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Fuzzy-logic-based Walking Context Analysis for Visually Impaired Navigation

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In this work, we present a walking context analysis for the electronic navigation of visually impaired persons. The walking context is defined as the safety level of the walking condition. An extensive literature review provided the framework for the model developed in this research. A hybrid fuzzy logic model is built to evaluate this safety level on the basis of several environmental and personal factors identified in the navigation. Range measurements related to the obstacles in the surrounding environment are acquired by sonar sensors, and personal information taken by the prototype is the input to the fuzzy logic model, which is used to evaluate the safety level of the current walking context of the visually impaired person. An audio feedback relevant to the walking context is provided, indicating the safety level and direction of motion. The obtained results proved the successful operation and effectiveness of the fuzzy control in reducing the navigation time and increasing safety because it clarifies the uncertainty in each situation as compared with the nonfuzzy approach. The current status of the work and future developments are presented in this paper.

1. Introduction

A person's mobility consists of several tasks such as path planning, navigation, obstacle avoidance, and environmental sensing. A visually impaired person may fail to accomplish the above tasks owing to the probability of high risk and failure associated with their impaired navigation. A guide dog and a white cane are the traditional navigation aids used by visually impaired persons. A guide dog is costly and has a limited lifetime, whereas a white cane can only aid visually impaired persons sense their immediate surroundings. Therefore, visually impaired persons' navigation can be supported by electronic travel aids (ETAs), which consist of appropriate sensors. This sensory information available from the ETAs can be used to provide knowledge about the context of the current environment.

Context-aware pervasive ETAs must be flexibly adaptable to changes in the current context and provide the information considered with the current context for navigators. Context

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awareness has recently become one of the active research topics in the area of pervasive computing, which was introduced in Ref. 1. Pascoe *et al.*[2] described context awareness as the capability of computing devices to perceive, detect, interpret, and respond to the characteristics of a user's surrounding environment and the computing devices themselves. As an essential rule in the design of context-aware ETAs, the user should be made aware of the sensory information of the current environment.

Visually impaired persons can benefit from context awareness in their navigation process. Adaptation and personalization are two such advantages of context awareness.[3] Adaptation enables the adjustment of an intelligent algorithmic behavior according to the current context, and personalization means that a prototype modifies its behavior according to the user's preferences, habits, skills, or tasks.[3] Pichler *et al.* stated that each person has a unique contextual description, which allows them to modify general contextual information for their own needs.[4]

Adaptation—Adaption to the current environment during visually impaired navigation provides added advantages in navigation. One of the key areas of research on adaptation is micronavigation in an indoor environment, in which visually impaired persons have to avoid an obstacle in a local environment. Obstacles can occur on the left, right, and front sides of a navigator. Therefore, the outputs (distances to the obstacles from left, right, and front sensors) of sonar sensors and the density of the nearest obstacles are further used to estimate the current walking context of visually impaired and blind individuals.[5]

Personalization—Personal factors have a significant effect on the walking speed of an individual. Factors affecting the pedestrian walking speed are as follows.

The literature shows that the walking speed of males is higher than that of females.[6] Therefore, gender is a significant factor that affects the walking speed of blind individuals. People who are older than 65 have a lower walking speed than their younger counterparts,[6] which shows that age affects the walking speed as well. People walking with baggage have a lower walking speed than those walking without baggage.[6,7] Pedestrians walking with a partner will have a lower walking speed than those walking alone, especially when they are accompanied by children. The height of individuals affects the walking speed, that is, tall people are considered to walk more speedily than their short counterparts.[6,8]

The above factors are generally derived from pedestrians regardless of their ability to gain visual information. Therefore, gender, age, and height can be considered as important factors affecting the walking speed of visually impaired and blind pedestrians.[6–8] The visual status of blind pedestrians also severely affects their walking speed.[9] The severity of the visual impairment (such as partially or fully blind)[9] and the length of time a person has been visually impaired/blind (such as blind from birth or a visual impairment occurring at a later age) can affect their navigation. For example, people who are blind from their birth rely more on tactile and hearing environmental information than those who become blind because of glaucoma. Therefore, as a conclusion, the personalization of visually impaired navigation is mainly affected by age, gender, height, and visual status. Therefore, in this research, we evaluated the safety level on the basis of the above factors under adaptation (distances to the obstacles and obstacle density) and personalization (age, gender, height, and visual status) for visually impaired navigation.

However, the effect of the above factors (distances to the nearest obstacles, obstacle density, gender, age, height, and visual status) on the walking context is rather vague and has a large number of uncertainties. How each element affects the walking context cannot be calculated precisely. Therefore, prior knowledge of how humans experience the same situations while walking is the primary source of information in this regard. Considering certain properties such as "uncertainty" and "prior knowledge", several approaches can be considered to deal with this kind of problem.

These approaches include the use of neural networks,(10,11) probabilistic approaches,(12–14) and fuzzy logic.(15,16) These three approaches have common attributes, namely, the ability to access nonlinear systems with uncertainties and to incorporate them with the prior knowledge for uncertainty reasoning. However, they handle uncertainty in different ways. The uncertainty reflected by probabilistic approaches such as Bayesian theory indicates a degree of belief. The uncertainty that fuzzy logic reflects is the degree of a fact being true. In the same way that neural networks imitate the human brain operation by having a set of "neurons" connected with different weights, fuzzy logic also imitates human inference by using logic rules and tunes these rules using sample data.

The goal of walking context analysis is to estimate the "amount of safety" in micronavigation in a local environment. The "amount of safety" is not a quantitative measurement, so it is not precise. Therefore, it would be more appropriate to use fuzzy logic to model the walking context than to use probabilistic approaches and neural networks. Fuzzy variables and fuzzy rules can be represented in the form of natural language, which makes fuzzy logic models especially suitable for doing reasoning in a natural way like a human. The benefits of fuzzy control in the design of a navigation system(17) are that it enables (i) the handling of uncertain information, (ii) real-time operation, (iii) the easy concatenation of various behaviors, (iv) the development of perception-action-based strategies, and (v) easy implementation. Therefore, amongst the techniques, fuzzy logic is selected to build and evaluate the walking context of visually impaired navigation in this research.

