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Identifying Indoor Objects Using Neutrosophic Reasoning for Mobility Assisting Visually Impaired People

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Abstract: Indoor object detection is a fundamental activity for the development of applications of mobility-assistive technology for visually impaired people (VIP). The challenge of seeing interior objects in a real indoor environment is a challenging one since there are numerous complicated issues that need to be taken into consideration, such as the complexity of the background, occlusions, and viewpoint shifts. Electronic travel aids that are composed of the necessary sensors may assist VIPs with their navigation. The sensors have the ability to detect any obstacles, regardless of whether they are static or dynamic, and offer information on the context of an interior scene. The characteristics of an interior scene are not very clear and are subject to a great deal of variation. Recent years have seen the emergence of methods for dealing with issues of this kind, some of which include the use of neural networks, probabilistic methods, and fuzzy logic. This study describes a method for detecting indoor objects using a rotational ultrasonic array and neutrosophic logic. A neutrosophic set has been seen as the next evolution of the fuzzy set because of its indeterminate membership value, which is absent from conventional fuzzy sets. The suggested method is constructed to reflect the position of the walls (obstacle distance) and to direct the VIP to move freely (ahead, to the right, or to the left) depending on the degree of truthiness, the degree of indeterminacy, and the degree of falsity for the reflected distance. The results of the experiments show that the suggested indoor object detecting system has good performance, as its accuracy rate (a mean average precision) is 97.2 ± 1%.

Keywords: indoor navigation; visually impaired people; neutrosophic logic; object detection

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1. Introduction

The World Health Organization (WHO) released research on the prevalence of persons with visual impairments, and they found that over 285 million people throughout the world are blind or visually impaired (VI). Of these individuals, 39 million are totally blind, while another 246 million have some degree of visual impairment. The vast majority of persons living with VI live in economically developing countries. People with VI have a far more difficult time than the general population with everyday tasks like navigating their surroundings safely, going to the store, or even recognizing friends and family members. One of the most challenging activities is moving about on one's own in a strange environment due to the high danger involved (i.e., a possible collision with static or dynamic obstacles). Because of this, the majority of VI individuals walk on routes that they are familiar with while consistently discovering new ones [1].

VIPs require assistance with autonomous displacement in order to properly orient themselves and navigate their surroundings. This assistance should include built-in capabilities for the detection and recognition of obstacles as well as desired destinations like rooms, staircases, and elevators. Within this context, it is of the utmost importance to create electronic travel assistance (ETA) solutions that may increase the safe mobility of VIPs indoors and outdoors and provide supplementary awareness of foreign surroundings [2,3]. However, despite the fact that the global positioning system (GPS) signal isn't particularly strong inside, VIPs still need to be able to find their way around in unfamiliar environments. This indicates that more specialized methods or technologies will need to be implemented [4].

There are now two types of indoor localization methods: those that rely on infrastructure and those that don't. To use infrastructure-based techniques, you must have access to WiFi, which is essential. Walls act as barriers that weaken the signal strength of WiFi access points, making this mode of data transfer inefficient. As the name implies, infrastructure-less techniques do not rely on any existing networks or infrastructure [5]. Fast processing, extensive coverage, an enhanced range of detection of static and dynamic obstacles, and the ability to operate day and night are the requirements of the VIP [6]. The interfaces and image processing subsystems are given special attention because of the fast technological advancements in this quickly growing field.

Context awareness is the capacity of computer systems to sense, detect, understand, and react to the features of the user's surrounding environment. The user must be made aware of the sensory data in the current environment, which is a core premise of designing context-aware ETAs. Ultrasonic signal processing is used often in non-destructive material testing, medical tissue characterization, robotic applications, etc. [5]. The categorization process is highly dependent on the retrieved characteristics used to represent the object [6,7]. Although there are situations in which just simple signal processing is necessary, there are other situations in which extracting these properties is a difficult endeavor. Several bits of information may be derived from the amplitude of a signal, but this is not always the most accurate representation of the signal. Sometimes, the frequency of a signal is more relevant when its frequency components conceal more particular information. Numerous earlier publications have proposed different sets of ultrasonic characteristics taken from the time and frequency domains (e.g., wavelet transform) and explored the viability of employing such parameters for ultrasonic signal classification [8,9].

The front, left, and right sides of a navigator are all possible locations for an obstacle to appear. Therefore, ultrasonic sensor outputs (distances to the obstacles from the left, right, and front sensors) are used further for VIP's current walking context estimation. Because this is not a quantifiable measurement, its accuracy cannot be guaranteed. The ability of fuzzy logic systems to effectively describe uncertainty across a wide variety of settings and applications is well established. In a nutshell, it provides a practical means of depicting the imprecise and uncertain features that are intrinsic to the real world. The use of fuzzy-based approaches in the context of adaptive techniques results in rapid convergence and decreased complexity in the context of nonlinear conditions that change over time. The merging of human expert knowledge into an already-available numerical dataset is well-suited for a fuzzy technique, which is highly appropriate for this purpose. Because of this, several articles over the last five years have addressed the explanation of fuzzy logic-based indoor navigation systems for VIPs [10–12].

Neutrosophic logic research in several disciplines is advancing rapidly [13–16]. A generalization of fuzzy logic called neutrosophic logic was introduced by Smarandache [17]. Similar to fuzzy logic, intuitionistic logic, and three-valued logic, in which a variable x is described by the triple values $\mathbf{x} = (t, i, f)$, where t stands for the degree of truth, f for the degree of false, and i stands for the degree of indeterminacy, neutrosophic logic is an extension of these approaches. A neutrosophic set has been considered the next evolution of the fuzzy set for indeterminacy membership values that are absent from the vague set. Compared to the vague and fuzzy sets, the neutrosophic set's three memberships are more expressive for making decisions. Only partially complete or inconsistent information is outside the scope of fuzzy set theory's ability to process. The purpose of the mathematically developed model known as neutrosophic logic (NL) is to account for several kinds of uncertainty, including ambiguity, inconsistency, redundancy, and incompleteness [14–16].

The neutrosophic controller is a novel system that, in comparison to its fuzzy analogs, is both more broadly applicable and more tolerant of indeterminacy. Like their fuzzy analogs, neutrosophic systems might benefit from the expertise of human operators. To further complicate matters, it is very unlikely that the data received by the system would be wholly complete and determinate, making it impossible to create a precise mathematical model that would represent system behavior. Non-linearity, time-varying processes to be regulated, significant unexpected external disturbances, deteriorating sensors, and other challenges to collecting accurate and trustworthy measurements all contribute to data that is incomplete and uncertain [17–19]. The concept of the range of neutralities is absent from fuzzy logic controller and allied logics because the focus of these logics is only on the membership or non-membership of a particular element to a certain class, and thus cannot account for the uncertainty that may arise in the data collection process for the reasons given above. Therefore, a neutrosophic controller is offered to cope with such circumstances when there is a chance of indeterminacy and incompleteness in the collected data [20,21]. The basic inference process of fuzzy logic and neutrosophic logic is shown in Figure 1.

