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Brainstorming Fuzzy Cognitive Maps for Camera-based Assistive Navigation

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Abstract. Motivated by the brainstorming process of human beings, a novel learning Fuzzy Cognitive Map (FCM) model named Brainstorming Fuzzy Cognitive Map (BFCM) is proposed. The proposed model is based on a state-of-the-art optimization algorithm, named Determinative Brain Storm Optimization, which is utilized to automatically adapt the weights of the FCM structure. In this study, BFCM is applied for safe outdoor navigation of visually impaired individuals. This application ensures the avoidance of static obstacles in an unknown environment, by taking into consideration the output of an obstacle detection system based on a depth camera. The simulation results show that the proposed model can effectively assist the users to avoid static obstacles and safely reach a desired destination, and they promise a wider applicability of the model to other domains, such as robotics.

Keywords: Camera-based navigation, fuzzy cognitive maps, brain storm optimization, visually impaired individuals.

1 Introduction

Fuzzy Cognitive Maps (FCMs) are mathematical models introduced by Kosko [10] and contribute to model dynamic systems with uncertain information. The design of an FCM relies mostly on the input given about a decision-making problem, usually by experts, relying on their experience and knowledge on the complex system. The main advantage of this method is that they enable a qualitative description of the degree of causality among the concepts, without requiring providing accurate numerical experiments. The simplicity of FCMs has enabled their usage in numerous applications in different fields, such as in healthcare for medical decision making [7], in economics for banking purposes and business management [5], in agriculture for planting issues [8]. In addition, FCMs have been used successfully in artificial emotion research [19], in pattern recognition applications [18], in mathematics for decision analysis and operation research. The numerous model variations of FCMs are concisely reviewed in [4].

The development of an FCM model almost always relies on human knowledge [1]. To avoid dependency on human intervention, different approaches for automated learning of FCMs have been used. These learning approaches can be categorized into three main types: Hebbian-based, population-based and hybrid learning approaches, which are evoked from the combination of the Hebbian and population-based ap-

proaches [16]. Population-based algorithms, aiming to perform the training of FCMs, have gained the interest of many researchers. Indicative examples of such algorithms used include Evolutionary Strategies (ES), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search (TS), Immune Algorithm, Game-based learning model, along with their modifications. Fuzzy logic, and more specifically FCMs, plays a decisive role in the formation of navigation tasks. In [12, 21], groups of autonomous mobile robots were tuned, using fuzzy logic techniques, in order to explore semi-unknown environments in simulated applications of rescue missions. In [26], FCMs were used to depict the causal relations between ship navigational risk factors, aiming to improve navigational safety. In [24], the Particle Swarm Optimization (PSO) algorithm was utilized for parameter adaptation of the presented navigational FCM, in order to reach the goal of keeping a robot moving within a specified bounded path. A Dynamic FCM combined with the Ant Colony Optimization algorithm (DFCM-ACO) was developed in [13] and evaluated in a simulation application, where adjusted robots aim to detect and rescue victims in unknown environments.

In this paper, a novel learning FCM model is introduced based on a state-of-the-art population-based algorithm named Determinative Brain Storm Optimization (DBSO)[22]. The proposed FCM, named Brainstorming Fuzzy Cognitive Map (BFCM), is inspired from the human brainstorming process. DBSO is used for the automatic adaptation of the weights of the FCM. Another novelty aspect of this work is that BFCM is applied in the context of a wearable camera-based assistive system for visually impaired individuals (VIIs) [3]. That system incorporates a depth camera and an obstacle detection system based on deep neural networks and fuzzy logic. The proposed BFCM application aims to assist VIIs to navigate safely in outdoor environments by giving them directions on how to avoid the static obstacles detected by the obstacle detection system. The remaining of this paper is organized in three sections. Section 2 provides a theoretical background description of FCMs and DBSO algorithm. Section 3 describes the BFCM camera-based navigation approach that is proposed, and the simulation results are presented in Section 4. Finally, Section 5 presents the conclusions derived from this study.