An extensive literature search showed that fuzzy logic assists in solving visually impaired navigation problems. Bangar *et al*.(18) used fuzzy rules to assign preferences to objects, where preferences are based on the properties of the objects. A humanoid robot using a fuzzy logic controller for visually impaired assistance was developed by Razali *et al*.(19) Mehta *et al*.(20) developed a path guidance mobile aid for visually impaired persons, which used a smart sensor logic system. The directional elliptical model using fuzzy logic is a guidance system proposed by Lin *et al*., which aims to monitor road conditions in the medium range in real time for visually impaired pedestrians, and this complements the white cane.(21) The road traffic sign detection and classification in the navigation system for blind persons developed by Kantawong(22) are performed by a vision-based robot guidance system that uses fuzzy logic. An innovative obstacle avoidance approach based on fuzzy control rules and image depth was used by Elmannai and Elleithy.(23)

A walking context analysis using fuzzy logic has been attempted in a limited number of these research studies. Context awareness using a multimodal profile model developed by Lin and Han(5) is one such approach, which used fuzzy logic to estimate the safety level of the walking context. They built a fuzzy inference model to estimate the safety level on the basis of outputs of moving scene analysis. A dual-field sensing scheme for the blind[24] is an extended version of the above research,[5] which also focuses on context estimation using fuzzy logic. Here, in addition to user context estimation, which is based on near-field sensing, road context estimation is also considered on the basis of far-field sensing. A fuzzy-logic-based context-aware navigation model was built by Yerubandi *et al.*[25] Distances measured by left, right, and center sonar sensors were taken as inputs to the fuzzy logic model, and a safe direction of motion was calculated as the output.

It is clear that most of the studies in the field of walking context analysis for visually impaired navigation[5,24,25] focused on estimating the context based on the changes around the current environment, such as distances to obstacles and the density of obstacles. There are a few studies[6–8] that considered only personal factors (i.e., age, gender, height, weight, and carrying baggage) when estimating the walking context. However, none of them considered the fusion of environment adaptation (i.e., how obstacles are scattered in the local environment) and pedestrian factors (i.e., age, gender, height, and visual status) when estimating the walking context for the next moment. By taking this gap as the main motivation of this research we considered how to estimate the walking context on the basis of both adaptation and personalization factors. On the basis of the findings of this research, a hybrid walking context estimation method based on environment adaptation and personalization is introduced. Adaptability to the environment is ensured by the real-time sonar sensor data acquired during local navigation. Personal factors are obtained through a customized smartphone application before starting the navigation. The prototype consisted of an audio-based walking context analysis based on real-time sensor data and individual personal factors. A wearable sensor belt that can be worn around the waist was designed to acquire obstacle information. Personal details (gender, age, height, and visual status) of the visually impaired pedestrians were inputted to a smartphone application by a separate person before starting the navigation.

2. Methodology

This research was carried out using a combination of a construction-based approach and a design science research approach, and it focused on the development of a wearable electronic navigation aid for visually impaired and blind persons. The architecture of the prototype is shown in Fig. 1. The details of the main architectural components are as follows:

An array of sonar sensors—When an object is in the path of a sonar signal, the signal is reflected by the object and received by a sensor receiver. Some sonar sensors are used to detect the obstacles emerging from the left, right, and front directions.

Sonar signal processing—Here, the distances to the obstacles are calculated on the basis of the time-of-flight characteristics of the sonar waves.

Walking context based on adaptation—On the basis of the outputs of the sonar sensors aligned in different directions, the walking context estimation evaluates the obstacle density and the distance to the nearest obstacle.

Walking context based on personalization—On the basis of the user inputs (age, gender, height, and visual status) taken from the smartphone application, the walking context is estimated on the basis of the walking speed of the pedestrian.

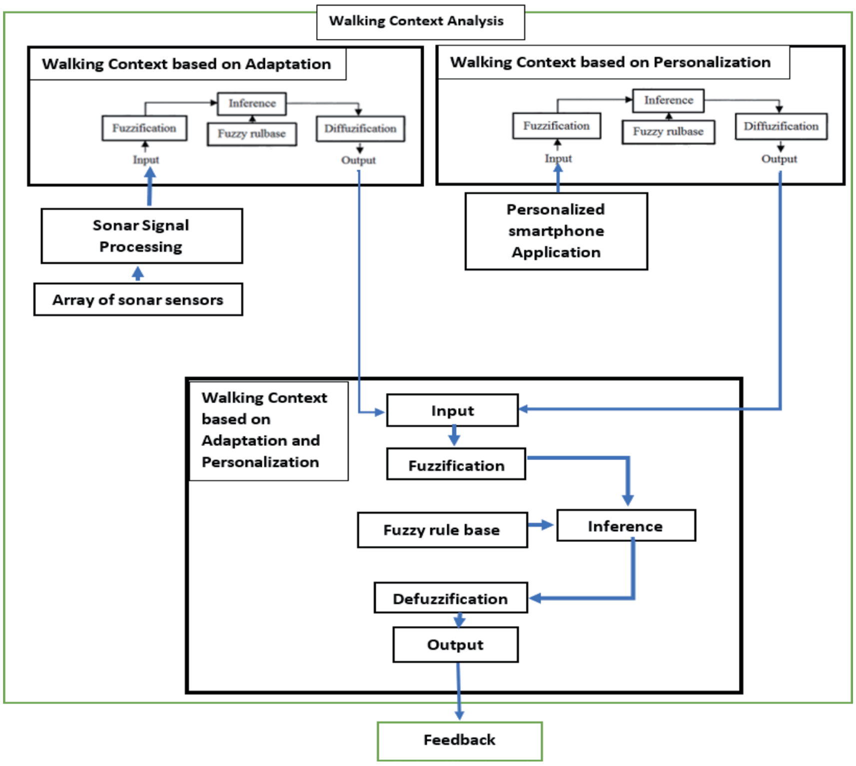


Fig. 1. (Color online) Architecture of prototype.

Hybrid walking context based on adaptation and personalization—The outputs of the walking context based on adaptation (obstacle density and distance to nearest obstacles) and personalization (walking speed) are taken as the inputs of this fusion module. Finally, the output of the hybrid module is the level of safety (safe or dangerous) in the current context.

Feedback—Obstacles detected by the sonar sensors are given as a tactile feedback, and an audio feedback pertinent to the walking context analysis model is given to the user.

3. Hybrid Fuzzy Inference System for Walking Context

3.1 Fuzzy inference system used in this research

Fuzzification—Considering the sampled data in this research, the input variables are largely scattered in a wide range. Therefore, linear functions such as triangular and trapezoidal functions are used to define membership functions. To build the membership functions of input variables, sampled data of these variables are collected in various scenarios. The collected data sets of the input variables are divided into two: a training set and a testing set. The training set is used for fuzzification and constructing the fuzzy rules. The testing set is used for testing the accuracy of the built fuzzy model.

Fuzzy control rules—Some of the relationships in the fuzzy rules are very similar, and some relationships contradict each other; thus, by combining similar ones and omitting contradicting ones, the fuzzy rules are generated in this research.