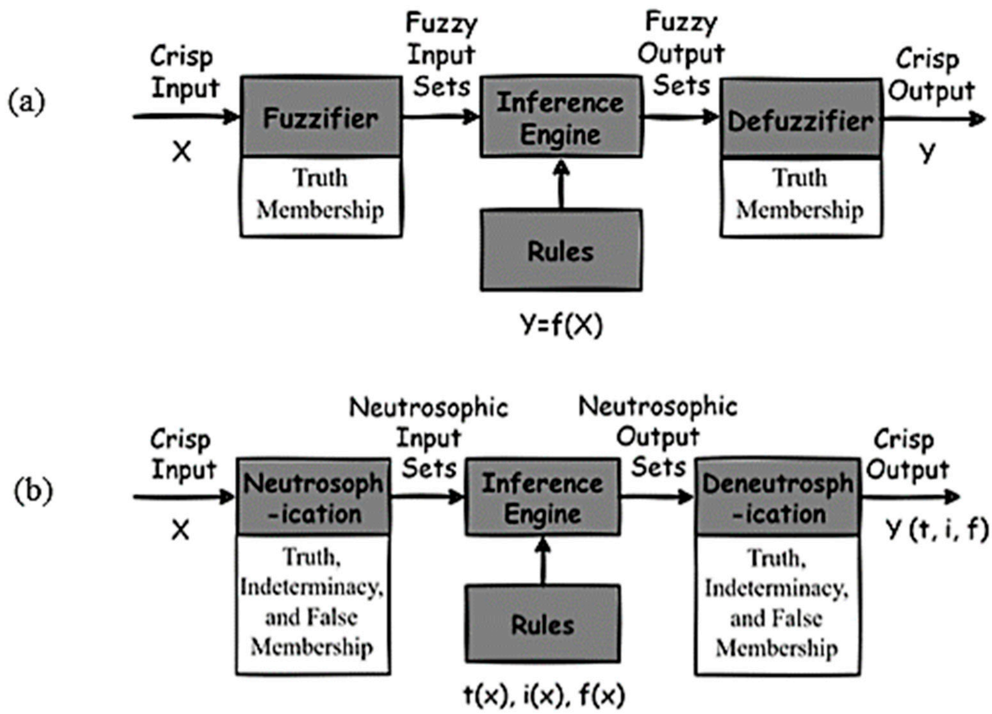

Figure 1. Inference systems: (**a**) fuzzy logic (**b**) neutrosophic logic.

Neutrosophic controllers are suggested to consist of four modules. (a) neutrosophication module, (b) neutrosophic rule base, (c) neutrosophic engine, and (d) de-neutrosophication module. First, data is gathered on all the factors that matter for the process under management. Second, we use the truth, falsity, and indeterminacy membership functions of neutrosophic sets to capture the truth, falsity, and indeterminacy of the obtained measures. The process at this point is known as neutrosophication. Third, the inference engine uses the neutrosophied measurements to assess the control rules recorded in the neutrosophic rule base. The results of this analysis will define one or more neutrosophic sets over the space of all potential actions. The fourth and last module of the cycle involves collapsing this neutrosophic set into a single (crisp) value using a triplet format like $x\,(t, i, f)$, which would be the most accurate representation of the derived neutrosophic set. De-neutrosophication is the term for this procedure [22–26].

1.1. Motivation

For the purposes of this article, ultrasonic sensors are of particular interest to us. This sensor has substantial potential for use in a variety of applications. One of the advantages of using ultrasonic sensors is the ease with which we can collect distance information from nearby objects without the need for expensive processing. They are also capable of functioning in poor visibility settings, which makes them perfect for use both during the day and throughout the night. Therefore, the ultrasound sensor seems like an excellent option for our system to detect and identify a variety of objects. Nevertheless, one of the difficulties that autonomous systems continue to face is recognizing objects in a variety of viewing situations. Therefore, the purpose of our research is to provide a challenge by using just a single ultrasound sensor for obstacle detection. We are also taking into consideration the limitations of this sensor type, which include the fact that the reflected distances are not always accurate.

Uncertain information is handled probabilistically and represented in numerical form during decision analysis. Due to the high levels of uncertainty, indeterminacy, and ambiguity that are present in the object detection domain, the same sensor might reflect multiple distances depending on the viewing conditions that are present. Therefore, neutrosophic logic will take into consideration the uncertainty that is present inside the indoor obstacle detection domain and will offer the degree of uncertainty for each distance. Incomplete or inconsistent information is outside the scope of the fuzzy set theory's capabilities.

1.2. Contribution

In this paper, we investigate using ultrasonic sensors to detect the location of the walls (obstacle's distance) and guide the visually impaired person to move freely (forward, right, or left). Because it is built from off-the-shelf parts, our solution is inexpensive and convenient to use because it does not need any specialized hardware. Additionally, our methodology took advantage of the wavelet form of ultrasonic waves. Ultrasonic sensors obtain range data associated with the obstacles in the surrounding environment, but these readings are inherently imprecise. This is the data sent into the neutrosophic logic model for locating and identifying items in a scene, regardless of their size, shape, or position.

Multi-criteria decision-making issues and other technical applications in uncertain settings benefit greatly from the usage of neutrosophic sets [16]. Our major goal in this article is to investigate the application of the concept of neutrosophic logic to the problem of obstacle identification in a dynamic, ambiguous indoor environment through (1) using trapezoidal neutrosophic numbers to represent input parameters (antecedents), (2) by modeling qualitative aspects of human comprehension through the AND operator, we may construct neutrosophic IF-THEN rules to estimate the location of the walls, and (3) analyzing the accuracy rate in light of the de-neutrosophication of the consequents. To the best of our knowledge and from the latest research, neutrosophic logic is not yet used to detect and recognize indoor obstacles for VIPs.

This article's remaining sections are organized as follows: The Section 2 performs a literature review on indoor object identification using machine learning approaches. The recommended strategy is discussed in Section 3, which is based on a review of existing approaches. The suggested model is validated in Section 4 via a series of experiments, followed by a discussion of the results. The concluding portion, Section 5, provides a summary of the work and proposes prospective future research topics.

