphones, as described in the review (Harikrishnan & Gopi, 2017; Sattar, Li, & Chapman, 2018; Wang, Huo, Li, Wang, & Wang, 2018). In some of described works, portable devices are mounted in standard holders and the data from the accelerometer is taken into analysis. The weakness of such solution is repeatability of measurements due to the difficulty of ensuring the same orientation of the smartphone in the vehicle at all measurements. Mechanical design of holder can also significantly affect quality of the data, which may additionally dampen or cause vibrations. Another approach is to determine quality of the road surface on the basis of recorded vibrations, regardless of the location of the smartphone in the car. Such approach requires use of methods that normalize orientation of the smartphone in relation to the car, which requires additional calculations and thus implies errors related to it. In this respect, at our work, we propose a novel approach to IoT infrastructure of wireless sensors, thanks to which it is easy and uncomplicated to install the system in the car. Contrary to smartphone-based solutions, in our case accelerometers are rigidly attached to the structural elements. Thanks

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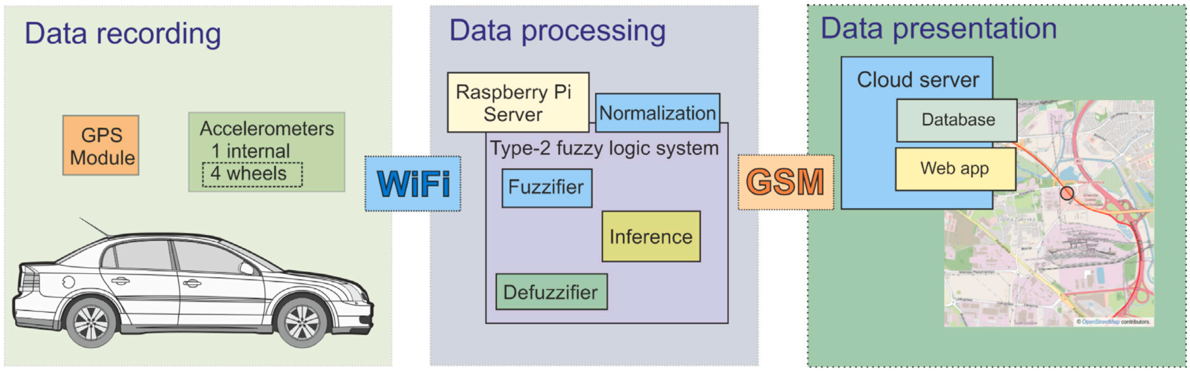

Fig. 1. System operation diagram of the proposed road anomaly detection system based on the type-2 fuzzy logic model.

to this, the elements of the measuring system do not move in relation to the car's structural elements. As a result of our proposed mounting method, we do not cause vibrations that would additionally disturb the test results. Our approach also guarantees repeatability of test results for a given vehicle.

1.1. Related works

In various application, the most efficient control models are reported for development by the use of fuzzy systems. This type of Artificial Intelligence (AI) is based on expert knowledge and can be efficiently modeled to solve control tasks considering changing conditions. We can read about smart grid controls applied in cars to help manage the load (Ali, Adnan, Tariq, & Poor, 2020), while a fuzzy model presented in (Sun, Qiang, Xu, & Lin, 2020) was monitoring condition of a train. Fuzzy systems are presented in diagnostics for engine maintenance and prediction of potential malfunctions. In Xiao, Cao, and Jolfaei (2020) was discussed how to model prediction of fault by using fuzzy approach, while in Zhang, Sun, et al. (2019) was presented an idea of deep fuzzy architecture for decision-making in machinery fault diagnosis. Fuzzy system proposed in Shen, Xing, Wu, Xu, and Cao (2019) was able to use static output in time shifting domain to control electric circuits, while model proposed in Zhang, Shi, Shen, and Wu (2019) was developed for actuator control. In car applications we can see a variety of potential fuzzy interfaces. The idea presented in Alyas et al. (2019) used Mamdani model for IoT car parking system. Fuzzy interference model presented in Li et al. (2019) was developed to automate impedance control. Fuzzy systems are also used in control modules for variety of electric engines. In Qu, Liu, Zhu, and Zang (2020) was presented how to implement a higher order fuzzy system for wind turbine monitoring. Developed system was able to predict condition of the turbine using multidimensional functions adjusted to variety of features. Due to flexible development and adjustable nature of fuzzy systems there is a very wide range of potential applications. We can read about expert systems which help in more efficient driving. Such models consider many different aspects of load, driving style, road or condition of the car. Fuzzy system presented in Mao, Dou, Yang, Tian, and Zong (2020) was developed to consider aeroservoelastic characteristic of a vehicle to improve driving, while the model proposed in Stan, Suciu, and Potolea (2019) discussed smart driving for connected cars.

The road surface quality detection process is complicated and not easy. Mostly it works based on the use of smartphones and individual measurement infrastructure, two basic directions of analysis can be found:

- First is based on threshold values recorded by the sensors,
- Second is machine learning based approach.

The first group of tests is sensitive to a large variety of cars, different driver skills and other individual characteristics. As a result, application of this approach is not flexible and may not fit all cases. The second group related to machine learning is also sensitive due to the driver's driving style and individual skills, quality of car suspension components, which in practice leads to the need for multiple databases. Thus, applicable methods of artificial intelligence should be flexible to change of driving style, car speed, etc. In Badurowicz, Montusiewicz, and Karczmarek (2020), the use of type-1 fuzzy logic to detect anomalies on the road was proposed. This work concerns performance of measurements with the use of a smartphone and the model itself combines fuzzy sets with assumed threshold based on expert knowledge. In addition to these studies, mention should also be made of works Cui, Han, and Wang (2019) and Basudan, Lin, and Sankaranarayanan (2017), which deal with building a general system based on multi-car data collection and processing in fog. These works do not concern methodology of substrate quality detection, but concern construction of the system, assuming model of detection method.

In this article we propose a new method of identifying anomalies on the road based on type-2 fuzzy system. Fuzzy sets of type-2 can be used in case of problems with uncertainty of measurement or subjectivity of their interpretation (Sanchez, Castillo, & Castro, 2015). Fuzzy sets of the second type naturally take into account variety of features related to user's driving style, car suspension features (different damping of vibrations), etc. The rules of the proposed system depend not only on the fuzzy values recorded by accelerometer system for accelerations in three axes, but also on fuzzy values of the speed of test vehicle. The idea presented in this paper is focused on smart driving. Proposed system is able to notify drivers about quality of the road and possible obstacles or anomalies on the road surface on the way. For this purpose, our system is using GPS location module and our developed IoT infrastructure. The research vehicle was equipped with accelerometers which measure driving features. The analog signal was assigned to the position data from GPS and then processed by the type-2 fuzzy logic analysis system implemented in Raspberry Pi microcomputer. The fuzzy logic of the second type was used for the analysis due to the specific nature of the measuring data and the uncertainty resulting from the individual driving behavior of each driver and individual damping characteristics in various types of test vehicles. General idea is shown in Fig. 1. We have tested this system in various road conditions to verify our model. Results show that proposed solution is efficient and perspective in further development.

2. System concept

The concept of our system 1 is based on commonly available GPS systems. General idea is presented in Fig. 2. We have developed IoT system for monitoring quality of road surface while driving. For the implementation of the system, it was assumed that individual vehicles registered in the system would be equipped with the necessary IoT infrastructure. Additionally, the implementation of our IoT was assumed based on simple, generally available sensors, e.g. accelerometers from the Arduino platform. The system is marking characteristic places on roads in the context of the surface quality by using GPS location system therefore it is necessary to access the Internet while traveling.