Fuzzy inference—After the fuzzification of a set of input variable values, the value of each input variable value is transformed and assigned to a set of membership degrees. Then, we combine all these desired membership degrees and use the corresponding fuzzy rules to produce a final fuzzy value for the walking context. This combination process is referred to as rule aggregation in the fuzzy inference process. There are different kinds of aggregation operation available, such as the minimum operation, product operation, and summation operation. Here, the minimum operation is used for rule aggregation as shown in Fig. 2.

Defuzzification—The defuzzification process is used to convert each aggregated fuzzy output into a single crisp value. Several defuzzification methods, such as the centroid, max-membership, and weighted average methods, can be used. Among them, the centroid method is the most widely used and is employed in this research. The centroid method determines the geometric center of gravity of the shape of the fuzzy output set.

3.2 Fuzzy logic inference model for adaptation

As shown in Fig. 1, the inputs to the adaptation model are given by the output of the obstacle detection module of the application; such inputs are the data from the left, right, and front sonar sensors. From these inputs, there are two outputs, namely, the obstacle density and the distance to the nearest obstacle. Therefore, this model has three inputs (left, right, and front sensor readings) and two outputs (obstacle density and distance to the nearest obstacle) as shown in Fig. 3.

Obstacle density—The obstacle density represents the number of objects that exist in a unit area of a given space. A high obstacle density implies a very crowded walking space that is filled with many objects and people.

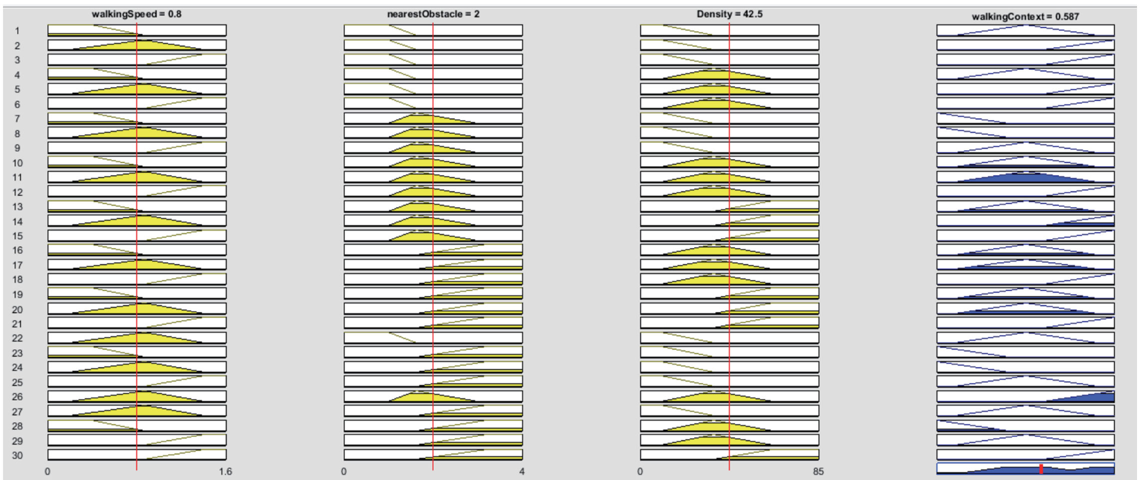


Fig. 2. (Color online) Aggregation of all the fuzzy rules.

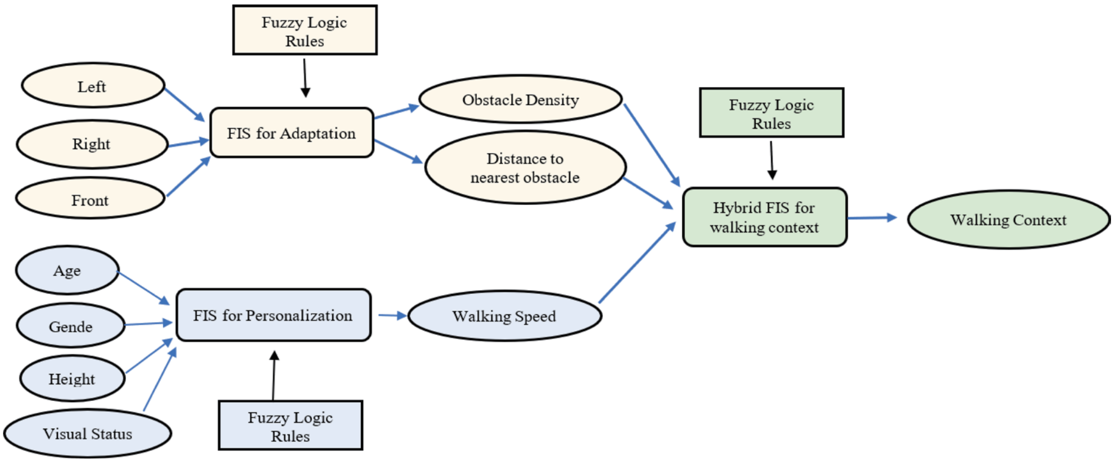


Fig. 3. (Color online) Hybrid fuzzy inference system for walking context.

In this research, the obstacle density around a visually impaired navigator at a particular time and location is determined in terms of the obstacles appearing to the left, right, and front of a visually impaired person. The obstacle density input variable has two membership functions called near and far depending on the distances of the sonar sensors as shown in Fig. 4. The maximum distance that can be sensed through the ultrasonic transducer is 4 m. Therefore, the fuzzy sets of each distance variable (left, right, and front) are near and far. The obstacle density output variable has three fuzzy sets called small, medium, and large. The taxonomy of these fuzzy sets is also shown in Fig. 4. The density range varies between 0 and 85. The obstacle density range is identified on the basis of obstacle densities calculated from the obstacle detection output. Therefore, the minimum obstacle density is 0 and the maximum is 85.

Table 1 shows the fuzzy rules for the output variable density based on the distances given by the left, right, and front ultrasonic sensors.

Distance to the nearest obstacle—The nearest obstacle in the left, right, or front direction is determined by the distance output given by the left, right, or front sonar sensor, respectively. Therefore, the nearest obstacle has the same three inputs as the obstacle density (left, right, and front). The taxonomy of the inputs and outputs of the nearest obstacle are shown in Fig. 5.

Table 2 shows the fuzzy rules for the output-variable nearest obstacle based on the distances given by the left, right, and front ultrasonic sensors.

3.3 Fuzzy inference model for personalization

The output of this model is the walking speed of the navigator. The walking speed depends on personal factors such as the gender, age, height, and visual status of the blind pedestrian. Therefore, this model consists of four inputs (age, gender, height, and visual status) and one output called walking speed as shown in Fig. 3.

Age—Age is one of the major factors affecting the walking speed of visually impaired persons. It is well known that older adults walk slower than their younger counterparts.