2. Related Work

In the literature, input modules used in indoor navigation systems are categorized into three classes depending on the navigation sensors employed: non-camera-based, camera-based, and hybrid [1,2]. Non-camera-based systems perceive the environment and display it to the user using a variety of sensors. Camera systems rely mostly on a live camera feed or pictures to represent the surrounding environment. Hybrid systems include both forms of inputs. Common in industrial contexts, non-camera-based technologies are often utilized for robot navigation. These technologies have been presented as a solution to the challenge of interior navigation for the visually impaired.

Visually impaired users of non-camera-based systems must carry the appropriate equipment (tag or tag reader, smartphone, or other receiver/transmitter device) when moving around their environment in order to be trackable. The electronic tags include data needed to search for further information in a database and to pinpoint the user's position on an environmental map. IR sensors for indoor navigation are typically used to determine the distance from an obstacle [27]. Numerous academics and researchers have a strong interest in real-time indoor object detection. The problem is to reliably and precisely recognize the item in an image or video. In general, interior settings vary from outside ones. Typically, indoor scenery consists of several backdrop pieces and decorations [27].

Various methods are reported in the literature for detecting and recognizing walls, holes, and descending and ascending stairs. Infrared sensors, laser sensors, and monocular cameras are common components in these systems [27–31]. Sensor-based ETA systems capture environmental data and communicate it to the VI user via a range of audible or haptic signals. Computer vision advancements have resulted in the fast development of assistance gadgets based on artificial intelligence for outdoor and indoor navigation. The authors were able to identify on-floor obstacles in real-time with no a priori training thanks to the use of traditional computer vision techniques, including color histogram representation and edge detection [1–3]. The technology violates the hand-free restriction imposed by VI users while being unobtrusive and cheap. In addition, it is unable to detect obstacles that hang over its path.

Indoor object identification based on machine learning methods is used in many other famous works as well [32–34]. The real-time restriction is frequently not satisfied by this kind of technique, which is heavily reliant on processing resources and has a very high computational cost. Recently, deep convolutional neural network (DCNN) models have received a lot of interest for a variety of computer vision applications. This method has been used to recognize indoor objects [35–38]. Feature extraction utilizing DCNN and posture estimation were used to solve the issue of indoor placement. Other navigational aids for the mobility of individuals with VIP have been developed by combining artificial vision with map matching and GPS [1].

Fuzzy logic was shown to be helpful in addressing navigational issues for those with visual impairments in a large body of research [39]. Fuzzy rules, for example, have been utilized by some academics to assign preferences to things depending on the features of the objects themselves. Another group of researchers used a sophisticated sensor logic system to create a mobile route guiding assistance for those who are blind or partially sighted. Fuzzy control principles and image depth were combined to develop a novel obstacle avoidance strategy. A new guiding system, the directed elliptical model with fuzzy logic, has been developed to monitor medium-range traffic conditions in real-time for visually impaired pedestrians [39,40].

Using Bluetooth Low Energy (BLE) beacons, the authors in [10] investigated several indoor localization techniques. A position-finding strategy based on fuzzy logic and the received signal strength indication from BLE beacons and the geometric distance between the current beacon and the fingerprint point was suggested. Based on their findings, the fuzzy logic type-2 fingerprinting approach might be used in conjunction with BLE beacons to provide accurate indoor positioning. With a mean localization error of 0.43 meters and a mean navigation accuracy of 98.21%, the algorithm performed well. In [39], the authors presented a new method for avoiding obstacles using image depth and fuzzy control principles. Their method uses fuzzy logic to precisely alert the VI user of possible impediments so that they may avoid them without the user needing any prior knowledge of the surroundings.

For a summary of the current state of research on the topic, readers might read the most up-to-date surveys [41–44]. They display a broad variety of indoor and outdoor wearable and assistive devices-based navigation approaches and provide an analytical analysis of each, pointing out its benefits and shortcomings. The authors furthermore provide a taxonomy of wearable and assistive technologies that are grounded in both qualitative and quantitative criteria for assessment. It is clear that every strategy has its benefits and drawbacks, and that no one strategy is sufficient. Here, after examining a wide range of technologies, we found that the tradeoff between accuracy and the cost of creating and implementing an indoor navigation system was a significant barrier to its widespread adoption. In this research, we build on this insight by proposing a unique system that combines sensor-based approaches with soft computing technologies to gather enough information to provide an accurate indoor navigation solution for people with VI.

The primary purpose of this study is to provide neutrosophic logic modifications to the widely utilized fuzzy-based indoor object detection. Like their fuzzy analogs, neutrosophic systems might benefit from the insight of human operators. The membership grade in Fuzzy Sets (FS) is utilized to deal with uncertainty, but in neutrosophic sets (NS), the truth, indeterminacy, and falsity membership grades are treated as separate entities [13]. The next section describes the suggested method.

3. Methodology

The majority of today's indoor navigation techniques depend on expensive and imperfect laser and optical sensors [41–44]. The ultrasonic technology's inexpensive price, insensitivity to the object's surface, and light make it a promising tool for locating obstacles within buildings [43]. Ultrasonic-based indoor object identification for VIPs has been the subject of a number of theoretical investigations, but there is still room for improvement in terms of both accuracy and processing efficiency.

In our research, using a neutrosophic logic controller, a reliable approach for obstacle avoidance, whether static or dynamic, has been proposed with low cost and acceptable accuracy. In order to correctly identify and categorize the object feature types, a neutrosophic classification model is constructed. This model includes rules for neutrosophicating data, reasoning with it, and de-neutrosophicizing it. Decision-making rules tailored to the needs of the visually impaired have been established. These messages are sent through any Internet-of-Things device in order to let a visually impaired person move about safely [14,15]. Figure 2 depicts the suggested framework's architecture.

3.1. Obstacle Detection Using Ultrasonic Sensor

Our model makes use of ultrasonic technology to determine the exact distance between the sensor and the target. The duration of the pulse may be used to calculate the distance [3]. An ultrasonic sensor has both a transmitter and a receiver. One sensor, the transmitter, broadcasts a sound frequency, while another, the receiver, picks up the frequency reflected off of the object. Calculating the distance between two points involves calculating the time it takes to transmit and receive a frequency by the frequency's speed divided by two. The operation of an ultrasonic sensor is shown in Figure 3 [7]. The ultrasonic sensor works equally well in bright and dim settings. Unlike other sensors like lasers and radar, it is not affected by the colors or materials of its target. Sensor types such as ultrasonic, laser, and radar are compared and contrasted in Table 1 [8].