It was assumed that the data obtained by many users would be processed in order to correctly identify the quality of the pavement. The system user will be informed on an ongoing basis about possible anomalies on the road in a certain environment. In addition, the system allows users to view the history of traveled routes, taking into account the recorded overloads, anywhere on the route. A local application running on the Raspberry Pi microcomputer monitors the reading from each of the built-in sensors on an ongoing basis and, thanks to the developed type-2 fuzzy inference system, determines the current condition of the surface. After identification of anomaly encountered while driving sends this information to the data server in a cloud to mark the place for other system users. The server application is responsible for processing of data reported by individual vehicles. This data is collected and, after analysis, made available to vehicles in specific locations.

As part of the project, measuring equipment installed in different cars was prepared in two variants. One variant of the apparatus uses one accelerometer mounted in the vehicle cabin and it is installation is limited to attaching the measurement module to any structural element in the vehicle cabin. The second variant is a more complex and consists of five accelerometers, four of which are mounted on the vehicle's suspension components. Both variants are independent of the car's structure and their assembly consists only in the permanent (play-free) attachment of sensors to the appropriate vehicle components. Sample idea of our developed IoT infrastructure is presented in Fig. 3.

The central part of the system is server module and is available to all registered users. Local apps from each car in the network send to the server current data about the condition of the pavement in specific locations and report all identified and unidentified anomalies. The server application, after logging in, allows the user to view all recorded routes on the map. For the selected route, it is possible to view graphs of vibrations recorded in a certain vicinity of this point and the vehicle speed graph plotted in the same area. On the basis of these data, the type-2 fuzzy system determines the condition of the pavement quality.

The system can be used for ongoing monitoring of the surface condition, which could be used by appropriate road services. Repeated reports of anomalies in a given place probably indicate the need to check the road quality in the indicated place and the need to improve it. From the perspective of road users, information on the quality of the surface could be included in packages of commonly used car navigation systems.

3. Developed IoT cyber–physical system

The central unit of the measurement IoT infrastructure is a Raspberry Pi minicomputer with access to the Internet via GSM network. The solution uses a Raspberry Pi version 4 model B with 4 GB of RAM. The local server (microcomputer) has two basic functions. On the one hand, it is responsible for collecting data from other modules with which it communicates via WiFi network. The Raspberry Pi acts as an Access Point creating a subnetwork for the rest of the modules mounted in the vehicle. In addition, Raspberry Pi has an application which processes the acquired data recorded by accelerometer modules and the GPS module, and performs local analysis of current data. Result of type-2 fuzzy logic expert system is sent in the appropriate format to the server application located in the cloud. The measurement infrastructure is be equipped with a localization module. The implemented solution uses the GPS system. Later in the work, the location module will be called the GPS module.

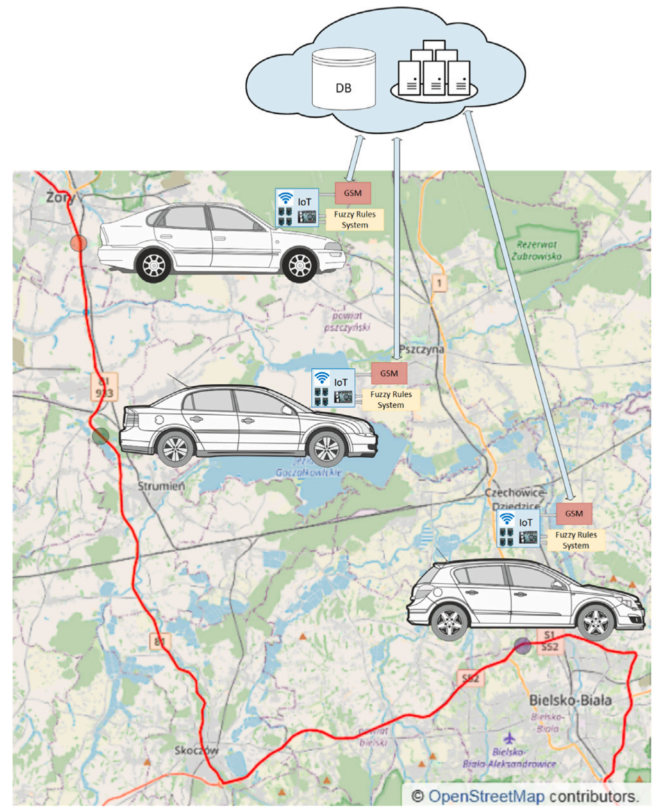

Fig. 2. The figure shows a diagram of the concept of the safe driving assistance system. Our system reads the location of the vehicle from the GPS module. Based on the positioned sensors and the proposed model of the fuzzy logic of the second type, our system examines whether the vehicle is subject to excessive fluctuations while driving on any part of the road. If the evaluation of the system is conclusive, this section is marked on the map so that the driver can be warned about possible potholes or poor road conditions in the future.

The schematic diagram of the IoT infrastructure for a single vehicle is shown in Fig. 4. This diagram shows all the possible modules used in both variants of our solution. Modules necessary in each of solutions are framed with a solid line, optional modules with a broken line.

All overload modules use the Arduino GY-61 accelerometer. At the output, this module has three analog signals representing overloads in three perpendicular axes. This signal is received by the ATiny 13 microcontroller. The accelerometer outputs are connected to three different inputs of the analogical-digital converter which the microcontroller is equipped with. The ATiny 13 microcontroller is connected to the ESP 8266 WiFi communication system. The program implemented by the ATiny 13 microcontroller works in such a way as to obtain the highest possible sampling frequency of signals from the accelerometer. For this purpose, the process of sampling and sending data was implemented in such a way that during the sampling of the signal from one input, the result of the previous sampling is sent to ESP 8266. The software output of the ATina 13 serial port is connected to the hardware input of the ESP 8266 serial port including mentioning the operation of the program implemented by the ESP 8266 module.

Due to the fact that only some cases are interesting for the operation of the system, given accelerometer modules operate in such a way that all samples go to the ESP 8266 memory, where they are buffered and their maximum and minimum values are determined for each subsequent second and such data is sent to a local application running on the Raspberry Pi and the local Artificial Intelligence system operates based on this data. The overloads registered by the internal accelerometer module are significantly damped by the vehicle's suspension system. The four remaining accelerometer modules are placed

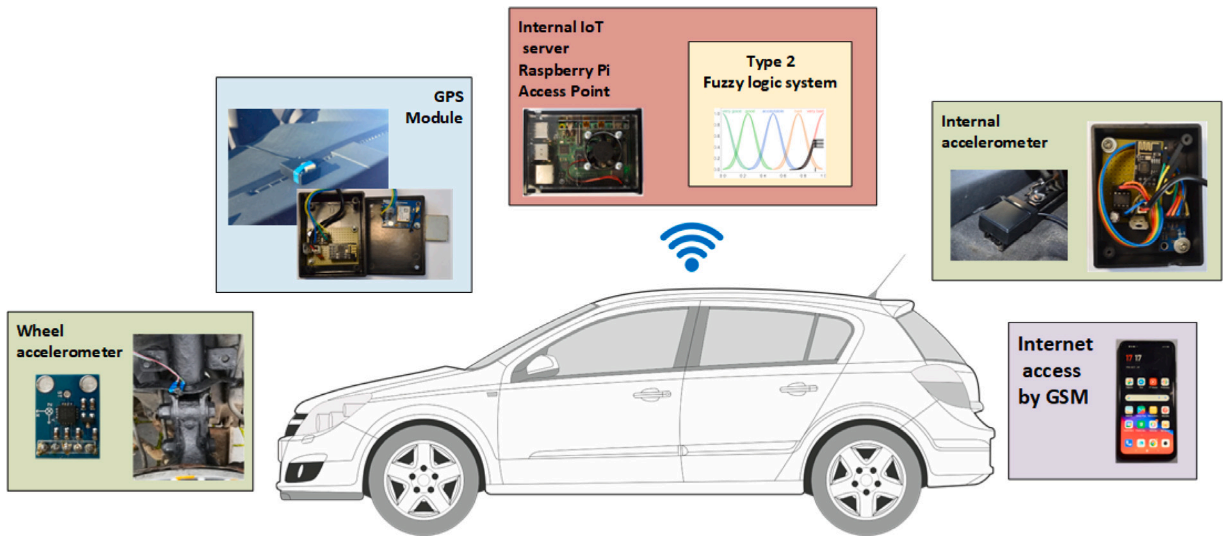

Fig. 3. Construction of our IoT system built into a test car. The aim is to create a system for notifying users about the quality of roads and about possible obstacles or other anomalies on the road surface causing vibrations. For this purpose, a system was created based on GPS location module and IoT infrastructure with accelerometers sensors. A vehicle is equipped with one or more accelerometers which measure the overload while driving the vehicle on an ongoing basis. The analog signal is assigned to the position data and then processed by the type-2 fuzzy logic in local analysis system implemented in the Raspberry Pi microcomputer.