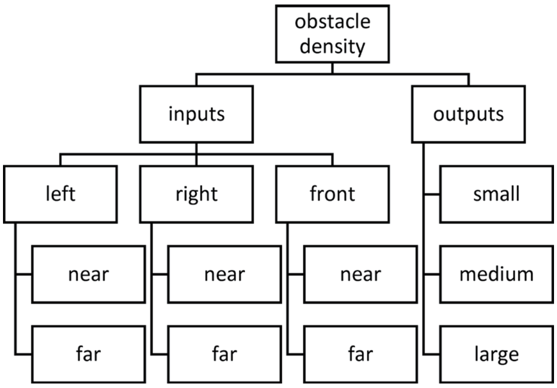


Fig. 4. Taxonomy of inputs and outputs of obstacle density factor.

Table 1
Fuzzy rules for the output variable density.

Left sonar	Right sonar	Front sonar	Density
Near	Near	Near	Large
Near	Near	Far	Medium
Near	Far	Near	Medium
Near	Far	Far	Medium
Far	Near	Near	Medium
Far	Near	Far	Medium
Far	Far	Near	Medium
Far	Far	Far	Small

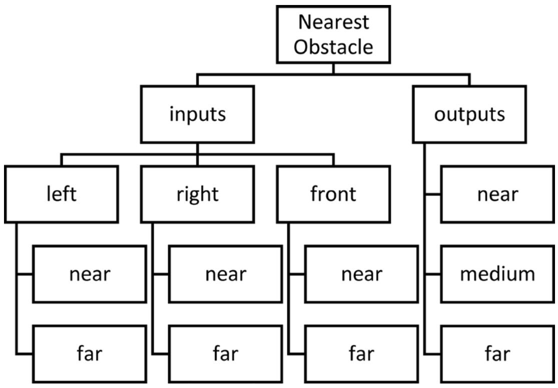


Fig. 5. Taxonomy of inputs and outputs of the nearest obstacle factor.

Table 2
Fuzzy rules for the output-variable nearest obstacle.

Left sonar	Right sonar	Front sonar	Distance to nearest obstacle
Near	Near	Near	Near
Near	Near	Far	Medium
Near	Far	Near	Medium
Near	Far	Far	Medium
Far	Near	Near	Medium
Far	Near	Far	Medium
Far	Far	Near	Medium
Far	Far	Far	Far

Therefore, in this study, visually impaired persons aged between 22 and 73 years are selected.

Height—People of various heights from 150 to 194 cm are considered in this research.

Gender—Male and female are the two fuzzy sets for the input variable gender.

Visual status—The visual status of visually impaired persons can affect their walking speed. Visual impairment is characterized by a loss of visual functions such as visual acuity. Visual impairment is classified into moderate, severe, or profound.[26] Various scales have been developed to measure the severity of vision loss on the basis of visual acuity. The subjects who participated in this research have moderate to severe visual impairments. According to the U.S. notation, the visual acuities of people with moderate visual impairment range from 20/80 to 20/160 and those of people with severe visual impairment range from 20/200 to 20/400.[26] In this research, a person with moderate visual impairment is considered partially blind and a person with severe visual impairment is considered blind. Therefore, the membership function of the visual status of this research ranges from 100 to 400.

The walking speed range of visually impaired pedestrians is taken as 0–1.6 m/s. The membership functions that depend on walking speed are slow, medium, and fast.

The taxonomy of the inputs and outputs of the walking speed is indicated in Fig. 6. Table 3 shows the fuzzy rules for walking speed with respect to the input variables (age, gender, height, and visual status).

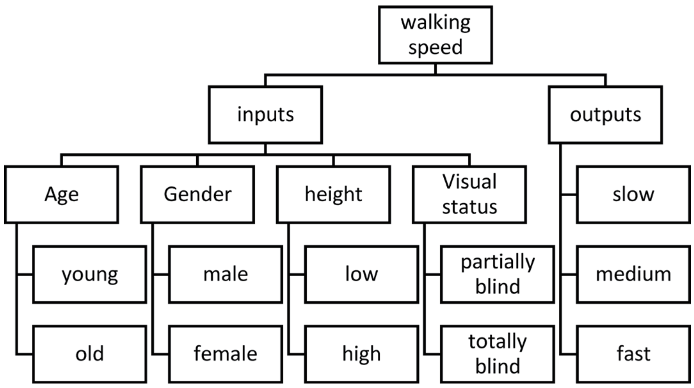


Fig. 6. (Color online) Taxonomy of inputs and outputs of walking speed.

Table 3
Fuzzy rules for walking speed.

Gender	Age	Height	Visual status	Walking speed
Male	Young	High	Partial	Fast
Male	Young	High	Blind	Fast
Male	Young	Low	Partial	Fast
Male	Young	Low	Blind	Medium
Male	Old	High	Partial	Fast
Male	Old	High	Blind	Medium
Male	Old	Low	Partial	Medium
Male	Old	Low	Blind	Slow
Female	Young	High	Partial	Fast
Female	Young	High	Blind	Medium
Female	Young	Low	Partial	Medium
Female	Young	Low	Blind	Slow
Female	Old	High	Partial	Medium
Female	Old	High	Blind	Slow
Female	Old	Low	Partial	Slow
Female	Old	Low	Blind	Slow

3.4 Hybrid fuzzy inference model for walking context

This model is the fusion of the above two fuzzy inference system (FIS) models, adaptation and personalization, as shown in Fig. 3. Here, the outputs of the above two models are inputted into this walking context module. Therefore, this hybrid model has three inputs (obstacle density, distance to the nearest obstacle, and walking speed) and one output, the walking context of the blind navigator, which indicates whether the walking context is safe or not.

The output of the hybrid model is named "the level of safety" during the navigation. However, there is no specific information to calculate this level of safety. Therefore, experiences from people with normal vision are used to define its membership function. Users are allowed to decide the safety level from their intuition and experience in this scenario.

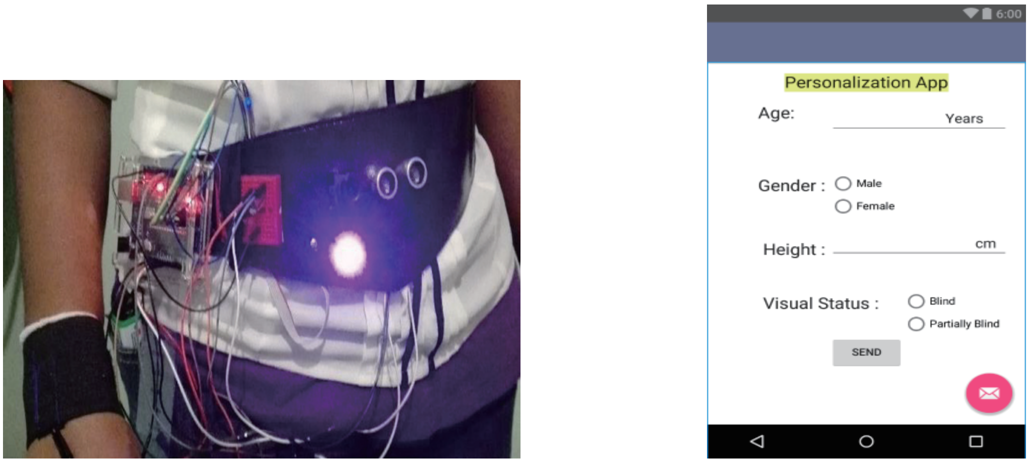
Table 4 shows the fuzzy rules of the walking context concerning the input variables, namely, obstacle density, distance to the nearest obstacle, and walking speed.