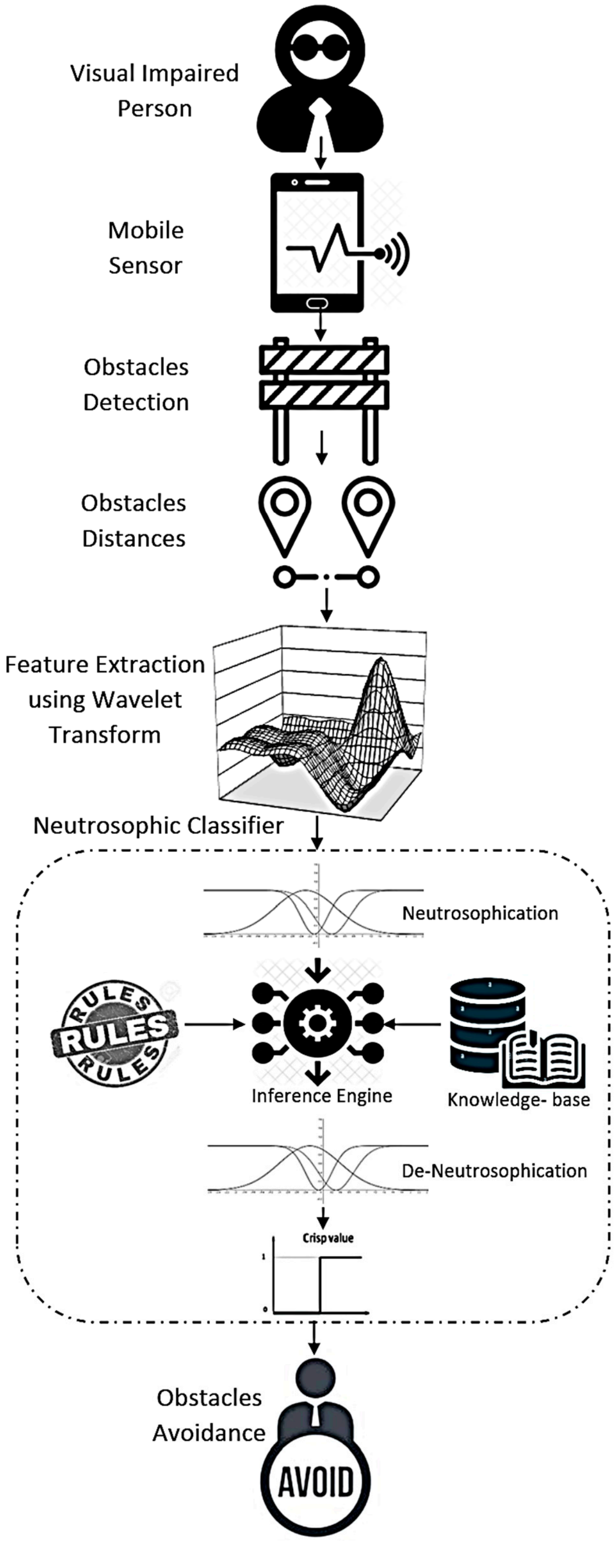

Figure 2. The technical description of the proposed framework's layout.

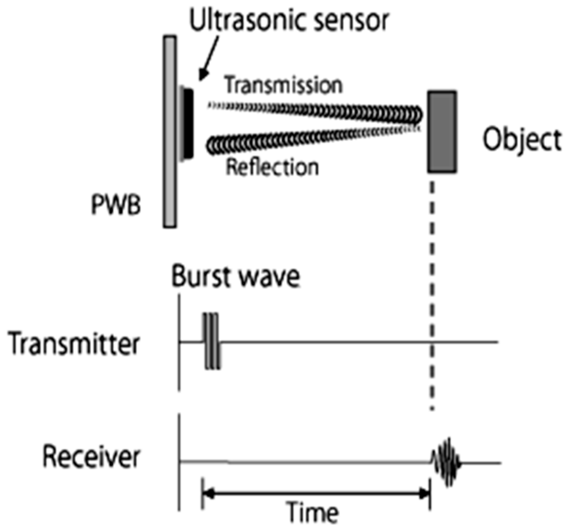

Figure 3. Ultrasonic sensor process.

Table 1. Sensors advantages and disadvantages.

Sensors	Advantages	Disadvantages
Ultrasonic sensor	• High sensitivity • High frequency • High penetrating power • The ease of detecting external and deep objects • High accuracy • Simple interface with a microcontroller or any type of controller, • Low power utilization • Low cost	• Some materials can distort an its reading, density, and consistency
Laser sensor	• Sensitivity • High resolution • Reliability • Wide measurement range	• Must be clean and free from dirt and other foreign materials otherwise accuracy will be affected • Narrow range of operating temperatures
Radar sensor	• Radar signal can penetrate through objects • Can be used in any environmental conditions • Can distinguish between moving and still objects • Count passing people • Accurate • Reliable	• Unable to distinguish between very close objects • Unable to recognize the color of objects • Unable to recognize objects that are placed behind a conductive sheet

For this application, the ultrasonic sensor specifications are as follows: a maximum detection range of 300 cm, a dead distance of 3 cm, a distance resolution of 5 mm, and a beam angle of 60°, see [30] for more information. As a result, an ultrasonic sensor may now be used to generate a distance dataset in enclosed spaces. Many measurements of room dimensions, floor levels, stair heights, and other features will be included in these files. The wavelet transform will be used to extract features from these observations (distance dataset). All these measurements will be filtered out except for the wall distances, which will serve as input variables for the neutrosophic model.

3.2. Feature Extraction Using Wavelet Transform

In order to extract characteristics from ultrasonic signals, a number of effective signal-processing algorithms have been proposed. These include the Hilbert-Huang transform, the fast Fourier transform, and symbolic dynamic filtering. However, owing to the nonstationary properties of ultrasonic defect signals, wavelet transform-based approaches have shown to be the most effective and commonly employed [3].

When working with signals collected at discrete intervals in time, the DWT (discrete wavelet transform) technique is used to get the wavelet transform. In the frequency domain, the DWT performs an analysis by first applying a high-pass filter and then a low-pass filter, to the signal in order to separate it into its coarse approximation and detailed information, as illustrated in Figure 4 [8,9]. Figure 5 depicts DWT with different decomposition levels of the simulated ultrasonic signal. In our case, clustered DWT will be utilized to overcome the time variance and huge dimension of DWT coefficients. It employs the energy of several frequency bands to cluster coefficients [45,46]. Clustering separates the discrete wavelet coefficient into disjoint clusters for which a single robust feature may be calculated. Finally, each component of the feature vector may be identified by calculating the energy of each cluster through its associated row vector. After employing a clustered discrete wavelet transform to extract features, the distance measurements are now complete.