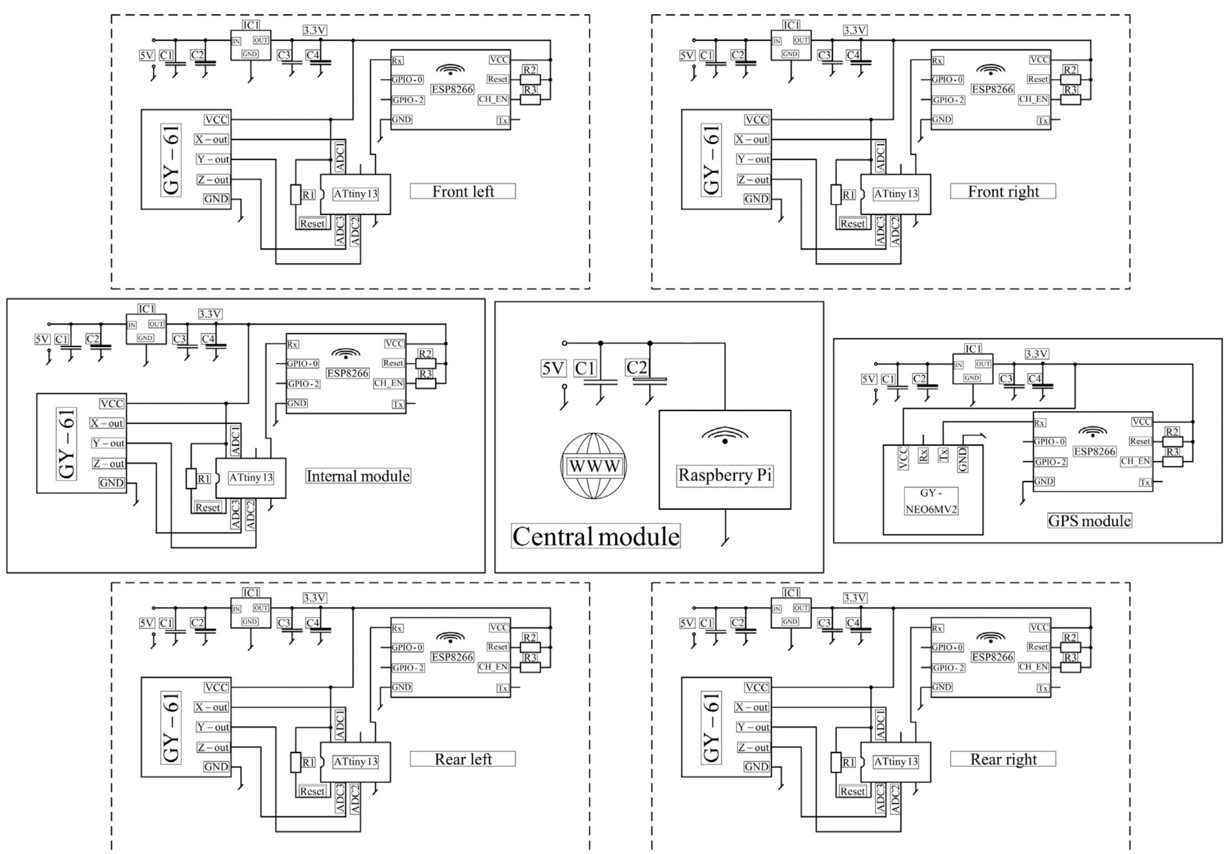

Fig. 4. Schematic diagram of implemented IoT measurement modules with the location of their installation in the vehicle. As our system can be installed in different versions, optional modules are marked with a dashed line.

on the suspension elements so that the accelerometer is placed on the elements the vibrations of which are damped only by the tire of the wheel. Therefore, it was assumed that the data downloaded from the accelerometer internal module are used by the local application as a criterion for detecting any anomalies. This means that exceeding the set level of overloads (max and min from 1 s) in the vehicle cabin (subjectively felt by the vehicle moving) triggers the download of data buffered in the memory of the ESP 8266 system within 5 s. ESP 8266 program cyclically buffers data from the last 5 s. The data download signal causes the data to be buffered for another two seconds and then the data from the entire buffer is sent to the local application. The local application, based on the data from the last 5 s, for each of the wheels carries out an analysis and possible identification of the existing anomaly.

The GPS module works independently of the other modules. It was created based on the GY-NEO6MV2 board of the Arduino platform. As in the previous modules, communication with the local application takes place via the WI-FI network. For this purpose, the serial port of the GY-NEO6MV2 module has been connected to the serial input of the ESP 8266 system, which sends the recorded data to the local server. The local application combines geolocation data with the results of congestion measurements, which is necessary to assign anomalies to the travel routes.

Measurement data is analyzed on an ongoing basis by a system based on type-2 fuzzy logic. The output from the system is information about the quality of the road in the examined place. The fuzzy logic of the second type was used for the analysis due to the specific nature of the measuring data and the uncertainty resulting from the individual driving behavior of each driver and individual damping characteristics in various types of test vehicles. Detection of poor road quality by the fuzzy system in the case of using the variant with five accelerometers results in the analysis of data from four additional accelerometers. The data buffered for 5 s in the ESP8266 systems are then sent to the Raspberry Pi and analyzed for possible determination of the nature of the obstacle. For this purpose, a decision-making system based on the created rules was created. In the case of the variant with one accelerometer installed in the cabin of the vehicle, only the analysis is performed based on the type-2 fuzzy system to determine the quality of the surface.

4. Developed type-2 fuzzy logic control module

The article proposes a fuzzy inference system of the second type, which allows decision making process based on measurement data from vehicle speed and overloads recorded by the accelerometer installed in the car cabin, with particular emphasis on overloads in the axis perpendicular to the ground on which the vehicle is moving. Due to the fact that our analysis will be carried out in different cars, driven by different drivers with individual personal characteristics affecting the driving style, we decided to use the type-2 fuzzy logic with the interval function of belonging to the second order. These sets will be the best choice to take into account a certain measurement uncertainty and take into account the diversity of features of individual vehicles and drivers.

4.1. Theoretical introduction to the developed model of type-2 fuzzy logic control system

In order to describe the concept of operation of the proposed fuzzy system, we will first introduce the mathematical description of type-2 fuzzy sets. Due to the fact that the membership function is a type-1 fuzzy set, they model the measurement uncertainty better than type-1 fuzzy sets.

