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ORIGINAL PAPER

FUZZY EVALUATION METHOD FOR ENVIRONMENTAL FACTORS AFFECTING A MOBILE ROBOT'S SENSOR SYSTEM IN VIEW OF DESIGN FOR LOGISTICS

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ABSTRACT. Background: The paper is devoted to mobile robot design problems with a focus on exteroceptive sensor systems for operation in a mixed environment (indoor with outdoor possibility). With a view to the design for logistics, the important concerns are, among others, minimization of the number of parts, reduction of weight, and reduction of dimensions. One of the challenges that arise here is the consideration of environmental factors, which vary among different application systems. It is necessary to reach a compromise between operational requirements and costs involved. Therefore, the relevance of the environmental factors should be evaluated to divide them into those that should be addressed and those that can be ignored. This will translate into the selection of sensors in sufficient quantity to provide the requirements without excessiveness.

Methods: We propose a novel three-stage method for assessing the relevance of environmental factors using fuzzy logic with occurrence, recovery, and impact level consideration. We take into account the impact level of each factor on the entire sensor system, restoration of functions lost completely or partially as a result of the factor (recovery), and the frequency of factor occurrence.

Results: The identified environmental factors, evaluated in term of their relevance are hierarchized from the most to the least relevant. The application of the method is presented on the basis of an autonomous forklift for indoor and outdoor use.

Conclusions: Based on the proposed method, it is possible to design a sensor system with consideration of any operation environment. The three-criteria method allows evaluation of any factor influencing sensor system on a five-point scale, both in terms of occurrence and severity (understood as impact level effect and recovery time). By evaluating the factors and thus prioritizing them using our method, only the most important factors from the designer's point of view can be taken into account. This can translate into minimizing the number of sensors and thus cost reduction and shorter implementation time.

Keywords: Design for Logistics, mobile robot, sensor system design, fuzzy set theory, mixed environment

INTRODUCTION

Design for Excellence (DfX) is a methodology that engages versatile groups with knowledge about different phases of the product life cycle to advise during the design phase. Issues are assessed here beyond base functionality understood as meeting customer expectations [Tulkoff and Caswell 2021]. The multidisciplinary nature of this approach is reflected in its key elements, such as Design for Manufacturing, Design for Reliability, Design for Environment, or Design for Quality. A part of DfX is also Design for Logistics (DfL). The concept was first mentioned in 1990, but it's assumptions are still relevant today. Following DfL, design actions should be aimed, among others, at minimization of the number of parts, use of standard parts, reduction of product dimensions and weight, and minimization of packaging use [Bielecki et al. 2021]. These activities are particularly important in products being developed in the era of Industry 4.0, which are often associated with high financial investments.

One of the products specific to Industry 4.0 are mobile robots [Freund and Al-majeed 2021;

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Żuchowski 2022] with varying degrees of autonomy and different industrial and service applications. When designing mobile robots, it is necessary to consider a number of factors that negatively affect proper operation and safety. In a limited, closed, structured area such as a warehouse, mostly static and dynamic obstacles (people) [Norton and Yanco 2016], overhanging infrastructure [Hedenberg and Åstrand 2016], and lighting [Y. Li and Birchfield 2010] can be problematic. In contrast, the outdoor environment has many uncertain, changing conditions that are difficult to predict, which are mainly weather (rain, snow, and low temperatures) [Vargas et al. 2021] and terrain features (uneven surfaces, plants, and unpredictable objects) [Ward and Iagnemma 2008]. It was also noticed that there is a clear division of the research according to the application area of the mobile robots under study. It was observed that solutions dedicated to the indoor environment are less demanding in terms of navigation, localization, and obstacle detection. It is associated with a known, mostly predictable environment and its conditions. The main challenge and source of uncertainty in this case is people, considered as dynamic obstacles. Therefore, the total cost of sensors in indoor-only applications is frequently lower than the total cost of sensors in outdoor applications, which must meet higher requirements. In relation to the above, environmental factors are unavoidable when considering the sensor system of mobile robots. The sensor system needs to be considered with relation to proprioceptive (measuring the robot's state) and exteroceptive sensors (measuring the environment's state). Our work is limited only to the exteroceptive sensors.

The design and later implementation of a mobile robot operating indoors and/or outdoors determine the need to study the sensor system with reference to environmental factors. Sensors have limitations resulting from their operation under various environmental factors. Regardless of the application area (only indoors, only outdoor, or indoors and outdoors), the number of factors interfering with sensor operation should be considered while designing a sensor system. The multiplicity of these factors makes it necessary to prioritize them depending on their influence on the tasks performed by the object.