2 Theoretical Background

2.1 Fuzzy Cognitive Maps

An FCM is a fuzzy directed graph that is constructed with a series of steps. Initially, information about a knowledge domain is collected by different experts in that domain, aiming to identify the appropriate N concepts $C = \{C_1, C_2, \dots, C_N\}$, define the weights, $w_{ij} \in E$ of the arcs connecting these concepts for $i, j \in [1, N]$ and $E = [-1, 1]$, and the causal relationships among them. This process can benefit from a brainstorming process among the involved experts, as it could optimize the resulting FCM model.

The effect of one concept to the others can be negative or positive, with a fuzzy degree of causation [9]. The determination of the sign and the description of the causal relationships, using a linguistic notion follows, and then linguistic weights, such as “strong”, “weak” etc., corresponding to fuzzy sets, are assigned to each arc. After that, all the linguistic values are combined by aggregation of the respective fuzzy sets,

and a final single linguistic weight emerges. Finally, the real weight values are obtained, by defuzzification, which transforms the linguistic weights to a numerical value within the range $[-1,1]$ [11].

Each concept is modeled as a linguistic variable C_i , $i = 1, 2, \dots, N$ and expresses the degree to which the concept occurs. The formulation of the calculation rule that is used to determine and update iteratively, at each time step, the values of concept is given by (1):

$$a_i^{l+1} = \mathcal{F}(a_i^l + \sum_{\substack{j=1 \\ j \neq i}}^N a_j^l \cdot w_{ij}) \quad (1)$$

where a^l is a state vector that represents the current state of the FCM, l counts the iterations; w_{ij} represents the weight value from node i to node j . Function \mathcal{F} is sigmoidal with saturation levels -1 and 1 , normalizing a_i^{l+1} within $[-1, 1]$, and contributing to the convergence of the FCM to a steady state [2, 23].

2.2 Determinative Brain Storm Optimization

Learning algorithms are mainly used to compute the fittest weights of FCMs that increase the efficiency of the model. In this paper, the proposed navigational FCM model is developed, using a state-of-the-art swarm-based algorithm, named Determinative Brain Storm Optimization (DBSO) algorithm [22], which is used for the first time for the adaptation of FCMs. DBSO is inspired from the human brainstorming process, particularly the fact that during a successful brainstorming process, a consensus is reached between participants that have similar ideas, and as a result the most appropriate solution for a given problem is determined.

DBSO algorithm proceeds in the following steps: **Step 1** represents the initialization of parameters needed and the generation of N potential solutions, called individuals and for our problem are the potential weight values. In **step 2**, k -means algorithm clusters the N individuals into $M < N$ groups. For each cluster, in **step 3**, the individual with the best fitness values (best individuals) are recorded as cluster centers and sorted ascendingly, in order to calculate the Euclidean distance and the corresponding similarity in **step 4**. Then, in **step 5** the best two individuals are identified and, their corresponding clusters are merged. In **step 6**, a new individual is generated based on one or two clusters, according to predefined criteria. In **step 7**, the generated individual is compared with the existing ones, and the one with the fittest value is kept and recorded as the most appropriate solutions to the given problem. The algorithm repeats until convergence.

3 Brainstorming Cognitive Maps

The learning approach for BFCM is performed based on the training of the weight matrix W . For that reason, the state-of-the-art DBSO algorithm is used for the minimization of the function given by (2) [17], which consequently leads to the acquisition and definition of an optimal weight matrix, proper for the design of the BFCM model.

$$\mathcal{M}(W) = \sum_{i=1}^m H(a_i^{min} - a_i) |a_i^{min} - a_i| + \sum_{i=1}^m \mathcal{H}(a_i - a_i^{max}) |a_i^{max} - a_i| \quad (2)$$