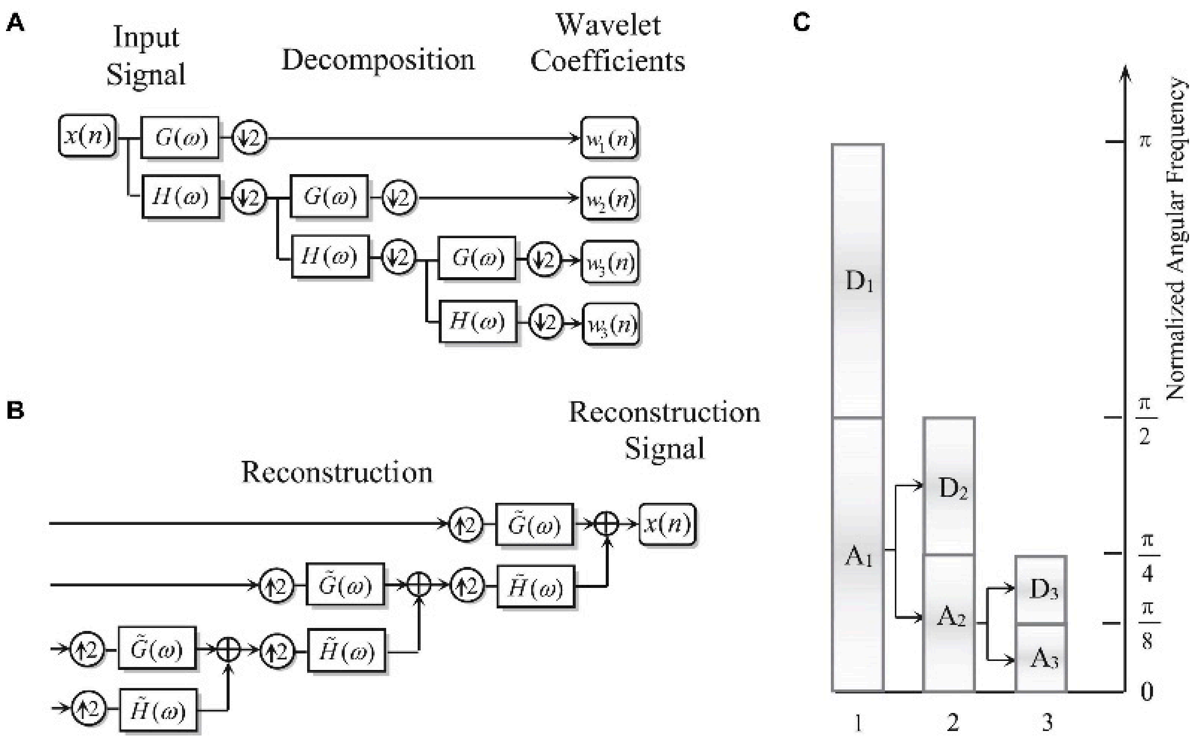

Figure 4. (**A**) The decomposition process of wavelet transform; (**B**) the reconstruction process of wavelet transform; and (**C**) the theoretical spectral passing band of wavelet transform.

Here, we use the clustered wavelet transform as a black box, with the wavelet transform serving not only as a signal representation but also as a dimension reduction technique. In this study, we use the Haar wavelet transform, one of the fastest but also simplest wavelet transformations available. Since the calculation can be done locally without the need for a temporary array, it is a memory-efficient and computationally-efficient method for studying the regional features of a signal. As a result, signal energies are conserved and compressed. The next phase involves feeding these features into the neutrosophic logic controller.

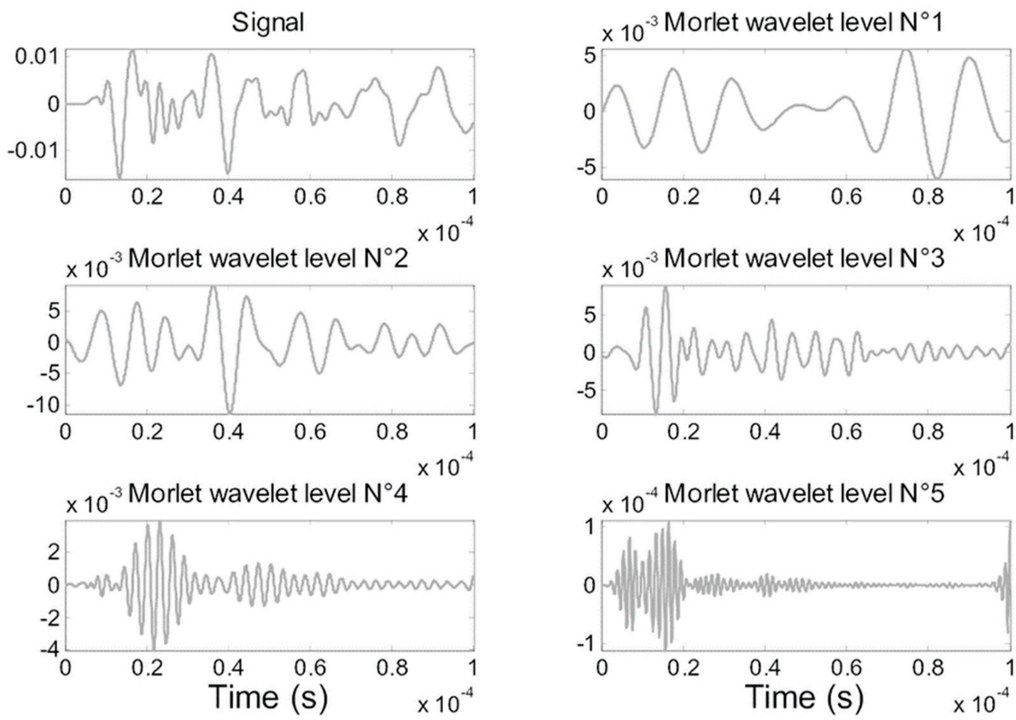

Figure 5. Discrete wavelet transform (with different decomposition level) of the simulated ultrasonic signal.

3.3. Neutrosophic Classifier

All real-world information has some degree of imprecision due to many factors. As used here, "imprecise" might mean anything from vagueness to a lack of detail. Such fuzzy information may be handled by a number of different theories, such as fuzzy set theory, probability theory, intuitionistic fuzzy set theory, and paraconsistent logic theory. These ideas can explain certain aspects of a complicated problem, but not all of them. For instance, partial and inconsistent data are outside the scope of fuzzy set theory. Mathematical models of ambiguity, vagueness, inconsistency, contradiction, redundancy, and incompleteness were the impetus for the creation of neutrosophic logic [14–16].