Among the tasks related to the problem of designing the sensor system of mobile robots, issues such as sensor fusion, sensor placement, sensor selection, and sensor testing are considered. There is also a broad group of studies addressing sensor signal processing, but these papers were not included in the literature review due to their indirect relationship to the sensor system design considered at the level of our study. Table 1 presents selected works that correspond to the above mentioned issues. Papers from the sensor selection group will be discussed in detail because of their strong connection to the problem we are considering and the need to outline the research gap later.

In the case of the sensor selection problem, there are many papers available in the literature as a form of comparative analysis. Attention is focused here on the parameters of sensors generally available in their technical specifications and the limitations due to various factors. In [Vargas et al. 2021], the effects of precipitation, fog, humidity, thunder, sun glint, dust storm on LiDAR, RADAR, camera, and ultrasonic scanner are discussed in detail. Available research results for each of the factors indicated have been summarized. The paper provides a descriptive comparison of various sensors by pointing out their advantages and limitations. A similar but more general comparison of the sensors is presented in [Rosique et al. 2019], where cameras, lidar, RADAR, and ultrasonic sensor were compared based on spider charts in the context of FOV, range, accuracy, frame rate, resolution, colour perception, size, weather affections, maintenance, visibility, and price. [Singh and Nagla 2020] focused on selecting a sensor for autonomous navigation. The proposed methodology consisting of 12 layers starts with environment characteristics, which can negatively or positively influence considered laser sensor, vision sensor, or sonar/radar. In [Yeong et al. 2021], camera, LiDAR, and Radar were compared on a three-level scale that started from operating competently under the specific factor then to performing reasonably well, and finally to the worst: not operating well under the specific factor. A common feature of the works cited is the consideration of selected types of sensors with reference to selected factors.

Table 1. Summary of selected papers concerning different problems with sensor system designing

Sensor system design problem	Ref.	Brief Summary (e.g., considered sensors, benchmarks, indicators, methods classification)
sensor selection	[Vargas et al. 2021]	Criteria: range, resolution, weather conditions affect, lightning conditions affect, speed detection, distance detection, interference susceptibility, size Sensors: LiDAR, RADAR, camera, ultrasonic
	[Singh and Nagla 2020]	Criteria: environment-connected (indoor, outdoor, harsh environment conditions, structured/unstructured environment, or geometrical constraints), navigation characteristics (accuracy, FOV, level of autonomy, 2D/3D navigation, computational load, speed), navigation application (aerial, ground, underwater) Sensors: laser sensor, vision sensor, sonar/radar
	[Rosique et al. 2019]	Criteria: FOV, range, accuracy, frame rate, resolution, colour perception, size, weather affections, maintenance, visibility, price Sensors: cameras, lidar, RADAR, ultrasonic sensor
	[Yeong et al. 2021]	Criteria: range, resolution, distance accuracy, velocity, color perception, object detection, object classification, lane detection, obstacle edge detection, illumination conditions, weather conditions Sensors: camera, LiDAR, Radar
sensor placement	[Kim and Park 2020]	Indicator: lidar occupancy rate (LO %) Sensor: 3D lidar
	[Nikolaidis et al. 2009]	Indicators: weighted ratio of visible to total area, minimum number of cameras Sensors: cameras
	[Dey et al. 2021]	Indicators: cost function, longitudinal position error, lateral position error, object occlusion rate, velocity uncertainty, rate of late detection, positive and negative lane detection rate, positive object detection rate Sensors: radar, camera
	[Keyes et al. 2006]	Indicators: total time on task, number of collisions Sensors: cameras
sensor fusion	[Qu et al. 2021]	multi-sensor fusion methods for navigation: visual sensor-dominant navigation, lidar dominant navigation, UWB combined wth IMU and others
	[Fayyad et al. 2020]	deep learning sensor fusion methods for perception, localization and mapping
	[Kocić et al. 2018]	sensor fusion methods for: 3D object detection (camera+lidar), occupancy grid mapping (cameras+lidar), moving object detection and tracking (camera, radar and lidar)
	[Q. Li et al. 2020]	different localization approaches with the use of multiple sensors: GNSS-based localization, GNSS + IMU localization, Lidar odometry (LOAM), NDT-based localization, NDT + IMU
sensor testing	[Tang et al. 2020]	Indicators: object detection success/failure under rainy and sunny weather Sensors: lidar, camera
	[Heinold et al. 2021]	sensors robustness verification with the Scenario-Based Noise Deployment involving assumptions of Quality Function Deployment (QFD)
	[El-Hassan 2020]	Indicators: lane detection, object detection, and collision avoidance with yes/no Sensors: lidar, ultrasonic sensor, camera, color sensor, microcontroller
	[Bijelic et al. 2018]	Indicators:: visibility, entropy (information content in the sensor stream), depth of target, contrast under foggy conditions Sensors: lidar, camera, gated camera

Another problem is sensor placement. The available work mostly focuses on the arrangement of homogeneous sensors as in [Kim and Park 2020], where the focus was on lidar. The placement was studied based on the occupancy rate and aimed at determining lidar's optimal position and orientation to maximize data density, reduce dead zone, and improve point cloud resolution.