Fuzzy set $\tilde{A}$ type-2, that $\tilde{A} \subseteq X$, where X is decision space we define a set of pairs:

$$\left\{x, \mu_{\tilde{A}}(x)\right\}, \tag{1}$$

where x is element of fuzzy set, and membership function $\mu_{\tilde{A}}(x)$ to the fuzzy set $\tilde{A}$ is type-1 fuzzy set defined in $J_x \subset [0,1]$. It means, that

$$\mu_{\tilde{A}}(x) = \int_{u\in J_x} f_x(u)/u. \tag{2}$$

To illustrate the definition of the fuzzy set of the second type, we present main idea of uncertainty in measurement represented in type-2 fuzzy model in Fig. 5, where the upper figure shows an exemplary fuzzy set of the second type (marked in gray). The point x_1 was marked here and $J_{x_1} = [y_1, y_2]$ the domain of the second type of uncertainty function, the two examples of which are presented in the form of a triangular function in the lower left figure and an interval function in the lower right figure, is marked for it. In the case of interval type-2 fuzzy sets, the membership function is an interval function, i.e. a constant in the field J_{x_1}.

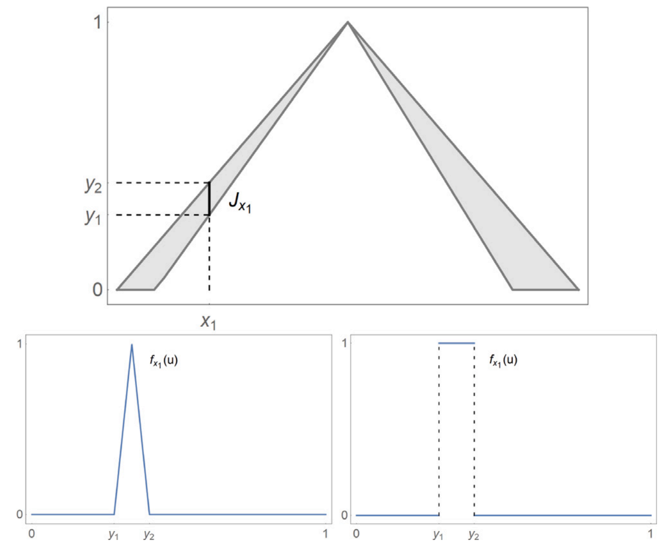

Fig. 5. The upper figure shows an example of type-2 fuzzy set, where J_{x_1} is marked for the point x_1 where the secondary membership function is specified, the two examples of which (triangular function — left and interval function — right) are shown in the figures below.

In our considerations, we will use interval type-2 fuzzy sets. In the inference system we propose, that fuzzy values will be composed for the speed of the car, and the values of the Z axis (perpendicular to the ground on which the car moves) and the X Y axis recorded by the accelerometer. The surface quality function will also be defined as the fuzzy set of the second type.

Another theoretical concept important for the implementation of the proposed fuzzy system is the concept of the trace of uncertainty.

Let $J_x \subset [0,1]$ denotes the basic affiliation of x. The trace of uncertainty SN of a fuzzy set type-2 $\tilde{A} \subseteq X$, is a limited area composed of all points of the basic affiliation of x elements:

$$SN(\tilde{A}) = \bigcup_{x\in X} J_x. \tag{3}$$

In Fig. 5 the trace of uncertainty for the presented set has the form of an area marked in gray. In practice, the trace of uncertainty is the domain of numerical calculations for a given fuzzy set of type-2. Another theoretical aspect necessary to build a fuzzy inference system is the sum and product operation defined for fuzzy sets of the second type.

Let sets $\tilde{A}$ i $\tilde{B}$ are defined:

$$\tilde{A} = \int_{x\in X}\left(\int_{u\in J_x^u} f_x(u)/u\right)/x, \tag{4}$$

$$\tilde{B} = \int_{x\in X}\left(\int_{v\in J_x^v} g_x(v)/v\right)/x. \tag{5}$$

Sum of sets $\tilde{A}$ i $\tilde{B}$ is a fuzzy set type-2 of membership function:

$$\mu_{\tilde{A}\cup\tilde{B}}(x) = \int_{u\in J_x^u}\int_{u\in J_x^v} f_x(u) \overset{T}{*} g_x(v)/u \overset{S}{*} v. \tag{6}$$

Intersection of sets $\tilde{A}$ i $\tilde{B}$ is a fuzzy set type-2 of membership function:

$$\mu_{\tilde{A}\cap\tilde{B}}(x) = \int_{u\in J_x^u}\int_{u\in J_x^v} f_x(u) \overset{T^*}{*} g_x(v)/u \overset{T}{*} v, \tag{7}$$

where T^* is t-norm for 2nd type membership.

In our considerations for interval type-2 fuzzy sets, we used the minimum operation as t-norm and the maximum operation as s-norm.

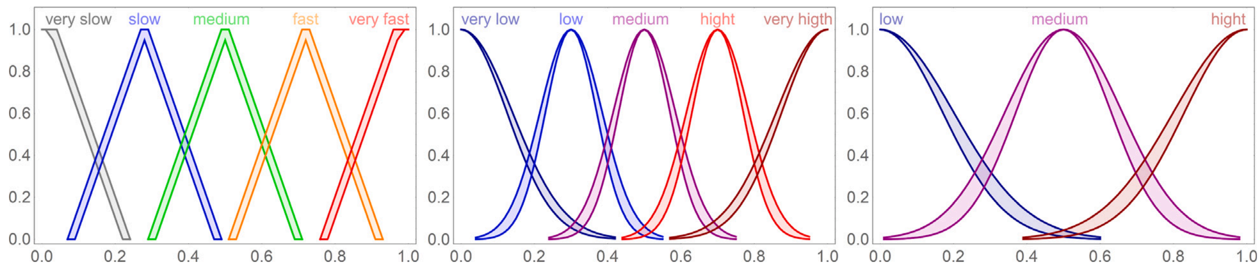

Fig. 6. The charts show the traces of uncertainty of the proposed fuzzy sets of type-2 for the measured quantities. Sequentially from the left we have a representation of speed, overload in the direction perpendicular to the ground (Z axis) and maximum overload in the direction of movement (X axis) and overload in the direction perpendicular to the direction of movement and the ground (Y axis).

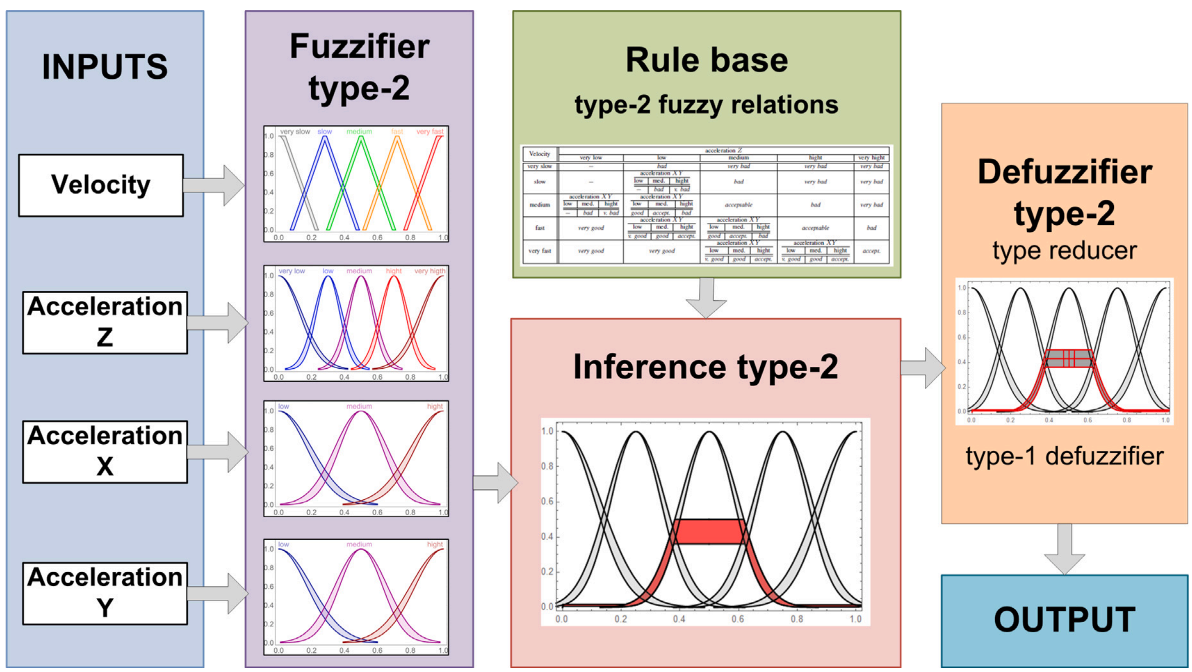

Fig. 7. Applied reasoning by using our proposed fuzzy inference system of the second type.