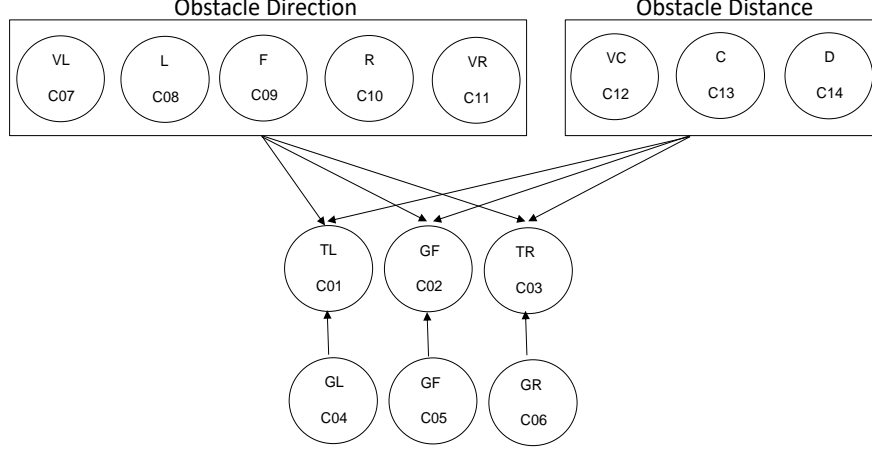


Fig. 1. Proposed BFCM structure for camera-based navigation.

where $a_i, i = 1, \dots, m$ are the steady state values of the output concepts, which are restricted by the user, in bounds $a_i^{min} \leq a_i \leq a_i^{max}, i = 1, \dots, m$ and \mathcal{H} represents the Heaviside function, given by (3):

$$\mathcal{H}(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \quad (3)$$

BFCM, which models the camera-based navigation for VIIs, is illustrated in Fig.1. As it is observed, BFCM consists of fourteen concepts which are defined as follows: C01-Turn Left (TL); C02-Go Forward (GF); C03-Turn Right (TR); C04-Goal Left (GL); C05-Goal Forward (GF); C06-Goal Right (GR); C07-Very Left (VL); C08-Left (L); C09-Forward (F); C10- Right (R); C11-Very Right (VR); C12-Very Close (VC); C13-Close (C); C14-Distant (D). It has to be clarified that in Fig. 1, there is a connection between all the concepts related to Obstacle Direction (C07-C11) and the output concepts (C01-C03), as well as, between all the obstacle distance concepts (C12-C14) with the output concepts.

Considering the obstacle avoidance problem, which is under investigation, the partition of an image is presented in Fig.2(a), along with the corresponding membership functions. The depth information of the scene is also defined, as it contributes to a greater awareness of the environment along with the risks that exist [3]. Thus, the membership functions that describe the distance between the navigator and the obstacles are presented in Fig. 2(b), where the linguistic values used are: Very Close (VC), Close (C), and Distant (D).

In order to perform the desired camera-based navigation for obstacle avoidance, an initial weight matrix (Table 1), was defined for the design of the FCM model, according to the standard approach described in Section 2. A. Specifically, the values of the initial weight matrix were empirically determined by opinion aggregation of experts on the assistance of VIIs, using the algebraic sum operator, and the Center of Gravity (CoG) defuzzification method. The sign and value of the causal relations, between the