The use of only one sensor is insufficient; hence, multi-sensor implementation requires consideration of sensor fusion, which has been comprehensively discussed in [Galar and Kumar 2017].

On the other hand, a separate group of papers deals with sensor testing, in which research is conducted on pre-selected sets of sensors, and various methods dedicated to object detection, navigation, and localization are proposed.

Environmental factors in the context of their influence on the sensor system have already been extensively studied in recent years, as evidenced by numerous review publications. The most commonly used exteroceptive sensors (lidar, radar, camera, and ultrasonic) are presented in terms of weather conditions, rough terrain, dynamic obstacles, or problematic infrastructure (overhanging elements, reflective surfaces). A specific type of sensor is considered with reference to a variety of factors. There may be more or less factors depending on the system's characteristics under study. The more factors identified and sensor parameters considered, the more complex the problem becomes. On the one hand, it is difficult to select sensors that perform well under given environmental factors and, on the other hand, to include all identified factors in the experiments. Research available in the literature addresses selected sensor types. Methods related to environmental factors are lacking. Instead of referring the sensor parameters to the impact of the environmental factor, it is worth taking the opposite approach. The identified environmental factor occurring in the system under study should be addressed by considering the sensor system as a whole, not as individual elements. In addition to the impact of the factor (already described in the literature), the frequency of occurrence and the system's recovery time must also be determined. This will allow the identified environmental factors to be assessed for relevance, i.e., it will be possible to identify those necessary for consideration and those to be ignored. The aim of this paper is to evaluate the relevance of environmental factors affecting the performance of mobile robot’s exteroceptive sensors.

The main contributions of this study are the following:

- We have proposed a three-stage fuzzy evaluation method for environmental factors affecting exteroceptive sensors of a mobile robot.
- We have defined and used three criteria (occurrence, recovery, impact level) to assess the relevance of the identified environmental factors.
- In contrast to the available studies, we have evaluated environmental factors with relation to the entire sensor system, and we did not consider each sensor separately.
- We considered the DfL in the context of mobile robot design.

A FUZZY EVALUATION METHOD

To the best of our knowledge, there is a lack of methods in the literature to support sensor system design in the context of environmental factors. Literature shows that predesigned sensor systems or its elements are tested under the influence of selected environmental factors. However, each system where a mobile robot is implemented will be characterized by different factors, so different solutions will be used for different systems. A mobile robot is designed by a group of people with knowledge mainly in the field of automation, robotics, and electronics. Therefore, it can be said that a group of experts from various fields makes decisions about the design of the whole object and consequently about its individual systems such as the sensor system discussed in this article.

When considering environmental factors, it is necessary to identify those relevant to the system under study. Determining the relevance of environmental factors is critical to avoid overprotecting the object in the form of an excessive number of sensors. The determination of relevance based on the classical logic of 0-1, meaning relevant or not relevant, is insufficient and difficult to determine. Each expert may consider relevance differently, and each factor may be more or less relevant. Additionally, when interviewing experts, one can get answers such as very high relevance, medium relevance, etc. Traditional quantitative methods do not account for the indicated uncertainty associated with human behavior in the decision-making process [Blanco-Mesa et al. 2017]. Classical 0-1 logic is not applicable here. Therefore, we decided to use fuzzy logic to model logical reasoning and to encode expert opinions based on experience and knowledge of the system.

In view of the above, fuzzy logic [Chen and Pham n.d.] will succeed in the problem of assessing the relevance of environmental factors in relation to the sensor system. When assessing the relevance, it is necessary to define the criteria to be taken into account. In our method, we propose three criteria: Recovery, Occurrence and Impact level. Finally, knowing the Recovery, Occurence, and Impact level, it will be possible to determine the Factor relevance, which should be referred to the designed sensor system.

A scheme of the proposed method for evaluating the relevance of environmental factors affecting the exteroceptive sensors is shown in Figure 1.