4.2. Reduction from type-2 to type-1, and defuzzification

Another important stage in creating the inference system is possibility of sharpening obtained result.

Defuzzification of type-2 fuzzy sets consists of two stages: reduction of type-2 to type-1 and then sharpening of type-1 set. Assuming the discretization of the X set to the R set, the values $x_1, \dots, x_R$, the fuzzy set of type-2 $\tilde{A}$ can be written:

$$\tilde{A} = \sum_{k=1}^{R} \left[\int_{u \in J_{x_k}} f_{x_k}(u)/u \right] /x_k. \tag{8}$$

The set resulting from the reduction of the type is called a centroid. For the discrete form of the set $\tilde{A}$, centroid is a set of type-1 and has the form:

$$C_{\tilde{A}} = \int_{\theta \in J_{x_1}} \dots \int_{\theta \in J_{x_R}} [f_{x_1}(\theta) * \dots * f_{x_R}(\theta)] \Bigg/ \frac{\sum_{k=1}^{R} x_k \theta_k}{\sum_{k=1}^{R} \theta_k}. \tag{9}$$

Based on approach discussed in Torshizi, Zarandi, and Zakeri (2015) on type reduction algorithms and considering that our system was designed for interval type-2 fuzzy sets, we will use Karnik–Mendel algorithm for reduction. Assuming that the secondary membership functions are interval centroids, it has the form of an interval and can be determined based on the iterative Algorithm 1.

4.3. Proposed type-2 fuzzy logic reasoning system

Prosed type-2 fuzzy logic reasoning was built according to the scheme shown in Fig. 7. We assume that all the sets used in the proposed model are fuzzy sets of type-2 for which the secondary membership function is an interval function. First, the input data speed and overloads registered inside the car must be blurred. It should be emphasized here that by entering the fuzzy system, the following are determined in 1 s time intervals: the maximum module overload values in the direction perpendicular to the ground (Z axis) and the maximum module overload value recorded in the directions consistent with the vehicle motion (X axis) and perpendicular to it and the ground (axis Y):

$$a_Z^{max}(t_i) = \max \left\{ |a_Z(t)|, < t_i \leq t < t_{i+1} \right\}, \tag{10}$$

$$a_{XY}^{max}(t_i) = \max \left\{ |a_X(t)|, |a_Y(t)|, < t_i \leq t < t_{i+1} \right\}, \tag{11}$$

where t_i is i second in iteration.

For the proposed reasoning, fuzzy sets of the second type representing the measured values were defined. Traces of uncertainty of these clusters are presented in Fig. 6. The first from the left concerns the vehicle speed, the middle one — overloads in the Z axis. The figure on the right shows the traces of uncertainty for the fuzzy sets representing the maximum overloads towards the X axis and the direction of the Y axis.

Table 1
Developed knowledge base for proposed driving support considering condition of the road.

Velocity	Acceleration Z: Very low	Low	Medium	Hight	Very hight
Very slow	–	*Bad*	*Very bad*	*Very bad*	*Very bad*
Slow	–	Acceleration XY: Low – / Med. *Bad* / Hight *V. bad*	*Bad*	*Very bad*	*Very bad*
Medium	Acceleration XY: Low – / Med. *Bad* / Hight *V. bad*	Acceleration XY: Low *Good* / Med. *Accept.* / Hight *Bad*	*Acceptable*	*Bad*	*Very bad*
Fast	*Very good*	Acceleration XY: Low *V. good* / Med. *Good* / Hight *Accept.*	Acceleration XY: Low *Good* / Med. *Accept.* / Hight *Bad*	*Acceptable*	*Bad*
Very fast	*Very good*	*Very good*	Acceleration XY: Low *V. good* / Med. *Good* / Hight *Accept.*	Acceleration XY: Low *V. good* / Med. *Good* / Hight *Accept.*	*Accept.*

Algorithm 1 Type reduction algorithm

Input: discretized type-2 set with interval function of secondary membership: $\tilde{A}$ Eq. (8) on decision space $X = \{x_1, x_2, \dots, x_R\}$. Let:

$$s(\theta_1, \dots, \theta_R) = \frac{\sum_{k=1}^{R} x_k \theta_k}{\sum_{k=1}^{R} \theta_k}.$$

Output: set of type-1 in the form of a range $[x_l, x_r]$.
Initialization: Calculate

$$\theta_k = \frac{\overline{\theta}_k + \underline{\theta}_k}{2}, \quad \text{for } k = 1, \dots, R$$

and calculate $s_0 = s(\theta_1, \dots, \theta_R)$ Eq. (1) and assume that $s_1 = s_0 + 1$
while $s_0 \neq s_1$ **do**
  Find j that $x_j \leq s_0 < x_{j+1}$
  for $k = 1$ to j **do**
    $\theta_k = \underline{\theta}_k$
  end for
  for $k = j + 1$ to R **do**
    $\theta_k = \overline{\theta}_k$
  end for
  $s_1 = s(\theta_1, \dots, \theta_R)$
end while
$x_r = s_0$
Repeat *Initialization*.
while $s_0 \neq s_1$ **do**
  Find j that $x_j \leq s_0 < x_{j+1}$
  for $k = 1$ to j **do**
    $\theta_k = \overline{\theta}_k$
  end for
  for $k = j + 1$ to R **do**
    $\theta_k = \underline{\theta}_k$
  end for
  $s_1 = s(\theta_1, \dots, \theta_R)$
end while
$x_l = s_0$
Return defuzzified set of type-1 has the form of a range $[x_l, x_r]$.

The road quality was also described with the use of type-2 fuzzy sets. Traces of uncertainty of the fuzzy functions for this parameter are shown in Fig. 8.

The knowledge for our expert system is represented by rules written in the general form:

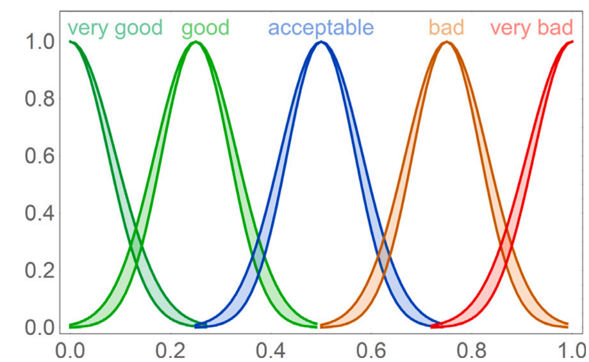

Fig. 8. Traces of uncertainty of the proposed type-2 fuzzy sets for road quality.

IF velocity is V **AND** acceleration Z is a_Z^{max}
AND acceleration XY is a_{XY}^{max} **THEN** quality of road is Q

All rules for fixed input values are listed in Table 1, where the – sign means that nothing can be said about the quality of the road in this case.