Due to its focus on membership and non-membership of an element to a particular class, fuzzy logic and related logics fail to address the indeterminate nature of data acquired due to factors such as incomplete knowledge, stochasticity, or the acquisition errors (intrinsically imperfect observations, the quantitative errors in measures). The non-membership value must be equal to one minus the membership value for the fuzzy logic notion to hold [38]. Neutrosophic logic is a non-traditional approach to tripartition analysis that takes into account qualifications like degree of truthiness (T), degree of indeterminacy (I), and degree of falsity (F) [47,48]. A comparison of neutrosophic and fuzzy classifiers is shown in Figure 6 [14].

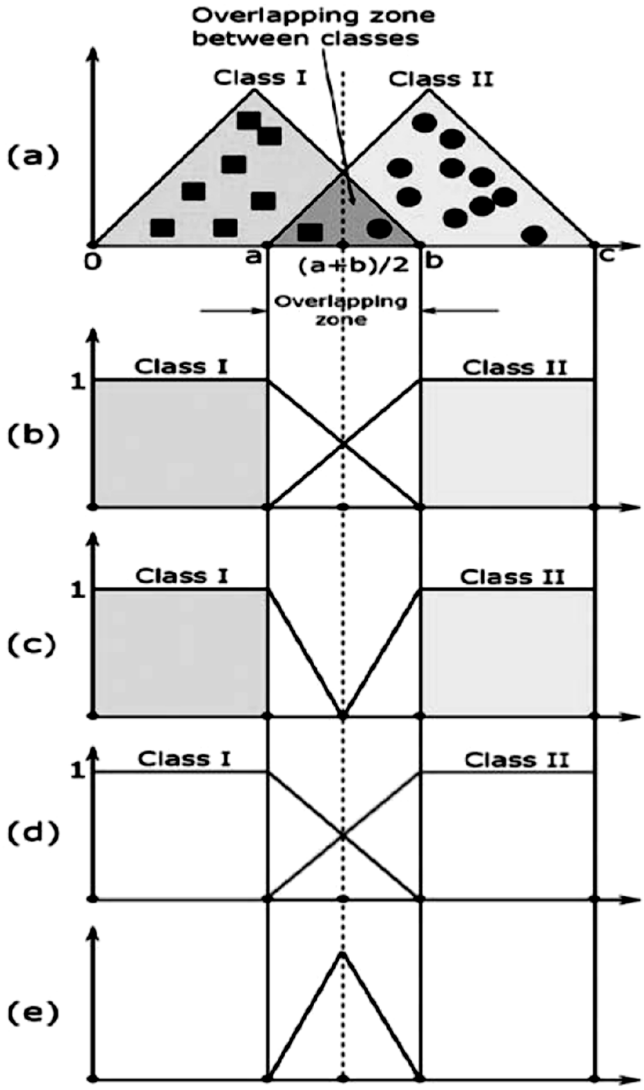

Figure 6. A look at how NS is like fuzzy logic. (**a**) The triangular fuzzy membership function of classes I and II; (**b**) a fuzzy verification; (**c**–**e**) are the neutrosophic truth, falsehood, and indeterminacy parts, respectively.

A single-valued neutrosophic set N through X taking the form $N = \{x, T_N(x), I_N(x), F_N(x) : x \in X\}$, where X be a universe of discourse, $T_N(x) : \mathrm{X} \to [0, 1]$, $I_N(x) : \mathrm{X} \to [0, 1]$ and $F_N(x) : \mathrm{X} \to [0, 1]$ with $0 \leq T_N(x) + I_N(x) + F_N(x) \leq 3$ for all $x \in X$. $T_A(x)$, $I_A(x)$ and $F_A(x)$ represent truth membership, indeterminacy membership and falsity membership degrees of x to N. A linear trapezoidal neutrosophic number is defined as $\widetilde{\mathrm{A}}_{Neu} = (a, b, c, d; e, f, g, h; i, j, k, l)$ whose truth, indeterminacy and falsity membership is defined as [49–51]:

$$T_{\widetilde{\mathrm{A}}\_Neu} = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x < b \\ 1 & b \leq x < c \\ \frac{d-x}{d-c} & c \leq x \leq d \\ 0 & x > d \end{cases} \quad (1)$$

$$I_{\widetilde{A}\_Neu} = \begin{cases} 1 & x < e \\ \frac{f-x}{f-e} & e \le x < f \\ 0 & f \le x < g \\ \frac{x-g}{h-g} & g \le x \le h \\ 1 & x > h \end{cases} \quad (2)$$

$$F_{\widetilde{A}\_Neu} = \begin{cases} 1 & x < i \\ \frac{j-x}{j-i} & i \le x < j \\ 0 & j < x < k \\ \frac{x-k}{l-k} & k \le x \le l \\ 1 & x > l \end{cases} \quad (3)$$

where $0 \le T_{\widetilde{A}_{Neu}}(x) + I_{\widetilde{A}_{Neu}}(x) + I_{\widetilde{A}_{Neu}}(x) \le 3, x \in \widetilde{A}_{Neu}$. The pictorial view is shown in Figure 7.

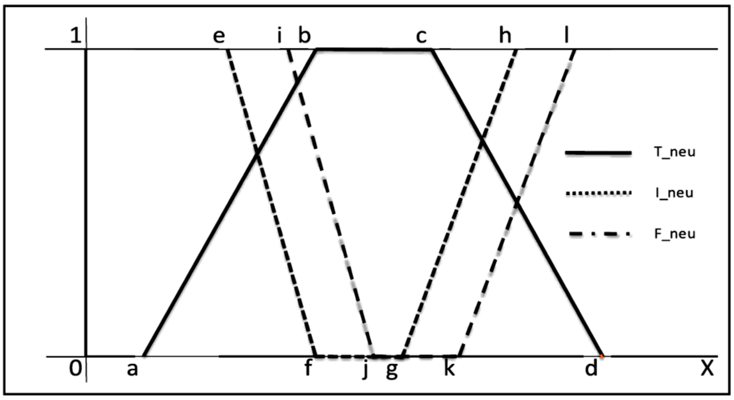

Figure 7. Linear trapezoidal neutrosophic number.

The suggested neutrosophic rule-based indoor obstacle detection expands upon the fuzzy rule-based system by making use of neutrosophic logic. Statements of neutrosophic logic, rather than fuzzy logic, are used as antecedents and consequences of "IF-THEN" rules in the proposed paradigm. It has three steps: First, there is neutrosophication, which entails transforming crisp inputs into the neutrosophic knowledge base through the truth-membership, falsity-membership, and indeterminacy-membership functions. In the second stage, the neutrosophic "IF-THEN" rules leverage the knowledge base to generate neutrosophic results. The third stage, "deneutrosophication," uses three functions similar to those used in "neutrosophication" to transform the neutrosophic results produced in the previous phase into a crisp one.