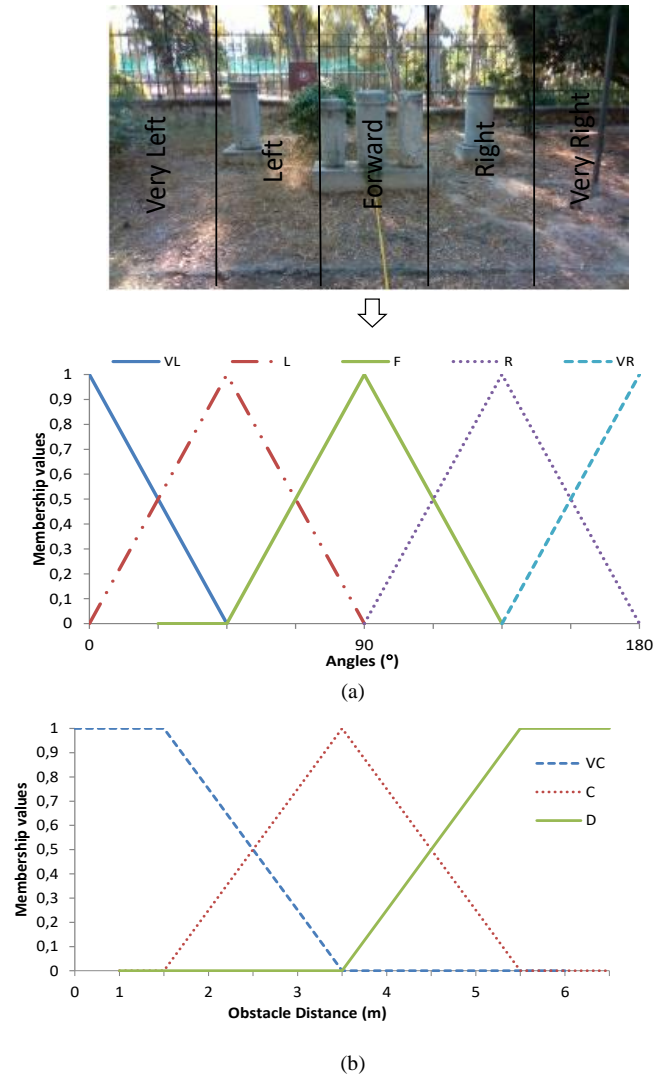


Fig. 2. Membership functions used to determine: (a) the partition of the image (upper figure) for obstacle avoidance, with linguistic values: Very Left (VL), Left (L), Forward (F), Right (R), Very Right (VR); (b) the depth information; the distance between navigator and obstacles in meters (m), using the linguistic values: Very Close (VC), Close (C), Distant (D).

concepts, depend on the influences and intensity among them, and are tuned in such a way as to provide VIIs with safe directions, minimizing the risk of collision with obstacles. Thus, in the BFCM model, C04-C06 have positive weight values, related to the output concepts (C01-C03), and they are equal to 1. This means that when a destination is set, VIIs are advised to move straight forward to that destination. The relationships between (C07-C11) and (C01-C03) have both negative and positive causality; if an obstacle is detected towards a direction, BFCM proposes VIIs to avoid that direction (negative causality) and move towards another direction, which is safer, given that

there is not a high risk of collision with obstacles (positive causality). For obstacle distance concepts (C12-C14) related to (C01- C03), they have negative weight values, for the same reason mentioned above, whereas the degree of causation depends on the type of distance, *e.g.*, when the obstacle is detected very close, then it has a greater negative effect to the output concepts, than being at a distance.

A part of the initial weight matrix (Table 1) is selected aiming to define the fittest optimized weight matrix that is needed for the adaptation of the BFCM and it is presented in a dashed box. This dashed box that represents the examined weight matrix includes only the non-zero input weights that are connected to each other and to the output codes; thus, they play the most decisive role to the design of the proposed FCM, and consequently to the determination of the position of VIIs. The values from the input and output concepts of the proposed model lie within the desired prespecified ranges presented in Table 2. Generally, these bounds are problem dependent.

The main goal of the paper is to ensure a safe navigation for VIIs, who have to travel from a starting point up to a predefined destination. Thus, the direction to be followed is considered to be known and given by a GPS. The new position of the entity is defined as (x', y') using basic trigonometric calculations:

$$x' = x + \cos(\varphi) \quad (4)$$

$$y' = y + \sin(\varphi) \quad (5)$$

where x, y are the previous positions and φ is the output direction angle of the BFCM, which is relative to the horizontal axis x and drives the entity towards the desired target goal, while avoiding possible obstacles, as it is presented in Fig. (3).

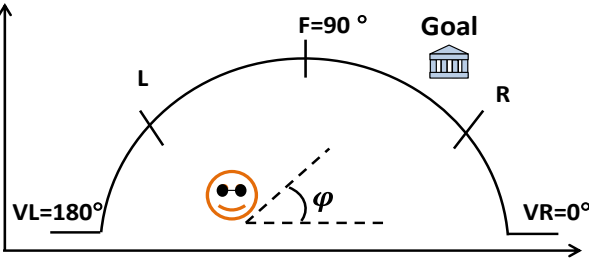


Fig. 3 The target direction concepts of BFCM.