Table 4
Fuzzy rules of the walking context.

	Walking speed	Nearest obstacle	Obstacle density	Walking context
1	Slow	Near	Small	Normal
2	Medium	Near	Small	Danger
3	Fast	Near	Small	Normal
4	Slow	Near	Medium	Normal
5	Medium	Near	Medium	Danger
6	Fast	Near	Medium	Danger
7	Slow	Medium	Small	Safe
8	Medium	Medium	Small	Safe
9	Fast	Medium	Small	Normal
10	Slow	Medium	Medium	Normal
11	Medium	Medium	Medium	Normal
12	Fast	Medium	Medium	Danger
13	Slow	Medium	Large	Normal
14	Medium	Medium	Large	Danger
15	Fast	Medium	Large	Danger
16	Slow	Far	Medium	Normal
17	Medium	Far	Medium	Normal
18	Fast	Far	Medium	Danger
19	Slow	Far	Large	Normal
20	Medium	Far	Large	Normal
21	Fast	Far	Large	Danger
22	Medium	Near	Small	Normal
23	Slow	Fast	Small	Safe
24	Medium	Far	Small	Safe
25	Medium	Medium	Medium	Danger
26	Medium	Far	Small	Normal
27	Fast	Far	Medium	Normal
28	Fast	Far	Large	Danger
29	Slow	Far	Medium	Safe
30	Fast	Far	Small	Normal

4. Prototype Implementation

As shown in Fig. 7(a), a wearable belt with three separate three ultrasonic sensors is used to detect obstacles. Distances to the obstacles are calculated by the time-of-flight method. Two sensors are located on the left and right of the belt to detect the left- and right-side obstacles, respectively. The other sensor is located in the middle of the belt to detect front obstacles. Sonar signal data are processed by a microcontroller unit in a prototype board called the Arduino UNO board. All sonar sensors are connected to the Arduino UNO board. To generate feedback, the system uses vibration motors, which are attached to the belt. The vibration motors are mapped to each sonar sensor to give relevant feedback, and the motors change their vibration intensity according to the distance to the obstacle. The specifications of the ultrasonic sensor and coin vibration motor are shown in Tables 5(a) and 5(b), respectively. The FIS has been designed in MATLAB. The fuzzy logic inference used to create the controller is based on the Mamdani approach, and defuzzification is carried out by the centroid method. Considering that the data of the three input variables are spread in a wide range, linear functions such as triangular and trapezoidal functions are used to define membership functions. The walking



(a) (b)

Fig. 7. (Color online) (a) Prototype of the sensor belt. (b) Smartphone application.

Table 5
Specifications of (a) ultrasonic sensor and (b) coin vibration motor of the prototype.

(a)

Working frequency	40 Hz
Maximum range	4 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 × 20 × 15 mm^3

(b)

Vibration frequency	10–55 Hz
Rated vibration speed	15000 rpm
Body diameter	12 mm
Body length	2.7 mm

context analysis module in this research takes charge of making decisions on the current walking status based on information obtained from the results of obstacle detection and the personalization app.

The user can adapt this wearable prototype according to their personal preferences by using a mobile device with Bluetooth communication. This research uses an Android smartphone as the customization equipment for personal factors. The smartphone application calibrates the wearable device according to the user's factors (age, gender, height, and visual status). A Bluetooth module is used to communicate with the prototype system. This smartphone application, as shown in Fig. 7(b), is used to send the personal parameters of the user to the walking context analysis module. Therefore, this application can be used to personalize the prototype according to the personal factors with the help of a third person.

5. Feedback Generation

Although a vast number of messages could be generated by the system, message flooding will cause severe latency for user feedback, and the user may easily become confused and annoyed. Therefore, it is better for the system to provide only the most important messages that suit the user's particular needs in an ordered sequence.

The feedback that should be delivered to the user is divided into two sets, as shown in Table 6. The output of the hierarchical walking context module is transformed into audio messages and delivered to the user with appropriate timing. In addition to the walking context feedback, distances to the nearest obstacles detected by the left, right, and front sonar sensors are given via tactile feedback.

Messages on distances to the closest objects are considered less critical than the user's context safety messages. In the "danger" context, it is more crucial to obtain a safe walking direction message instantly than in the normal or safe context. In cases when changes in the safe direction and walking context are detected simultaneously, the safe direction message is delivered before the walking context message.

However, information on the distance to the closest object is difficult to deliver using audio messages as the distance changes continually. Therefore, tactile feedback is defined, and the intensity of vibration changes in accordance with the distance to the closest object, i.e., if the object is at a long distance, the intensity of vibration is low, and if it is very close, the intensity gradually increases. On the basis of both audio and tactile messages, the user may obtain a complete perception of the surrounding environment.

Table 6
Message definitions.

Message type	Message example
Walking context	"Danger context attention" "Safe/normal to navigate"
Distance to closest obstacle	Tactile feedback based on change in vibration intensity

6. Results and Discussion

Ten subjects of both genders (hereafter, users; four female and six male) and different ages (eight young users, 22–37 years; two elderly users, 70 years old) were recruited in this research. Five of the subjects were blindfolded and assumed to be blind. Three subjects had some visual impairments such as refractive error and age-related visual losses, and two subjects were blind. All the participants had normal hearing ability, and they confirmed that they did not have any other disabilities.

The indoor navigation environment included an area with different kinds of obstacles such as tables, chairs, corridors, and dynamic obstacles (e.g., moving people). This navigation environment for evaluation was set up beforehand and was not seen by the participants before participating in the evaluations.

A pilot study of the prototype system was conducted. There were two main aims of the pilot study: (1) The first was to determine whether the input, processing, and output modes of the prototype were working correctly. This helped to identify any issues and practical problems that should be considered when conducting the actual user experiment. (2) Since the users were not familiar with the equipment and technologies associated with the prototype, they required suitable training before evaluating or using the system. Therefore, the pilot study users were trained in a modeled environment before the evaluation phase was carried out in the actual indoor environment.