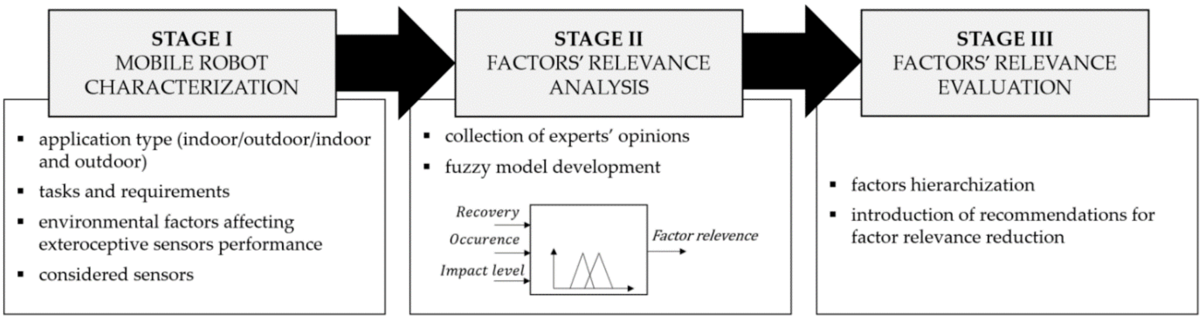


Fig. 1. A general scheme of the proposed fuzzy evaluation method

There are three stages in the proposed method: mobile robot characterization, factors' relevance analysis, and factors' relevance evaluation.

Stage I. Mobile robot characterization

A sensor system is one of the many systems of a mobile robot. The selection of its elements is connected with requirements and tasks, environmental factors occurring in the environment, and type of application with consideration of safety and costs. The type of application, being either indoor-only, outdoor-only, or mixed, significantly affects the reduction or increase in the number of environmental factors, which may interfere with the sensors. Among the tasks and requirements to be fulfilled by the object, one should, for example, take into account the assumed performance, type of transported load, and safety in the context of human presence in the working area. When examining the set of sensors under consideration, a key issue is the environmental factors that depend on the object's application system. These factors may interfere with the operation of the object to a greater or lesser extent. Therefore, it is reasonable to assess them in terms of relevance. The output of the first stage are the identified environmental factors specific to the system under study and description of the mobile robot in the context of its requirements, type of application, and the considered sensor system concept.

Stage II. Factors' relevance analysis

Identified environmental factors negatively affecting sensor system performance are considered based on three criteria: recovery, occurrence, and impact level using fuzzy logic. In this way we take into account the impact level of the factor, restoration of functions lost completely or partially as a result of the factor (recovery), and the frequency of factor occurrence. Characteristics of the fuzzy model with the indication of the input and output variables and the types of membership functions used are presented in the Table 2.

Table 2. Characteristics of the fuzzy model

Linguistic variable name	Linguistic variable type	Membership function name	Membership function type
Occurrence	input	very unlikely unlikely possible likely very likely	trapezoidal triangle triangle triangle trapezoidal
Recovery	input	very short short average long very long	trapezoidal triangle triangle triangle trapezoidal
Impact level	input	negligible moderate significant	trapezoidal triangle trapezoidal
Factor relevance	output	very low low average high very high	trapezoidal triangle triangle triangle trapezoidal

Recovery (Re) is the time required for the system to return to a fully operational state without maintenance actions. The membership functions for the linguistic variable Recovery are shown in Figure 2. Five membership functions describing the duration of recovery were assigned to this variable as very short, short, average, long, and very long. We propose considering the variable in minutes, so the Recovery can be rated in general on a scale of 0 to positive infinity. However, determining the parameters of the functions adequate for the system under study will limit this range.

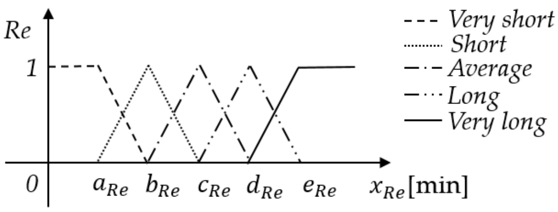


Fig. 2. Membership functions of the linguistic variable Recovery

Occurrence (Oc) determines the frequency of occurrence of an environmental factor. The climate in the studied area determines it (e.g., frequency of precipitation, sunny days, frosty days) and the characteristics of the studied system (e.g., type of ground resulting in lower/ higher dustiness). It is related to the probability of occurrence of a factor as the ratio of days with an observable factor and all days. The use of probability determines the Occurence range from 0 to 1. The membership functions for the linguistic variable Occurrence are shown in Figure 3.

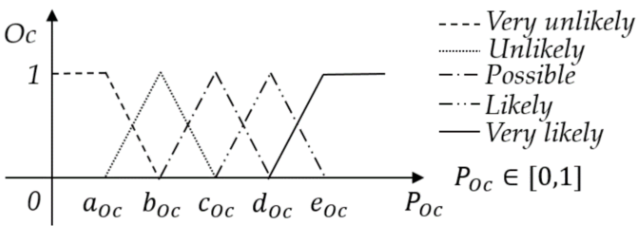


Fig. 3. Membership functions of the linguistic variable Occurrence

Impact level (Il) addresses the effect of the environmental factor under consideration on the sensor system. A three-level scale describes this criterion:

1. Negligible – the effects of the factor cause a limitation in the operation of one of the sensors, but in terms of the entire system, there is no loss of operational reliability.

2. Moderate – the influence of the factor is significant for the sensor system and causes its partial malfunction, e.g.: by limiting the field of view of the sensors, affecting the whole system.