Step 1: Neutrosophication

In our case, two ultrasonic sensors were combined to assess the distance of an obstacle in front of and to the left of the user who obtained that information through a VIPs belt-like assistant device that interacts with the smart watch to provide an alarm message for obstacle avoidance. In the universe of discourse, the inputs SD_{front} and SD_{left} are retrieved in accurate numerical form. By applying membership functions to the inputs, we may ascertain how deeply they are embedded inside the specified neutrosophic category. There is no set membership percentage; it might be zero or one. In our example, there are three linguistic categories, "Low," "Medium," and "High," all with linear membership functions. In our suggested procedure, we use trapezoidal neutrosophic numbers with linear membership functions for the two sensors readings:

- SD_{front}: minimum sensor reading within a 60 degree arc located at the front of the belt;

- SD_{left}: minimum sensor reading within a 60 degree arc located at the left of the belt.

Statistics on these measurements are provided in Table 2, and their categorization according to distance is shown in Table 3. These readings are classified based on the expected movement into four classes: move-forward (*MF*), slight-right-turn (RT_{slight}), sharp-right-turn (RT_{sharp}), and slight-left-turn (*SLT*). The distribution of these readings is as follows:

- move-forward: 2205 samples (40.41%);
- slight-right-turn: 826 samples (15.13%);
- sharp-right-turn: 2097 samples (38.43%);
- slight-left-turn: 328 samples (6.01%).

Table 2. Ultrasonic Sensors data statistics for raw distances.

Sensor Data	Max	Min	Mean	Standard Deviation
SD_{front}	5	0.4950	1.29031	0.62670
SD_{left}	5	0.3400	0.68127	0.34259

Table 3. Range classification for raw distances.

Level	From	To
Low	0.000	0.499
Medium	0.500	0.899
High	0.900	5.000

Step 2: Inference Engine and Rule Evaluation

Using two layers of linguistic variables, nine rules are formulated to classify data from SD_{front} and SD_{left} sensors readings. The design of the IF-THEN rules in neutrosophic logic takes into account the knowledge and experience of experts. Each rule is listed in Table 4 below. Once the membership degree of each antecedent component has been obtained, the rule that will be executed may be determined. When more than one component of an antecedent appears in a rule, the AND operator is employed to get a single value. When this is done, just one truth value remains. The AND operator is symbolized by *min* (minimum) in this context. The fired IF-THEN rules and the *min* operator are used to get a final decision concerning expected movement.

$$\mu_r = min(\mu_{S1,r}, \mu_{S2,r}) \tag{4}$$

μ_r is the single truth value for the rth rule, $\mu_{s1,r}$ is the membership value of SD_{front} for rth rule, and $\mu_{s2,r}$ is the membership value of SD_{left} for rth rule. *EM* is the output variable (consequent) representing the expected movement. *EM* expressions are also given in linguistic variables that includes '*MF*', 'RT_{slight}', 'RT_{sharp}', and '*SLT*'.

$$EM = \left\{ \begin{array}{l} max(\mu_{1,r}, MF); max\left(\mu_{2,r},\ RT_{slight}\right); \\ max\left(\mu_{3,r},\ RT_{sharp}\right); max(\mu_{4,r}, SLT) \end{array} \right\} \tag{5}$$

Table 4. Neutrosophic logic-based indoor detection: a set of basic rules.

Rule	Antecedent SD_{front}	Antecedent SD_{left}	Consequent *EM*
1	High	High	RT_{sharp}
2	High	Medium	SLT
3	High	Low	SLT
4	Medium	High	RT_{sharp}
5	Medium	Medium	RT_{sharp}
6	Medium	Low	RT_{sharp}
7	Low	High	RT_{sharp}
8	Low	Medium	MF
9	Low	Low	SLT

Step 3: De-Neutrosophication

To guarantee that the output values are distributed fairly across the surrounding neutrosophic *EM* sets, they are normalized before de-neutrosophication. The lower trapezium (a, b, c, d), the left-most upper trapezium (e, f, g, h), and the right-most upper trapezium (i, j, k, l) each contain fuzzy numbers corresponding to any real integer $\alpha \in R$. The de-neutrosophication of the linear trapezoidal neutrosophic number is provided by using the area removal approach for the de-neutrosophication of the single-valued trapezoidal neutrosophic number [49].

$$R(\widetilde{D},\alpha) = \frac{R(\widetilde{A},\alpha) + R(\widetilde{B},\alpha)R(\widetilde{C},\alpha)}{3} \tag{6}$$

For $\alpha = 0$,

$$R(\widetilde{D},0) = \frac{a+b+c+d+e+f+g+h+i+j+k+l}{12} \tag{7}$$

4. Evaluation and Discussion

The goal of this analysis is to find a solution that will make it easier and more affordable for people with VI to go about their daily lives (obstacle detection). The experiments were conducted on an $\times$64-based processor and 8 GB of DDR3 memory on an Intel®CoreTM i7-5500 CPU running at 2.50 GHz. We used the Python programming language to build the suggested obstacle detection model and handle the neutrosophic rules. The following are the characteristics of an ultrasonic sensor: working frequency: 40 Hz, maximum range: 5 m, minimum range 2 cm, trigger input signal: 10 µS TTL pulse, echo output signal: input TTL lever signal and the range in proportion, dimensions: 45 $\times$ 20 $\times$ 15 mm^3, a 60° beam angle. The user can adapt this wearable prototype according to their personal preferences by using a mobile device with Bluetooth communication. The suggested model was constructed based on the distance of the obstacle using two belt sensors and a single output (expected movement direction). After the activation of the device, the distances of the obstacle from two sensors will be sent to the neutrosophic controller. Then, a determination will be made using the nine neutrosophic rules. The user will get this input via their headphones. The whole procedure will be used iteratively. In the absence of a barrier, the user's route will remain unchanged (straight).

A machine learning method based on neutrosophic logic has been developed to extract relationships, modeled as rules, from a dataset (the raw distances of an obstacle from two ultrasonic sensors). There are nine rules that are built according to the statistics of these dataset and their range classification summarize the strongest connections among the two variables SD_{front} and SD_{left}. These could be employed to predict the expected movement that must be taken into account during the movement of the VIPs to avoid obstacles for an unseen piece of data collected under the same conditions, using the belt-like assistant device that interacts with the smart watch to provide an alarm message for obstacle avoidance, with a significant level of accuracy, while at the same time providing a linguistic snapshot of the inherent pattern in the data set. This makes neutrosophic logic an important modelling tool in control systems where non-crisp inputs are required.