The pilot study was carried out in modules (obstacle detection, context analysis, and feedback modules) for convenience of the evaluation and to obtain a better outcome than a focused study on system modules. After the pilot study, the system was evaluated with the same group of users in actual indoor environments.

On the basis of the results obtained from the pilot study, the modifications and improvements that must be carried out were determined and concluded before the user evaluation phase. The most important consequence of the pilot study was that the vibration intensity of the motors in the sensor belt was increased. Also, since users had difficulties in identifying the command within the given period of 500 ms, the period was increased to 1000 ms.

6.1 Modulewise evaluation

The goal of this research is to evaluate how to improve visually impaired navigation with walking context analysis. To realize this goal, several subtasks, such as obstacle detection, current context analysis, and understanding the feedback given by the prototype were carried out.

6.2 Evaluation of obstacle detection

The evaluation of obstacle detection covered obstacle types classified as left-side, right-side, and front obstacles. Users were given three attempts to complete one local navigation in this research. During these attempts, obstacle detection and confusion were designated as “hit” and "miss", respectively. When the user successfully avoided an obstacle, it was calculated as a hit. When the user became confused by the feedback, it was counted as a confusing situation or a miss. For a single attempt, there were five left-side obstacles, four right-side obstacles, and two front obstacles in the indoor environment. For all users, the user detection/hit percentage for each obstacle type was analyzed and the results are shown in Fig. 8.

According to the average obstacle detection rate for users shown in Fig. 8, left-side obstacle detection was about 89%, right-side obstacle detection was about 86%, and front obstacle detection was 98%. When there was more than one obstacle around the user, he/she became confused in reacting to multiple-vibration feedback.

6.3 Evaluation of walking context

The intuition and experience of people are used to define the membership function of the walking context variable. For each sampled scenario with a set of fuzzy values of input variables, users are allowed to decide the level of safety in this scenario on the basis of their intuition and experience. To estimate the effectiveness of the walking context analysis module, the system is tested using real scene data collected from a set of sonar sensors and personal data obtained from the personalized smartphone application.

6.3.1 FIS model for adaptation

Figure 9 shows the membership functions of the inputs of obstacle density. These membership functions are the same in all three inputs (left, right, and front). In the output of obstacle density, the major data divisions, namely, small, medium, and large densities, were identified as in Fig. 9.

Figure 10 shows the membership function of an output variable (nearest obstacle), which consists of three fuzzy sets called near, medium, and far, and the distance to the nearest obstacle varies between 0 and 4.

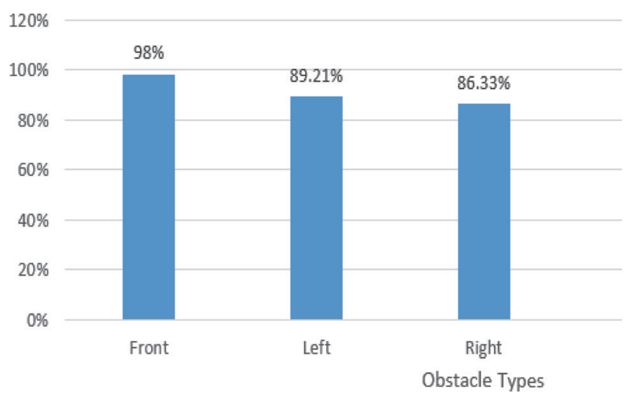
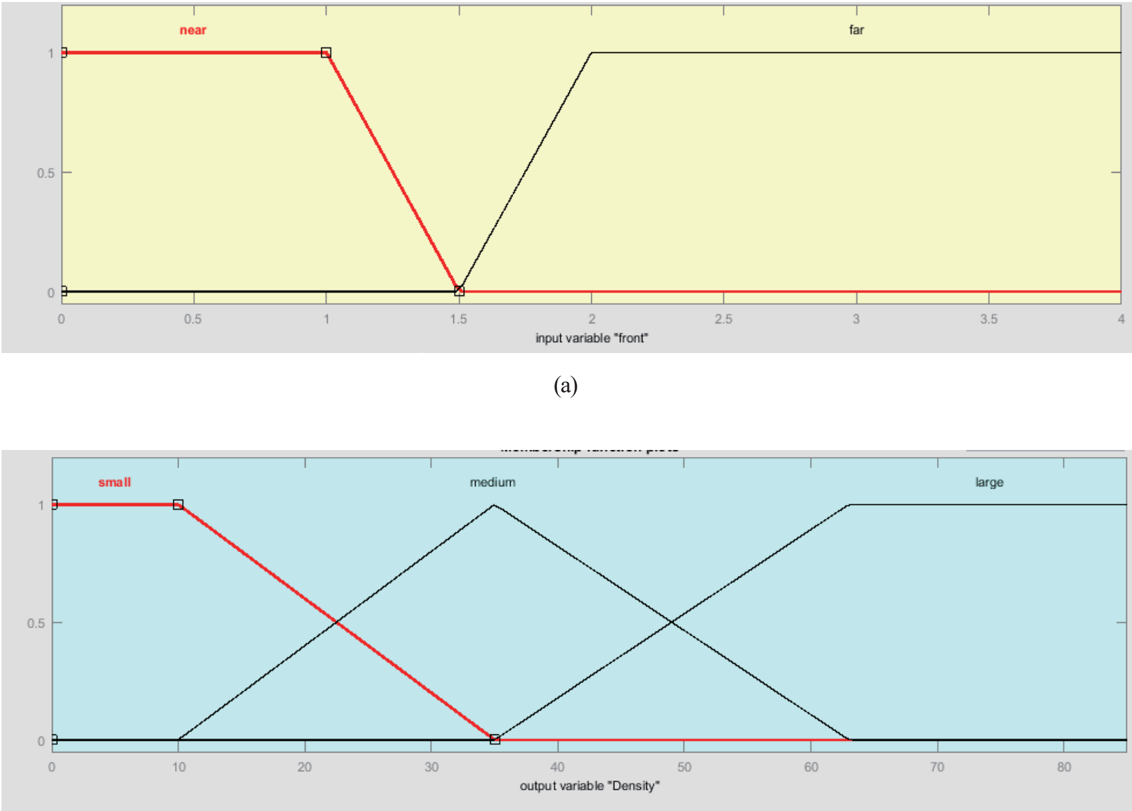


Fig. 8. (Color online) Successful detection of obstacle types.



(a)

(b)

Fig. 9. (Color online) Membership functions of (a) inputs and (b) outputs of obstacle density factor.