DBSO is a population-based, swarm algorithm that is applied to optimize the proposed model of Fig. 1, and enhance the navigation, by defining the trajectories of a VII, after updating the nonzero weight values of the examined weight matrix, presented with a dashed box in Table 1. In this study, DBSO is performed with a population of 20 individuals, for 50 iterations, whereas the rest of the parameters of DBSO were set as suggested in [22]. DBSO tuned the weight matrix and converged to a set of optimum weights, minimizing (2). As a result, an optimal weight matrix was obtained (Table 3). In addition, as it is observed, all the generated weights of Table 3 are within the ranges determined in the previous section. Compared to the initial matrix, there are differences between some weight values. In particular, the majority of weights have been

modified except from $W_{10 \rightarrow 1}, W_{10 \rightarrow 3}, W_{11 \rightarrow 1}, W_{12 \rightarrow 2}, W_{12 \rightarrow 3}, W_{13 \rightarrow 2}$, which remained the same, as the initial ones.

Table 1. Initial weight matrix of BFCM

w	1	2	3	4	...	14
1	0	0	0	0	...	14
2	0	0	0	0	...	0
3	0	0	0	0	...	0
4	1.00	0	0	0	...	0
5	0	1.00	0	0	...	0
6	0	0	1.00	0	...	0
7	-0.45	-0.20	0.60	0	...	0
8	-0.65	-0.30	0.90	0	...	0
9	0.60	-0.90	0.60	0	...	0
10	0.90	-0.30	-0.85	0	...	0
11	0.90	-0.30	-0.55	0	...	0
12	-0.50	-0.45	-0.50	0	...	0
13	-0.60	-0.45	-0.60	0	...	0
14	-0.75	-0.70	-0.75	0	...	0

Table 2. Examined weight matrix.

$-0.75 \leq w_{7 \rightarrow 1} \leq -0.35$	$-0.60 \leq w_{11 \rightarrow 2} \leq -0.20$
$-0.50 \leq w_{7 \rightarrow 2} \leq -0.10$	$-0.75 \leq w_{11 \rightarrow 3} \leq -0.35$
$0.40 \leq w_{7 \rightarrow 3} \leq 1.00$	$-0.60 \leq w_{12 \rightarrow 1} \leq -0.20$
$-1.00 \leq w_{8 \rightarrow 1} \leq -0.60$	$0.40 \leq w_{12 \rightarrow 2} \leq 0.80$
$-0.60 \leq w_{8 \rightarrow 2} \leq -0.20$	$-0.60 \leq w_{12 \rightarrow 3} \leq -0.20$
$0.60 \leq w_{8 \rightarrow 3} \leq 1.00$	$-0.60 \leq w_{13 \rightarrow 1} \leq -0.20$
$0.55 \leq w_{9 \rightarrow 1} \leq 0.95$	$-0.50 \leq w_{13 \rightarrow 2} \leq -0.10$
$-1.00 \leq w_{9 \rightarrow 2} \leq -0.60$	$-0.60 \leq w_{13 \rightarrow 3} \leq -0.20$
$0.55 \leq w_{9 \rightarrow 3} \leq 0.95$	$-0.85 \leq w_{14 \rightarrow 1} \leq -0.45$
$0.60 \leq w_{10 \rightarrow 1} \leq 1.00$	$-0.85 \leq w_{14 \rightarrow 2} \leq -0.45$
$-0.60 \leq w_{10 \rightarrow 2} \leq -0.20$	$-0.85 \leq w_{14 \rightarrow 3} \leq -0.45$
$-0.60 \leq w_{10 \rightarrow 3} \leq -1.00$	$0.60 \leq w_{11 \rightarrow 1} \leq 1.00$

Table 3. Optimized weight matrix

w	1	2	3
7	-0.70	-0.49	0.89
8	-0.95	-0.55	0.77
9	0.71	-0.80	0.74
10	0.90	-0.49	-0.85
11	0.90	-0.47	-0.73
12	-0.38	-0.22	-0.48
13	-0.55	-0.70	-0.75
14	-0.46	0.50	-0.58