3. Significant – the impact of the factor makes it impossible to perform the basic tasks defined for the system (e.g.: loss of safety as a consequence of, for example, loss of human detection capability).

The membership functions for the linguistic variable are shown in Figure 4.

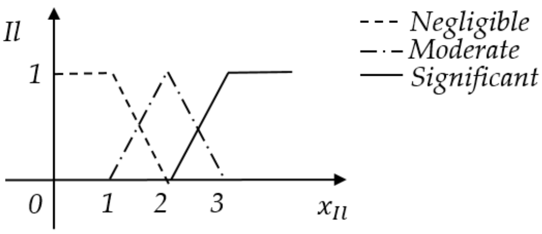


Fig. 4. Membership functions of the linguistic variable Impact level

Based on fuzzy input parameters (Recovery, Occurrence, Impact level) and inference rules, it is possible to provide for each of the identified environmental factors its Factor relevance with a range from 0 to 6. Membership functions for a linguistic variable Factor relevance are shown in Figure 5.

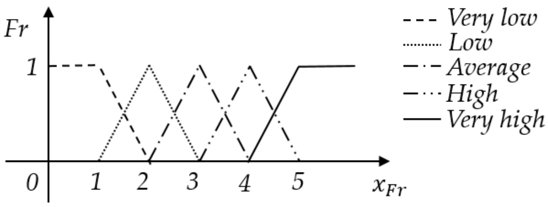


Fig. 5. Membership functions of the linguistic variable Factor relevance

Defuzzification of Factor relevance (output variable) is performed after the application of the center of gravity method. Fuzzy value of Factor relevance is transformed into crisp one.

Stage III. Factors' relevance evaluation

Having defined the Factor relevance, it is possible to prioritize the examined environmental factors and on its basis, to introduce actions for reducing this relevance. It is desirable to achieve the lowest possible Factor relevance for a given factor. However, its acceptable value depends on the system's specifics and the designer's assumptions. For some, relevance at the upper range of values will signal the need to adjust the system, and for others, it will be at the lower range. If an unacceptable factor relevance is obtained, it is necessary to modify the sensor system concept under investigation.

METHOD APPLICATION BASED ON AUTONOMOUS FORKLIFT

Stage I. Mobile robot characterization

According to the described stages of our method, initially (within stage I) it is necessary to characterize the analyzed mobile robot. The application of the proposed method will be demonstrated using an example of an autonomous forklift being developed as part of a research project POIR.01.01.01-00-0691/19 funded by the Polish National Centre for Research and Development. The project's theme focuses on the development of an autonomous forklift performing transport tasks within a mixed work environment, mostly indoor, but with outside possibility. The project's objectives included the selection of sensors, enabling the implementation of transport tasks under the described conditions while maintaining the maximum level of safety. Among the tested exteroceptive sensors of the forklift are three Intel Realsense 435i 3D cameras and three SICK S300 Advanced laser safety scanners. The sensors are to allow localization, navigation, and detection of objects (obstacles and cargo to be picked up). One of the sensor arrangements considered is placing two scanners and two cameras at the front of the forklift (at the contact points between the body surface and the side surface and at the inner mast and carriage, respectively) and one scanner and one camera at the back. Despite the need to consider the operation of the object outdoors, we consider a laser scanner dedicated (according to the specifications) to indoor applications. Thus, we want to test the limitations of such a solution in the system under study, which will reduce costs if acceptable results are achieved.

An autonomous forklift performing indoor and outdoor transportation tasks faces several disruptive factors. We can divide these factors based on the level of uncertainty into controlled and uncontrolled. Within the first group (controlled), we distinguish factors resulting directly from the system's characteristics. These include: the changing topology of the maneuvering area, diversity of transport units, lack of characteristic landmarks (empty yard). The second group (uncontrolled) includes all factors of random nature, including: weather conditions (fog, harsh lighting, operation in the absence of light, precipitation, changing temperature, etc.) and the impact of the system environment (e.g.: dust resulting from the operation of other equipment).

The fuzzy evaluation method will be applied to the second group of factors. The following factors were evaluated: condensation, low temperature (below zero), fog, and dustiness.