To ensure the accuracy of our system, we used a dataset consisting of readings from two sensors (5456 samples) as input; 75% of the dataset was used to train the model, while the other 25% was used to evaluate its performance. The characteristics of the datasets used for the objective evaluation are mentioned in detail in the neutrosophication step. We separated the objects in each scene into two categories after realizing that certain objects don't count as obstacles unless they're directly in the way of the user or preventing him or her from moving forward.

To evaluate the performance of the neutrosophic classifier in the process of detecting obstacles, two versions of the proposed model were built based on the core modules: one using a neutrosophic classifier and the other using a traditional fuzzy logic classifier inspired by the work in [39]. Table 5 shows the obstacle detection rate in the used dataset. The results reveal the superiority of the neutrosophic classifier, with an improvement of about 6%. Neutrosophic logic, with its three levels of membership, is able to effectively capture ambiguity and provide solutions that are close to reality. By including a neutrosophic set in the model, we may reduce the number of times visually impaired people collide with obstacles.

Table 5. Evaluation results for the tested dataset.

Model Version	Accuracy for Avoiding Obstacles
Neurotropic-based version	97.71%
Fuzzy-based version	91.27%

In the second set of experiments, we compared the effectiveness of our proposed model to that of one that uses visual sensors to determine the shape of obstacles as in the work presented in [39]. The results are shown in Table 6. The efficiency of the proposed model in increasing accuracy by about 3% can be attributed, to the fact that the neutrosophic module in our model uses wavelet-based ultrasonic distance characteristics rather than user position based on two visual sensors, as is the case with the conventional camera-based obstacle detection paradigm.

Table 6. Comparative results for different type of sensors for obstacle detection.

Model	Accuracy for Avoiding Obstacles (Average)
Ultrasonic sensor-based model	97%
Visual sensor–based model [39]	94%

In general, there are still issues with current methods of object detection using cameras. These issues include viewpoint variation, deformation, occlusion, illumination conditions, a cluttered or textured background, and finally intra-class variation. Make sure there is enough variety in the training data to develop a strong object detector capable of resolving these typical object detection issues. Take use of different viewpoints, illumination conditions, and objects in different backgrounds. Data augmentation methods (e.g., ultrasonic sensors to extract distance measurements) may be used to synthesize the necessary data if you cannot locate real-world training data with all these variables.

According to the average rate of obstacle detection for users, as seen in Table 7, left-side obstacle detection was 89%, right-side obstacle detection was 86%, and front obstacle detection was 97%. Many-massage feedback caused the user to get confused when there were multiple obstacles in the user's immediate vicinity.

Table 7. Successful detection of obstacle types.

Obstacle Type	Accuracy for Avoiding Obstacles (Average)
Front	98%
left	89%
Right	86%

To calculate the time complexity of the whole system, we had to combine the time complexity of the detection algorithm with the time complexity of the obstacle avoidance algorithm. Our method for obstacle avoidance is implemented after a sensor-based feature extraction technique for object recognition has been implemented, which takes less memory and computation time than prior systems [39]. The suggested obstacle avoidance method has a linear time complexity of O (n), where n is the number of identified obstacles. This indicates that our system as a whole delivers a quicker and more reliable obstacle avoidance mechanism. For more experiments close to this field of research, the reader can refer to [52–60].

Limitations of the Proposed Model

In the context of indoor object identification, neutrosophic logic has several advantages. These include the following: the ability to handle data from multiple sources; the resolution of complex problems using only partial or imprecise information; and the production of trustworthy outcomes in numerous cases of multi-criteria decision-making. The neutrosophic controller is a revolutionary system that is more generalizable and tolerant of uncertainty than its fuzzy counterparts. In cases where there is a potential of indeterminacy and incompleteness in the acquired data, as in ours, a neutrosophic controller is employed as a means of dealing with the situation. Using neutrosophic logic has its benefits since it can tell the difference between a truth that holds true in only one or a few worlds and a truth that holds true in every world. To the same extent, neutrosophic logic delineates between relative and absolute falsehood.

Although the suggested model makes use of neutrosophic logic, doing so presents a number of challenges that severely restrict its effectiveness. These restrictions are a result of how the neutrosophic inference engine was built. According to the proposed model, in neutrosophic sets, truth, falsehood, and indeterminacy are all independent; it is unknown how they influence one another in the decision-making process. Not only that, but the sets of inference rules and the membership functions were also developed by hand by a specialist in the field. It's preferable to produce them automatically based on data you already have. Finally, the variables used to characterize the distance to the obstacle have a significant impact on the performance of the proposed model. Selecting these characteristics requires an optimization method.

5. Conclusions

This study presents a new approach that utilizes sensors and artificial intelligence technology to make it easier for visually impaired people to move safely in indoor buildings. The hardware for the suggested system consists of a standard smartphone, some ultrasonic sensors, and a belt worn around the waist. One of the most novel aspects of the suggested assistive gadget is the software that combines data from ultrasonic sensors with a neutrosophic reasoning-based controller. Despite the object's position, size, or shape, the system is able to confidently identify it as a part of the scene.

The primary focus of this research is on enhancing popular methods of fuzzy-based indoor object avoidance using neutrosophic logic. The neutrosophic approach uses permutations of three independent factors (truth, indeterminacy, and falsity). On the other hand, the fuzzy approach uses permutations of two independent factors (truth and falsehood) to handle uncertainty. Therefore, the neutrosophic approach is more generalized than the fuzzy approach. Decision-makers and problem-solvers attempt to promote truth and decrease indeterminacy and falsity.

Extensive experimental assessment using benchmarks and real data from VIPs demonstrates the dependability and robustness of the proposed system. We begin with an objective assessment of the obstacle detection and classification modules, and then go on to provide a subjective assessment of our system by presenting the level of satisfaction and comments from the VIPs who have used our prototype. Subjects deemed our technology to be user-friendly, lightweight, wearable, and unobtrusive, meeting both the hands-free and ears-free criteria. In addition, calculation time is minimized, and warning signals are delivered quickly enough for the VIP to walk properly. In the future, in order to apply more control over one's surroundings, a more in-depth comprehension of the scenario will be required using another type of logic, such as spherical and picture fuzzy sets [61,62]. Furthermore, the proposed technology may be expanded to recognize other commonplace interior objects including doors, stairs, elevators, signs, text, and furniture.

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