The iterative algorithm described in the previous section was used to sharpen the result. Fig. 9 shows 4 example drawings illustrating the calls of the fuzzy system with the black line marked visualizing the operation of the sharpening algorithm.

5. Experimental results

The research confirms effectiveness of the proposed method. Our tests were carried out for 5 different passenger cars. The tests lasted 6 months and the cars covered a total distance of 52,350 km. The basis for the research were fixed routes for the participants of the experiment along the home work route, which allowed to test the effectiveness of the proposed system. Two of the experimental cars were equipped with a system of additional 4 accelerometers which, apart from the overloads measured in the vehicle cabin, measured overloads on each of the vehicle wheels without taking into account vibration damping by the vehicle suspension system. The second version of the system is expanded by an additional 4 accelerometers. The advantage of the proposed expansion of the system is the additional ability to detect not only poor-quality surface — because it is similarly provided by the system in the first version, but the identification of the type of obstacle thanks to a thorough analysis of overloads on all 4 wheels of the car. The accuracy of the method was determined on the basis of 10

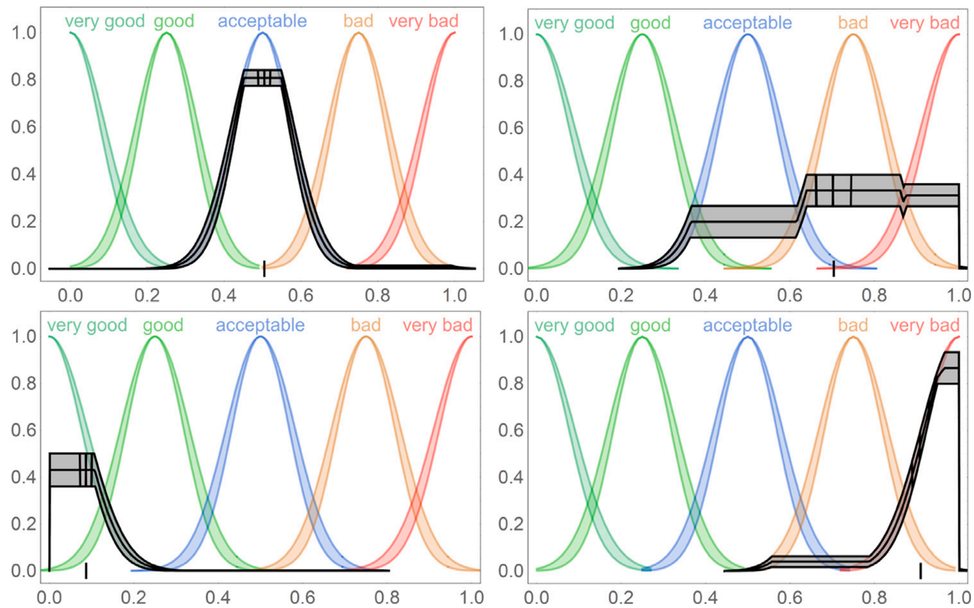

Fig. 9. A few sample illustrations showing the operation of our developed inference system, with black lines showing the operation of the sharpening algorithm.

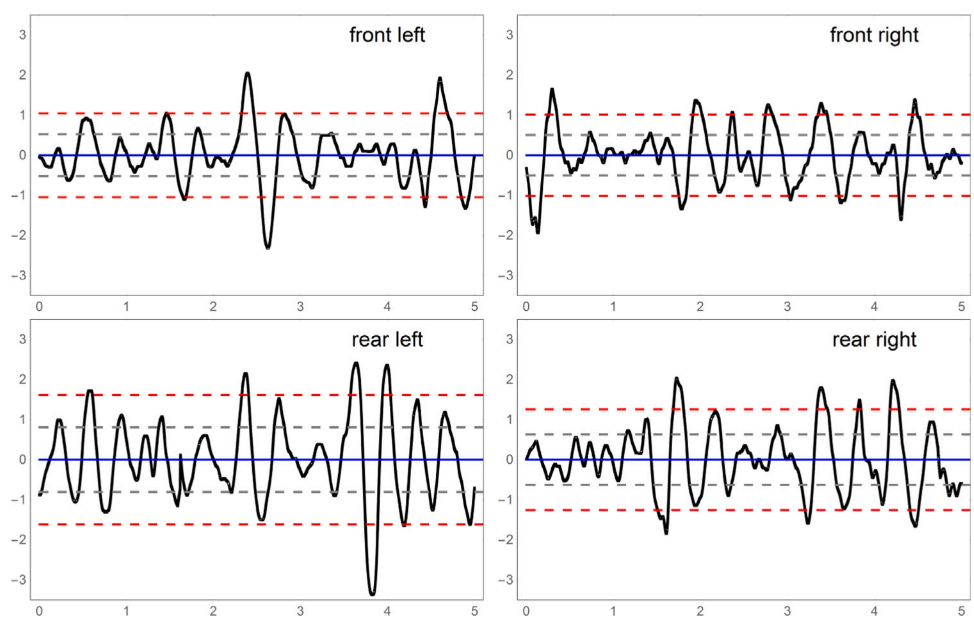

Fig. 10. Waveforms of overloads for individual wheels along the axis perpendicular to the surface, with marked mean (blue line), standard deviation (dashed gray lines) and anomaly detection threshold (red dotted lines) for a very poor condition of the road (damaged railway crossing).

test route sections, each of them approximately 20 km long. On these routes, after 10 test runs, the anomalies were marked manually. For each route, 20 representative points (being anomalies and representing an acceptable quality) were selected. Then, many test runs (100 runs) were made on these routes. Due to the fact that the GPS measurement is performed with a frequency of 1 Hz and assuming that the maximum speed of the car does not exceed 40 m/s and taking into account the accuracy of GPS measurements, we treat two points on two different routes as similar if the distance between them is not greater than 50 m. At the stage of marking the route, the point of the anomaly was determined as the average of the latitude and longitude determined by the GPS sensor in 10 test runs. In this way, determining the similarity of the run as the accuracy of the method, we define the arithmetic mean of the accuracy of detecting each of the anomalies occurring on all test routes, where the accuracy of detecting a single anomaly meant the percentage share of anomalies correctly marked by the system to all performed tests.

$$precision = 100 \frac{\sum_{i=1}^{N} \sum_{j=1}^{k_i} \frac{positive_i^j}{all_i}}{\sum_{i=1}^{N} n_i \cdot m_i} \% \tag{12}$$

where n_i i m_i mean the number of measurements and the number of test points for i-th test section, $positive_i^j$ number of positively identified surface condition detections in j-th test point i of this route test route and all_i means the number of all test runs on i-th of this test route, N — the number of routes. For our research, we obtained the score of $precision = 91\%$.