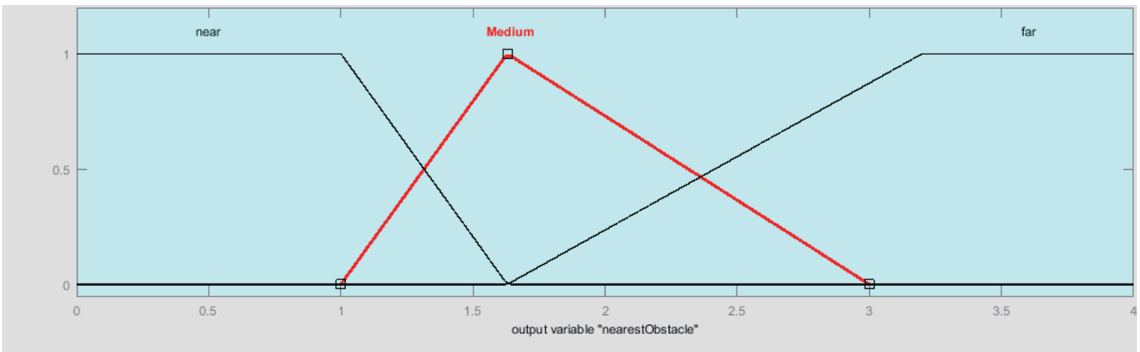


Fig. 10. (Color online) Membership function of the output variable (nearest obstacle factor).

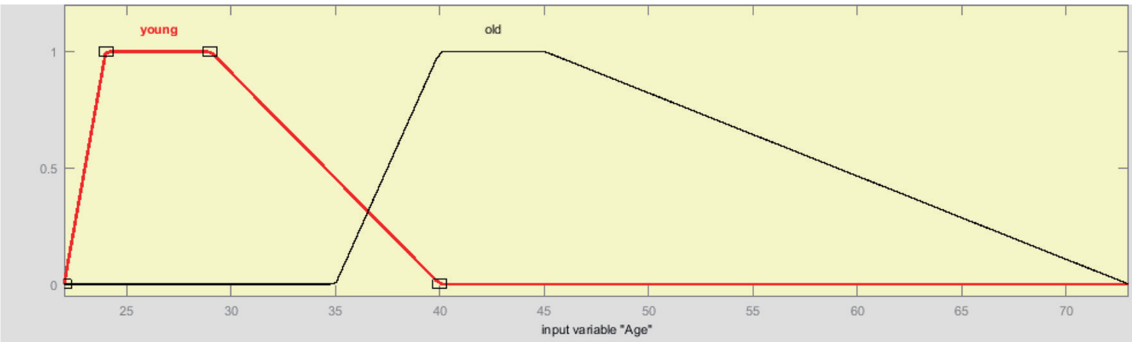
Direction of motion—To avoid an obstacle, the visually impaired navigator should be informed about which direction it is necessary to turn to avoid the obstacle. The direction of movement needs to be determined on the basis of the distances given by the left, right, and front sensors. Here, the priority is given to the front direction, i.e., whenever the front sensor indicates a small distance, the navigator is advised to continue in the front direction. If both the left and right sensors indicate a large distance, priority is given to the right sensor, and the navigator is instructed to turn right, as shown in Table 7.

6.3.2 FIS model for personalization

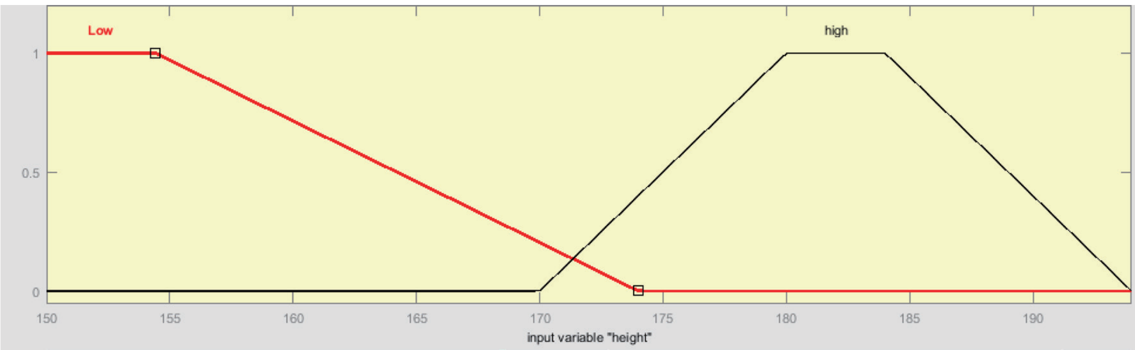
Figure 11(a-i)–11(a-iv) show the membership functions for age, height, gender, and visual status, respectively. Figure 11(b) shows the membership functions of the fuzzy sets of the walking speed.

Table 7
Predefined directions of motion based on three sonar sensor readings.

Left sonar	Right sonar	Front sonar	Direction of motion
Near	Near	Near	Right
Near	Near	Far	Straight
Near	Far	Near	Right
Near	Far	Far	Straight
Far	Near	Near	Left
Far	Near	Far	Straight
Far	Far	Near	Right
Far	Far	Far	Straight

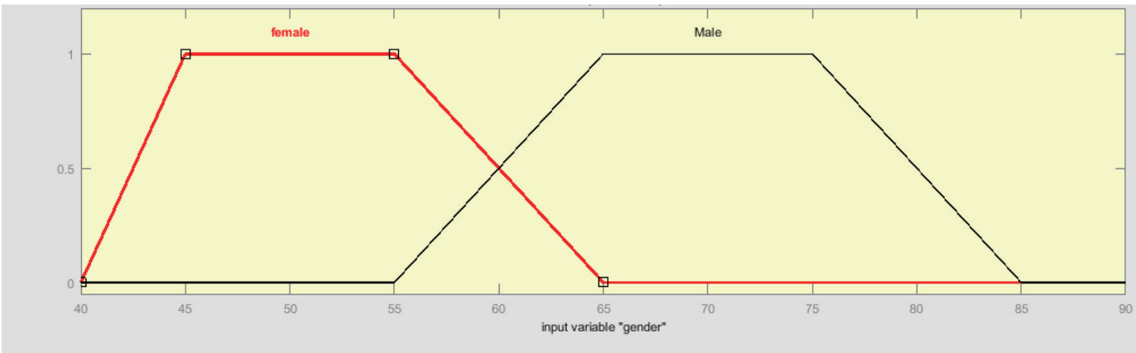


(a-i)