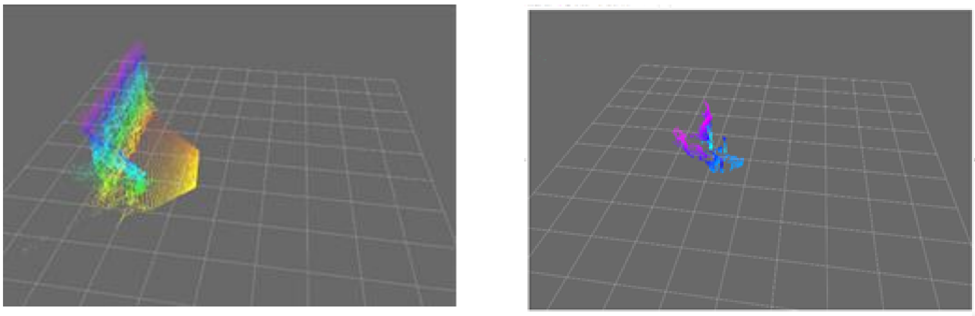
Stage II. Factors' relevance analysis

For the identified factors, within Stage II, a factor relevance analysis is performed. Expert opinion supported by dust and fog tests of varying severity and climate chamber tests were used for relevance analysis.

The tests in the climate chamber aimed to verify the selection of sensors for the implementation in outdoor conditions. The impact of temperature and humidity changes on the operation of scanners and cameras was analyzed. The climate chamber used in this study has the following parameters:

- dimensions 5,2x5x4 m
- temperature range from – 20 °C to + 50 °C
- humidity range from 5 to 20 g/m3 (above 10 °C).

Sensors placed in the climate chamber lowered their temperature to ambient temperature (verification based on measurements from a thermal camera). We only verified the temperature of the housing, we did not take measurements inside the device. Despite the temperature drop, the sensors were working properly. We could not read the differences in signals coming from scanners of different temperatures. However, as expected, the problem turned out to be each time the device was taken out of the chamber. As a result of differences in the temperature of the surroundings and the measuring equipment, condensation of water vapor on the sensor's surface occurred every time. Water vapor condensing on the surface of the sensors made measurement impossible. Both the cameras and the scanners lost their proper operation capabilities. It can be seen in the 3D visualization produced by using Rviz (Figure 6). The time of device inoperability lasted until the device was warmed up to room temperature and the water evaporated. At a room temperature of 21°C, the time required for full recovery was over 15 minutes. The measurements obtained clearly indicate that the transition of the forklift between indoor and outdoor environments is an important issue.



a) b)

Fig. 6. View from the sensor before and after taking it out of the climate chamber: a) correct 3D camera view b) interfered 3D camera view

In addition to verifying the effects of temperature on sensor performance, the effects of dust and fog were also analyzed. A fog generation device with efficiency 215 m3/min was used to study the effect of fog. It was applied in a room of 90 m3. Additionally, as part of our research, we wanted to verify whether and to what extent dust grain size affects sensor performance. Another goal was to verify what level of dustiness is the limiting level for the performance of individual sensors.

The first test was under fog conditions. After only 20 seconds of operation, the amount of fog generated (71.6 m3) limited the operation of the safety system based on the SICK S300 Advanced scanner to an area with a radius of 500 mm. Tests performed to verify the effect of grain size on scanner performance showed that regardless of grain size, a 100mm stream fed at a velocity of 2 to 10 g/s was identified by the scanner as a solid obstacle. In contrast, a significant result was observed as an indirect effect of the dusting. Dust falling to the floor rose uniformly in all directions after a few seconds of testing; even though the dust was practically invisible, it caused a clear performance limitation of the scanner. Grain size did not matter when the stream was dosed in front of the scanner, but it did affect the particle persistence time in the air. The test was carried out in a room, so it is difficult to assess the results of the measurements in relation to conditions occurring outside. However, dust, for example, which can appear in summer, raised by vehicles working in the surroundings of the forklift may cause interference with the scanner.

Taking into account the tests performed and the expert opinions obtained, the parameters of the membership function for the linguistic variables Oc, Il, Re, and Fr were adopted, which are shown in Table 3.

For the assumed parameters of the membership function and inference rules, plots of the dependence of the output variable on the studied input variables were obtained (Figure 7).

Table 3. Definition of the linguistic variables for the case under consideration

Linguistic variable name	Membership function name	Membership function parameters	Supporting research for parameter estimation
Occurrence	very unlikely unlikely possible likely very likely	[0, 0, 0.04, 0.08] [0.04, 0.08, 0.12] [0.08, 0.12, 0.16] [0.12, 0.16, 0.2] [0.16, 0.2, 1, 1]	analysis of meteorological conditions over recent years
Recovery	very short short average long very long	[0, 0, 1, 2] [1, 2, 3] [2, 3, 4] [3, 4, 5] [4, 5, 6, 6]	testing in the climate chamber, simulation of dust and fog
Impact level	negligible moderate significant	[0, 0, 1, 2] [1, 2, 3] [2, 3, 4, 4]	
Factor relevance	very low low average high very high	[0, 0, 1, 2] [1, 2, 3] [2, 3, 4] [3, 4, 5] [4, 5, 6, 6]	