We will now present a few examples to illustrate how the system works. Figs. 13–15 show a screenshot of the application created as part of the work. The current location of the car is marked with a blue circle on the map (on the right). The graphs on the left side show the measurement input data as a function of time expressed in seconds. The

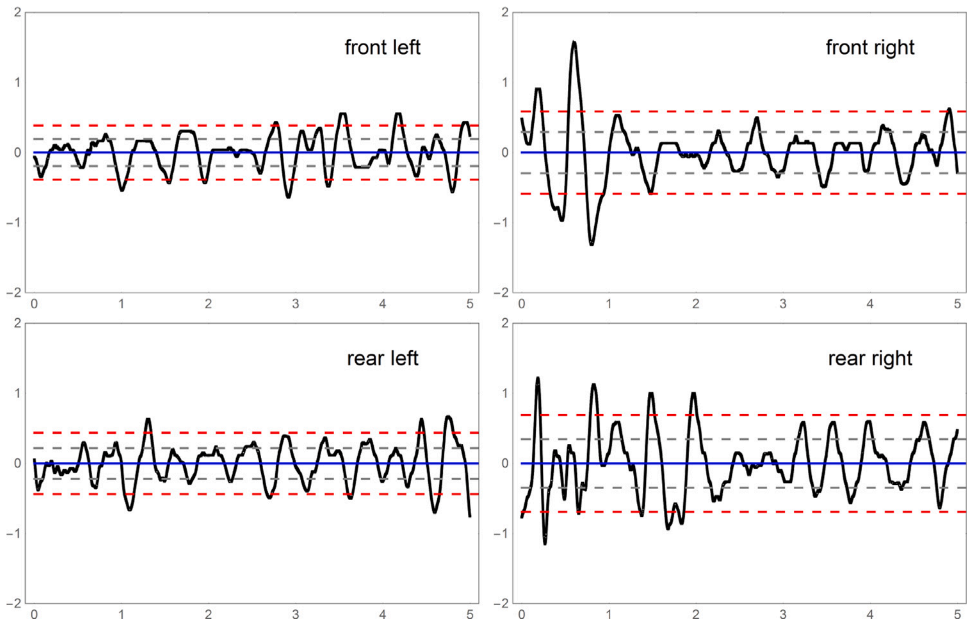

Fig. 11. Waveforms of overloads for individual wheels in the axis perpendicular to the road, with marked mean (blue line), standard deviation (dashed gray lines) and anomaly detection threshold (red dotted lines) for the damaged right part of the road-shoulder.

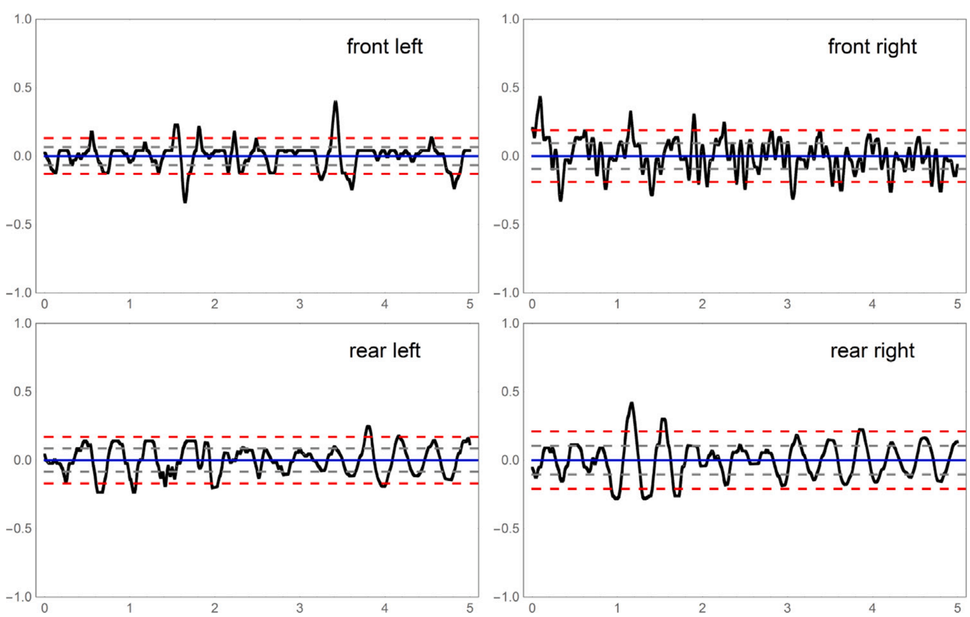

Fig. 12. Waveforms of overloads for individual wheels along the axis perpendicular to the surface, with marked mean (blue line), standard deviation (dashed gray lines) and anomaly detection threshold (red dotted lines) for a very good quality road-highway.

first three charts show, respectively, the overloads in the X, Y and Z axes, where the shaded area represents the area between the maximum and minimum overload values determined from the data recorded by the cabin accelerometer determined at 1 s intervals. The results are presented as overloads, i.e. they represent the recorded acceleration value divided by the gravitational acceleration. The last fourth graph shows the vehicle speed function, expressed in m/s. All four charts are synchronized. Additionally, the map shows a fuzzy set with its elevation, which is the result of the operation of the fuzzy system for the current measuring moment.

We will now present three examples of the system operation for large anomalies on the road and for a very good quality pavement. In all of these cases, we will show the results from the accelerometer inside the car and a summary of the exact results from the other 4 accelerometers mounted on all wheels.

The first case concerns the detection of a damaged road at a railway crossing. The screen shot of the created system is presented in this case in Fig. 13. The next three charts on the left show the overloads in the X, Y and Z axes, respectively. The fourth graph shows the graph of the speed of a moving car. The map shows the route and the point in the vicinity of which the data is plotted on the charts. Additionally, there is a graph showing the operation of our type-2 fuzzy logic control system.

The detection of a very poor road quality triggered the addition of data from 4 accelerometers on wheels. For this case, the data is presented in Fig. 10. From the presented detailed data, the system detected numerous anomalies on both sides of the road, which corresponded to a seriously damaged surface at the railway crossing.

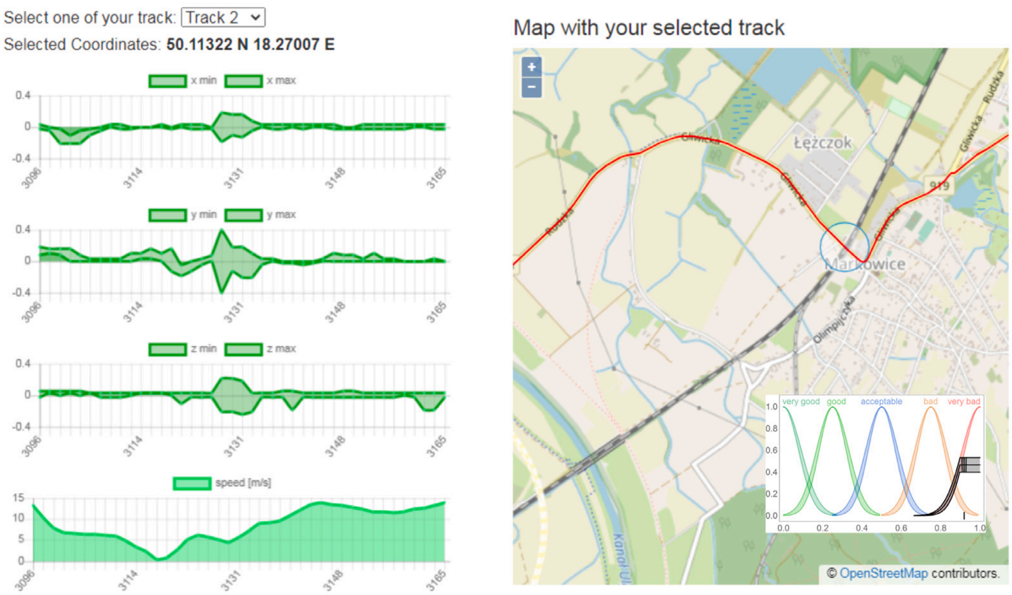

Fig. 13. Result from our system. On the left recorded accelerometers signals in each of axis, on the right GPS positioning result of detection of a large anomaly on the road (used railroad crossing) with presentation of resulting from our developed type-2 fuzzy logic system.