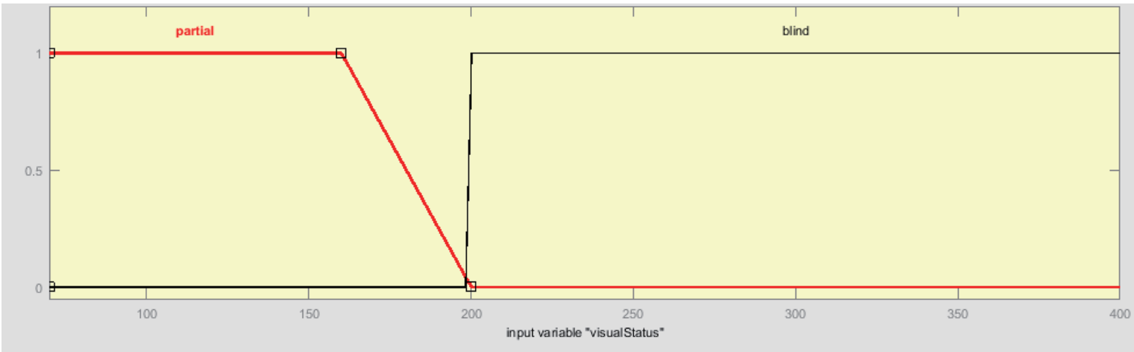


(a-ii)

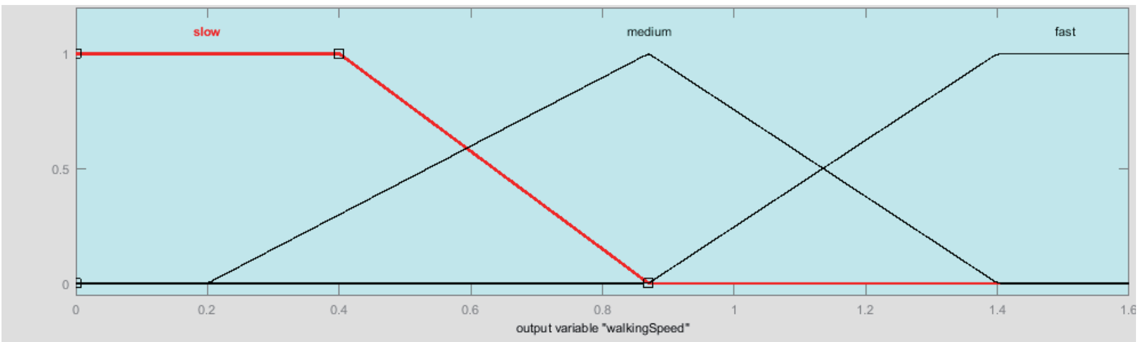
Fig. 11. (Color online) Membership functions of (a) inputs: (a-i) age, (a-ii) height, (a-iii) gender, (a-iv) visual status, and (b) outputs of obstacle density factor.



(a-iii)



(a-iv)



(b)

Fig. 11. (Continued)

6.3.3 Hybrid FIS model for walking context analysis

When the input variables, namely, obstacle density, distance to the nearest obstacle, and walking speed, are inputted to the fuzzy system, the output variable is given as the walking context. This output variable consists of three fuzzy sets called safe, normal, and danger, and the membership functions of these fuzzy sets is shown in Fig. 12. Figure 2 shows a graphical representation of the fuzzy rules of the walking speed, which are indicated in Table 4.

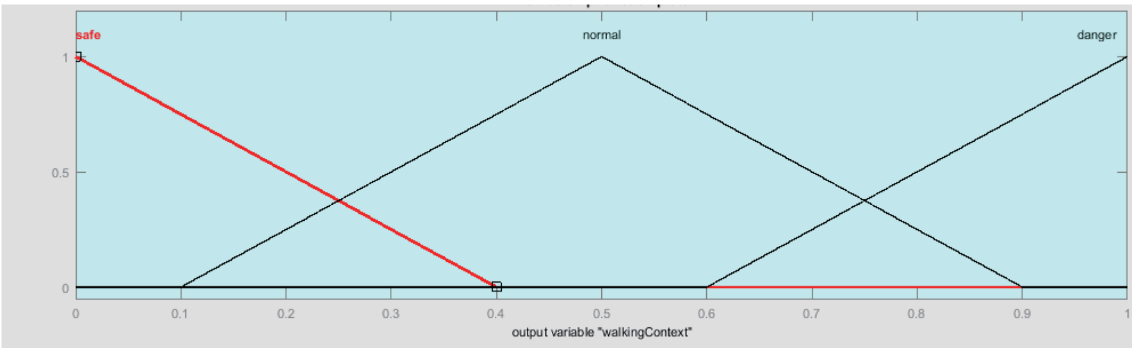


Fig. 12. (Color online) Membership functions of the walking context.

Table 8
Voice and tactile feedbacks of users.

	User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8	User 9	User 10
Voice feedback	10	10	10	9	9	9	10	8.5	10	8.5
Tactile feedback	8	7	7	6	7	6	7	8	6	7

6.4 Evaluation of feedback

When giving feedback to people with visual impairments, alternative sensory skills, such as auditory and tactile senses, are taken into consideration. Users who participated in the evaluation were previously confirmed to have no hearing impairments or any other disabilities. Extensive prior training was given to all the users who took part in the experiments to familiarize them with the auditory and tactile gadgets and their functionalities before participating in the actual evaluation.

To evaluate only the ability to identify feedback, users were given ten voice commands and ten tactile commands through a user training module. Each command was given to the users in actual environments, and then the results were recorded and are shown in Table 8. This process was carried out to identify the more convenient feedback method and how the fusion of different feedback mechanisms can improve visually impaired navigation.

Voice feedback achieved a higher identification count than tactile feedback. The tactile belt feedback module was given identification counts in the range of 6–8. The voice feedback and the tactile belt both showed acceptable performance as the feedback module. Therefore, the system functioned properly with the help of an integrated dual-feedback system.

7. Conclusion

In this study, we showed how context awareness can improve the safety and efficiency of visually impaired navigation. The context-aware module in this research consisted of two parts based on adaptation and personalization. Inputs to the adaptation module are taken from the outputs of obstacle detection of the prototype, in which the obstacle detection unit consists of a set of sonar sensors that detect obstacles in the left, right, and front directions. Inputs to the personalization unit are taken from the personalization smartphone application of the prototype. They are the age, gender, height, and visual status of the current user. Finally, the hybrid fuzzy inference module is created by combining these two fuzzy inference modules (personalization and adaptation). Audio feedback is generated to inform the user about the status of the current context (safe, normal, or dangerous). In addition, tactile feedback is generated to inform the user about the closest objects in each direction. The obtained results proved the successful operation and effectiveness of fuzzy control in reducing the navigation time and increasing safety by understanding the uncertainty in each situation.

As future work, the feedback mechanism is expected to be improved by measuring the real-time walking speed of blind pedestrians and giving them messages to adjust their pace of walking according to the current context, i.e., “increase your speed” or “decrease your speed”. In addition to the nearest obstacle distance, the most adjacent obstacle name/type is expected to be given as an audio message, which will improve the perception of the surrounding environment.

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