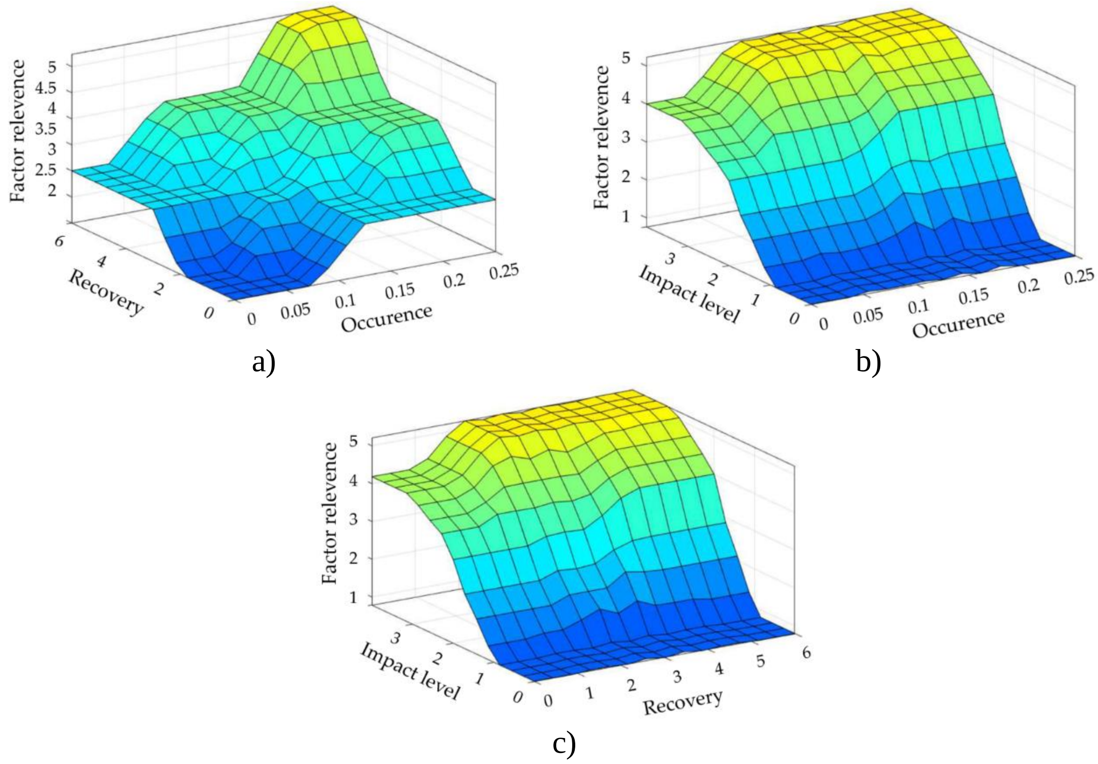


Fig. 7. The dependence of the output variable on the input variables: a) Recovery and Occurrence b) Impact level and Occurrence c) Impact level and Recovery

A three-dimensional output surface provides the entire range of the output data based on the entire range of the input data. Because of the consideration of three inputs, it was necessary to compare two of them with the obtained output. Thus, the three combinations shown in Figure 7 were analyzed. Recovery and Occurrence similarly affect Factor relevance (Figure 7a). The higher the Recovery and Occurrence, the higher the Factor relevance. The dark blue area at the bottom indicates the lowest Factor relevance, resulting from very unlikely Occurence and very short Recovery. Imbalanced influence on Factor relevance is observed when comparing Impact level with Occurrence (Figure 7b) and Impact level with Recovery (Figure 7c). In both cases, the strong influence of Impact factor on Factor relevance is noticeable. Negligible Impact level results in receiving the lowest factor relevance, the value of Occurence, or Recovery is then irrelevant.

Stage III. Factors' relevance evaluation

The final stage (III) is based on the interpretation of the results. Table 4 summarizes the results of the analysis of selected factors interfering with the sensor system of the autonomous forklift truck characterized in Subsection 2.1.

Table 4. Results of factor relevance fuzzy-based analysis

Considered environmental factor	Occurence	Recovery	Impact level	Factor relevance
condensation on the sensor surface	0.58	5.5	4	5.24
sub-zero outside temperature	0.1	0.01	0.05	0.84
fog	0.1	6	4	5.19
dust	0.01	1	1	0.768

The Occurrence criterion was considered first for the possibility of condensation on sensor surfaces. The minimum, maximum, and average temperatures in 2021 for each month were considered. For an assumed indoor temperature of 21 °C and humidity of 60%, a dew point of about 13 °C was calculated. When the temperature of the sensor housing is reduced to below 13 degrees, condensation will occur. Seven months out of twelve in 2021 (similar in 2020) had undesirable temperatures; hence, the Condensation Occurrence was determined as 0.58. Based on the testing performed in the climate chamber, Recovery was assigned a rating of 5.5. The occurrence of condensation leads to an inoperability of the sensors and thus to an inability to perform basic tasks. The impact level was assessed as 4.