4 Experiments and Simulation Results

Simulation experiments were performed to evaluate the capacity of BFCM to provide guidance for obstacle avoidance. To assess the effect of the optimization process performed by DBSO in the navigation of the VIIs, the results of BFCM are compared to those obtained without the use of DBSO. The unoptimized model will be referred to simply as FCM. The difference between these two models relies solely on their weight matrices, as the first approach is designed in terms of the initial weight matrix, whereas the second model uses the weights presented in Table 3. The safety of the proposed model is estimated using a collision avoidance metric $c(t)$ commonly used in related studies [14, 20]:

$$c(t) = \begin{cases} 0, & d_{min} \geq d_s \\ \frac{1}{d_{min}} - \frac{1}{d_s}, & d_{min} < d_s \end{cases} \quad (6)$$

where d_{min} represents the closest distance of a VII to an obstacle, and d_s represents the distance to an obstacle that poses no danger for collision. For our experiments, $d_s = 2$, as the desired detection distance for the early avoidance of an obstacle according to the requirements of the visually impaired users is up to 2 m [6]. Moreover, in order to quantify the safety of $c(t)$, the first norm ($p = 1$) is calculated, according to (7), and taken as a performance criterion.

$$\|c(t)\|_p = \sqrt[p]{\int c(t)^p dt} \quad (7)$$

The effectiveness of the proposed method has been tested on 16 different scenarios, *i.e.*, for 16 different unknown environments that consist of static obstacles. Each scenario included a different starting position and different directions and routes with static obstacles. The results, with respect to collision avoidance metric, are summarized in Fig. 4. BFCM in Fig.4 is represented with red-color bars, whereas green-color bars show the results of the FCM. It can be observed that BFCM is safer in all cases than original-FCM, in terms of the norm of the defined metric, with an average collision norm equal to 0.19, while FCM results to 0.33. Thus, BFCM is 73.68% safer than the original FCM.

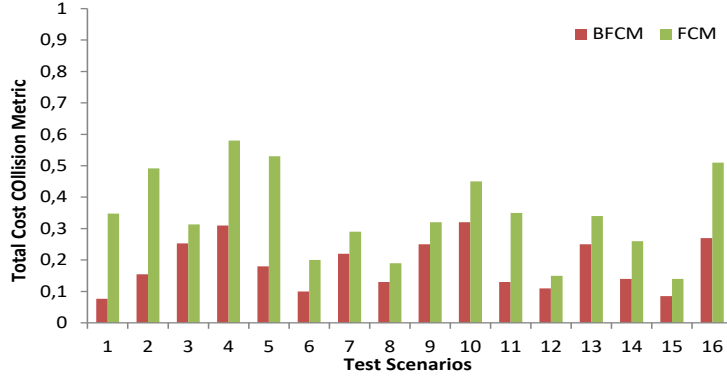


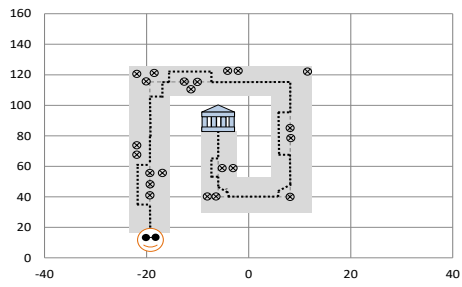
Fig. 4 Total cost of collision metric for different scenarios.

In addition, indicative simulation results of BFCM are illustrated in Fig. 5, for the first four out of the 16 different scenarios, with different starting points and destinations with target goals, which are known a priori. The results show that a VIIs efficiently manage to avoid all the obstacles and reach the final destination, which is symbolized with a miniature of a monument, in all the scenarios. However, concerning the navigation based on BFCM Fig. 5(a-d), the tuned, by the DBSO algorithm, weights contribute to a safer camera-based navigation, compared to the FCM Fig. 5(e-h), as the proposed indicates the correct directions of a route, after taking into consideration the distance between the position of the VIIs and the obstacles. On the contrary, the FCM model navigates the VII to the desired destination, with a less adaptable distance of the existing obstacles that results in the moving person approaching the obstacle very close, with the risk of colliding with it. Consequently,

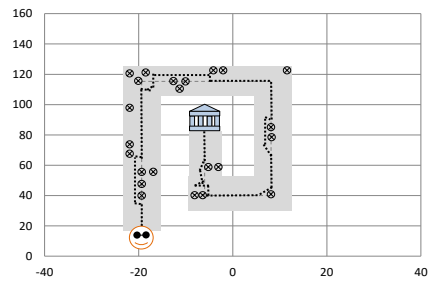
the navigation based on the FCM model is not so safe, as it has a higher collision risk, regarding both the calculated collision metric (Fig. 4), as well as the illustrated results of Fig. 5.