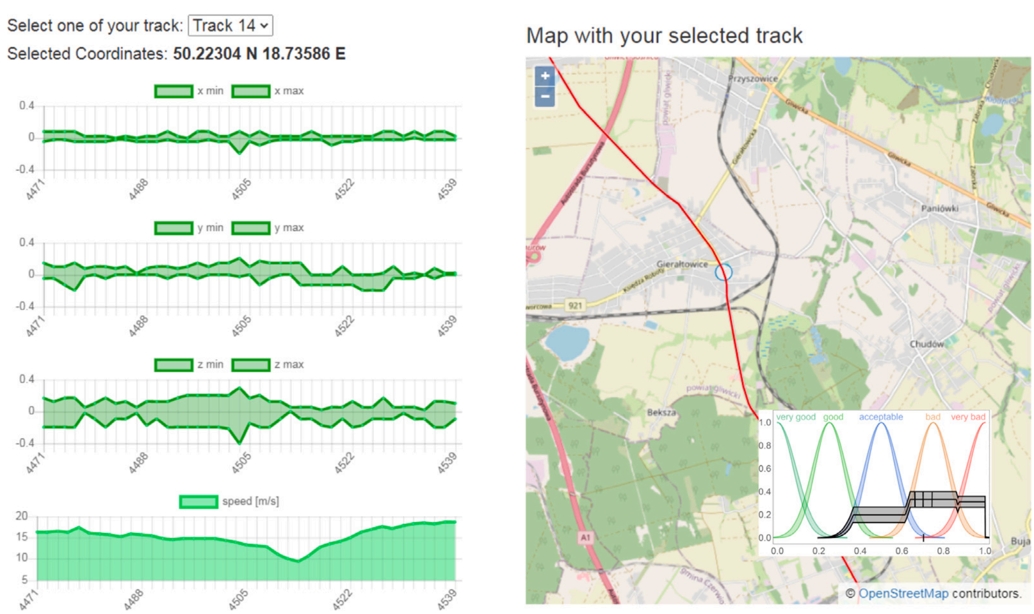

Fig. 14. Result from our system. On the left recorded accelerometers signals in each of axis, on the right GPS positioning result of detection of a large anomaly on the road (damaged roadside) with presentation of resulting from our developed type-2 fuzzy logic system.

The second presented case shows the damaged road shoulder. The screenshot of the system operation is presented in Fig. 14. It can be noticed here that the car was moving at medium speed and encountered a large overload in the vehicle cabin. A detailed analysis of Fig. 12 shows result of a significantly greater overload recorded on the right side of the car (damaged road shoulder).

In addition, as an example, there is also a screenshot showing fast driving on a highway with a good quality surface. In Fig. 15 we can see that a very fast car registers small vibrations on the highway. An accurate record was also triggered by the operator (our fuzzy system did not report poor road quality) in order to show the readings also from the accelerometer on the wheels when driving on the highway. A detailed analysis is presented in Fig. 11.

Table 2 presents comparison of the methods proposed in research related to the road quality and effectiveness of the developed decision support systems. Compiled data shows that most of related models which use more complex reasoning approaches do not take into account the measurement uncertainty caused by different driving styles. In contrast, our proposed model is more flexible to different conditions on the road and also can adjust to different driving styles. As a result of using type-2 fuzzy logic approach we have developed a new model, which is flexible and reliable at the same time. Results show that proposed in this article decision support reaches highest effectiveness among compared models.

6. Conclusions

In this article we present a type-2 fuzzy system for smart driving support. Proposed system is working in IoT infrastructure of accelerometer sensors placed in a car. Data collected in the car is stored in

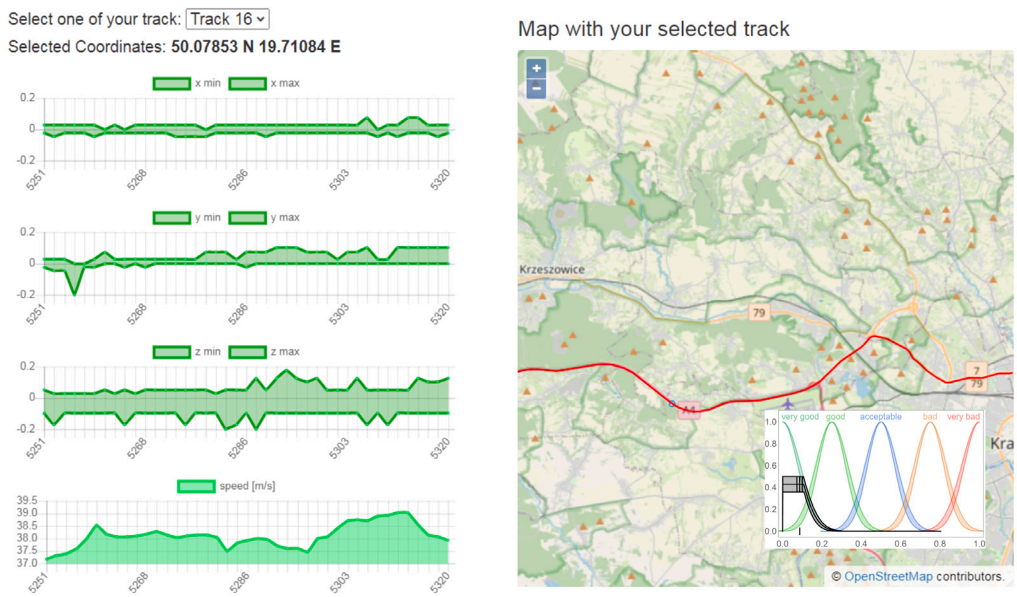

Fig. 15. Result from our system. On the left recorded accelerometers signals in each of axis, on the right GPS positioning result of detection of a no anomaly on the road (highway) with presentation of resulting from our developed type-2 fuzzy logic system.

Table 2
Comparisons of models developed for road quality detection and their effectiveness.

Article	General characteristic	Applied model	Effectiveness
Our	Rule based model	Type-2 fuzzy logic control system on accelerometers data and car geolocation	91%
Wang et al. (2018)	Signal transform	Mahalanobis–Taguchi System, Daubechies wavelet transform	Error 6%
Singh, Bansal, Sofat, and Aggarwal (2017)	DTW technique	Dynamic Time Warping	88.66%
Harikrishnan and Gopi (2017)	Threshold-based	Fitting Gaussian models to normal roads and comparing accelerometer sensor data value on Z component with the mean of fitted model	Speed dependent error which increases with increasing speed (up to 30%)
Devapriya, Babu, and Srihari (2016)	Threshold-based	Standard deviation of the Z component of the accelerometer	Not provided
Yi, Chuang, and Nian (2015)	Threshold-based	Two steps of pothole verification based on the standard deviation of sensor data	Not provided
Bhoraskar, Vankadhara, Raman, and Kulkarni (2012)	Machine learning	SVM	Not provided
Perttunen et al. (2011)	Machine learning	SVM	80%
Mednis, Strazdins, Zviedris, Kanonirs, and Selavo (2011)	Threshold-based	Z-THRESH, Z-DIFF, STDEV-Z	68–90%
Ndoye, Barker, Krogmeier, and Bullock (2011)	Signal processing	Multi-scale CA Algorithm	Not provided

data base from which can be shared with other users of the system, so that results of each driving can be compared to other drivers and also all users can benefit from shared knowledge of road conditions in different localizations. Our proposed model is using knowledge base developed for expert system evaluating road conditions. Proposed model composition enabled better adjustment to driving style which may differ for different people. Thus, all the features of driving can be better evaluated with tolerance to the style of driving of different people.

Results of our experiments showed that developed system is very efficient. We have done experiments by using different cars in various locations. We have also asked various drivers to collect data for us. Proposed type-2 fuzzy logic system enabled flexible adjustment to various driving style and various expectations of drivers, however showing correct result of road condition evaluation in each case.

CRediT authorship contribution statement

Marcin Woźniak: Conceptualization, Methodology, Research management. **Adam Zielonka:** Conceptualization, Methodology, Software. **Andrzej Sikora:** Conceptualization, Methodology, Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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