Temperatures below zero in 2021 occurred for 40 days, so the Occurrence was determined as 0.1. Our tests show that sub-zero temperatures do not adversely affect the sensors. For this reason, the Recovery and Impact level were assigned 0.01 and 0.05, respectively.

Based on tests performed, publicly available fog statistics in Poland, and expert opinions, the Occurence of fog was determined as 0.1, recovery as 6, and Impact level as 4.

The ratings assigned to the dust factor are based on the characteristics of the ground present in the system under study.

Factor relevance obtained the lowest for dust and the highest for condensation indicating the necessity of considering the condensation and fog factors in the design of the sensor system of the autonomous forklift truck. The dust and sub-zero temperature factors can be ignored due to very low Factor relevance.

DISCUSSION

The proposed method allows the design of a mobile robot’s sensor system considering any operating environment. Three defined criteria form the basis for the evaluation of any factor influencing the sensor system on a five-point scale, both in terms of occurrence and severity (understood as impact level effect and recovery time). It allows the ranking of the identified factors occurring in the studied robot work system in terms of their relevance. Determination of the most relevant factors results in a reduction in the number of sensors, fulfilling the Design for Logistics assumptions. However, the method does not set a fixed boundary indicating for which value of Factor relevance the system needs to be modified. This is because the accepted Factor relevance level will vary depending on, among other things, the system designer's requirements. With people sharing the workspace with the mobile robot in the system, the acceptable level of the indicator will be much lower than in a system with no humans.

The general aim of our method is to support the mobile robot’s sensor system design in the context of Design for Logistics concept assumptions. A literature review has shown a definite lack of such methods. The effects of different environmental factors on different types of sensors are known. However, individual sensors are considered rather than the whole system. Additionally, the selected sensor is always tested in relation to the selected factor. The frequency of Occurrence of the factor is not taken into account, neither is resilience defined by us as Recovery. Our method is a novel method for evaluating environmental factors for their relevance. To the best of our knowledge from the literature review, there is a lack of such methods supporting sensor system design. Therefore, it is not possible to compare our results with the results of other methods.

Experts are able to directly design a sensory system without any support method; currently, this is how sensor system design is approached. However, our method allows us to indicate which factors can be ignored and which will significantly influence the considered variant of the sensor system design. In this way it is possible to decide whether to accept the system's current design (meeting the requirements) or to make changes due to the need for greater protection against environmental factors in the system. Experts are able to identify the environmental factors present in the system; however, determining their importance is a complex issue. Occurence, Impact level and Recovery should be taken into consideration here. Omission of these criteria and omission of factor relevance analysis may result in protection against all identified factors, leading to redundancy and additional costs.

SUMMARY AND FUTURE STEPS

Designing a sensor system for a mobile robot requires separating two groups of sensors: exteroceptive and proprioceptive. With regard to exteroceptive sensors, the problem arises in selecting the appropriate number and type of sensors, their proper placement, interpretation of data coming from different sources (sensor fusion), and further testing of the developed solution. Inherent in all of the listed groups of issues are undoubtedly environmental factors. These factors may more or less negatively affect the operation of a sensor system. In the literature, interferences of sensor operation in indoor and outdoor applications under the influence of environmental factors have already been indicated more than once. However, the focus each time is only on the effect of the selected factor on the sensor under consideration. Thus, selected sensors are evaluated with respect to selected factors. Additionally, the sensor system is not considered comprehensively, but through the prism of its individual components. In addition, the occurrence frequency of the factor and the time for the system to return to full operability after the factor is no longer present are ignored.

In view of the above, we propose a reverse approach to that used in the literature. Instead of evaluating the sensor in relation to the factor, we evaluate the identified factors with reference to the entire sensor system. We proposed a three-stage evaluation method based on fuzzy logic. The evaluation does not only consider the impact of the factor, but also the frequency of occurrence and the time for the object to return to a fully operational state. In this way, we consider the resilience and robustness of the sensor system in terms of environmental factors, which is very rarely considered in the literature despite its significance in mobile robot operation. The multiplicity and diversity of environmental factors is the biggest challenge when implementing mobile robots in a changing, uncertain environment. By evaluating the factors and thus prioritizing them using our method, only the most important factors from the designer's point of view can be taken into account. This can translate into cost reduction and shorter implementation time. In addition, the assumptions of DfL are met.

The implementation of the proposed method is presented on an example of an autonomous forklift designed for indoor operation with outdoor capability. However, the method can be used in the design of the sensory system of any mobile robot.

Our future work in the considered research field will focus on the development of the proposed method. In expert methods (such as the one proposed by us), a non-negligible key step is the selection of experts whose opinions determine the validity of the obtained results. Therefore, we plan to consider the expert selection problem.

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