5 Conclusion

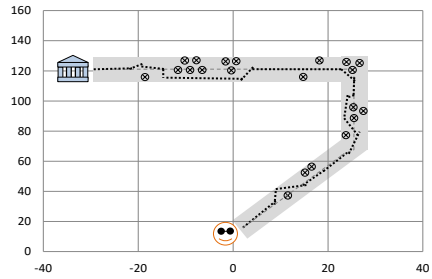
In this paper, a novel learning FCM applied as a navigational tool named Brainstorming Fuzzy Cognitive Maps (BFCM) was introduced. BFCM was created based on a state-of-the-art algorithm named Determinative Brain Storm Optimization (DBSO). The proposed model was applied for outdoor navigation of visually impaired individuals. This application contributes to the avoidance of static obstacles in unknown environments, after taking into consideration the output of an obstacle detection system based on a depth camera. The simulation results showed that the proposed approach can be used by the VIIs to effectively avoid obstacles and reach a desired destination safely. Further investigation of BFCM is needed mainly towards its capacity to adapt in dynamic scenarios, with moving obstacles, and validation of the results by human subjects in different outdoor environments. Future research directions, emerge by the application of the proposed model to other domains, where navigation is necessary for obstacle avoidance, *e.g.*, for obstacle avoidance by robots, autonomous vehicles *etc.* Further improvement of the proposed methodology could be achieved by considering additional components enhancing its robustness to uncertainties originating from different sources, *e.g.*, in the image processing stage [25].



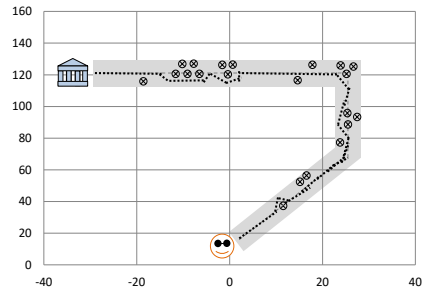
(a)



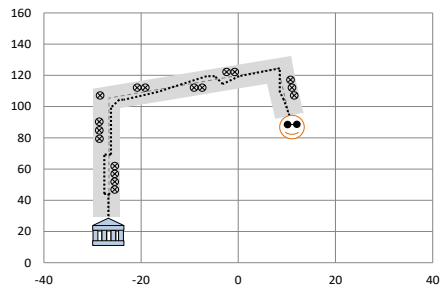
(e)



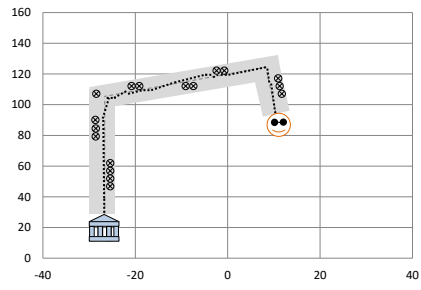
(b)



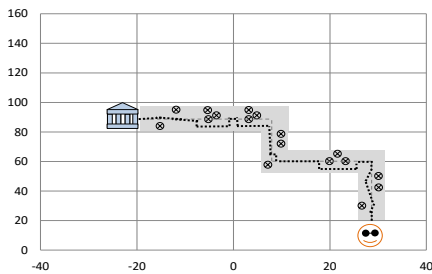
(f)



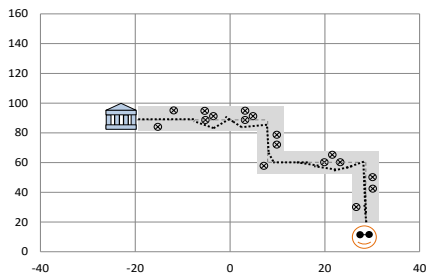
(c)



(g)



(d)



(h)

Fig. 5. Simulation results using BFCM (left) and FCM (right).

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