Surveillance Rapid Detection of Signs of Traffic Services in Real Time

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***Abstract*—This study aims to compare the efficiency of Intuitionistic Fuzzy Neural Network with Genetic Algorithm (IFNN-GA) in detecting real-time traffic signs in different road conditions compared with the human eyes in order to prove that they are more efficient in understanding the surrounding environment, support safe driving, and overcome human defects. Highlighting the driver's obstacles such as weather conditions, uneven lighting, shadows everywhere, intensity and brightness fluctuations and contrast in shape and texture of traffic signs and time spent for entry and exit. In order to realize all aspects of the road, a model was proposed: Intuitionistic Fuzzy Neural Network with Genetic Algorithm (IFNN-GA).**

***Index Terms*—Fuzzy Logic; Fuzzy Graphs; Intuitionistic Fuzzy Sets; Intuitionistic Fuzzy Neural Network; Genetic Algorithm.**

I. INTRODUCTION

Traffic congestion is a daily phenomenon that is challenging for every road user. Drivers have preoccupied the best roads that are free of congestion because it's sometimes forcing them to delay reaching their destination [1][2]. This indicates that immersion in the congestion on the roads on a daily basis has psychological and health consequences. The traffic congestion battle is a battle fought by drivers around the world on a daily basis. If we ignore the wasted time, which is precious to drivers, the issue of stress comes when passing through thousands of cars to reach work or home, and therefore inhaling the smells of exhaust cars throughout this period. In addition, the traffic congestions had many health-related consequences especially on the respiratory system and efficiency of breathing [3]. Drivers as well need to stay focused all the time which might eventually lead to stress, tightness and anger. The outrage, back pain, and headache that drivers suffer from. After getting out of the congestion, you need at least an hour to relax to get back to normal and brighten up at the expense of work and family.

II. FUZZY LOGIC AND LEARNING

Fuzzy logic is a deeper concept of the classic (crisp) black-and-white Include matter of Degree of membership, such as Human Knowledge. Information can be classified into numerical and linguistic data, as follows: 1) Numerical Information is obtained from mathematical models, physical laws or digital data collected by detectors. 2) Linguistic Information refers to the subjective information that is represented by the rules or linguistic terms based on the experience and knowledge collected from experts. To design a fuzzy control system the following steps are required: 1) Choosing the fuzzy controller inputs and outputs. 2) Choosing the pre-processing that is needed for the controller inputs and possibly post-processing that is needed for the outputs. 3) Designing each of the four components of the fuzzy controller, it is Rule-Base, the Inference Mechanism, the Fuzzification Interface and the Defuzzification.

III. INTUITIONISTIC FUZZY SETS

The Intuitionistic fuzzy set (IFS) is a part of Zadeh's fuzzy set, developed by Atanassov [4][5][6]. An IFS is more general and comprehensive than fuzzy set and a powerful tool. It works to deal with vagueness. Connectedness concepts help to find the Cut Node (CN) in fuzzy graphs. CutNode (CN) is useful for identifying areas of density when choosing a path that does not contain node CN. The fuzzy logic is used to represent imprecise data which are called an Intuitionistic fuzzy database (IFDB). Interval-Valued Fuzzy Sets (IVFS) is more adequate of uncertainty and wider than traditional, fuzzy sets and Intuitionistic fuzzy set (IFS). The Intuitionistic Fuzzy Set (IFS) developed by Atanassov, is a powerful tool to deal with vagueness and use it more general and comprehensive than fuzzy set. The IFS constitutes an extension of Zadeh's fuzzy set, and assigns to each element of membership degree. Applications of IFS for artificial intelligence are used with expert systems, neural networks, decision making, machine learning, and semantic representations. Intuitionistic Fuzzy Sets (IFS) have two values and they are $\mu_{A\,(x)}$ and $V_{A\,(x)}$. A $\mu_{A\,(x)}$ is a degree of membership [7]. $V_{A\,(x)}$ is a degree of non-membership. The sum of the two values has to be less than one (1), we introduce some definitions from IFS, which are necessary for our research; it can be expressed as follows: IFS $A=\{\langle x, \mu_{A(x)}, V_{A(x)}, \Pi_{A(x)}\rangle : x \in X\}$.

A. *Intuitionist Fuzzy Database*

To find inaccurate information to extract more accurate conclusion and minimize the search we use Intuitionistic Fuzzy Set. We present an example of vehicle driver to take a decision within seconds recognizing the image of road sign. The fuzzy logic is used to represent imprecise data and it is called an Intuitionistic Fuzzy Data-Base (IFDB) [8][9]. We introduce an application or case that using the intuitionistic fuzzy relation as following: 1) Intuitionistic Fuzzy Tolerance Relation. 2) Intuitionistic Fuzzy Similarity Relation (Equivalence). We constitute the IFS tolerance relation and equivalence of the attributes included database to reduce doubt ours. An intuitionistic Fuzzy Relation R on the Cartesian product (X × X), is called: An Intuitionistic Fuzzy Tolerance Relation if R is reflexive and symmetric relation.

An Intuitionistic Fuzzy Similarity (Equivalence) Relation if R is reflexive, symmetric and transitive relation, as following: Reflexive relation $\forall\ x \in A \Rightarrow \mu R(x,x)=1$, Symmetric relation $\forall\ (x,y) \in A \times A$, $\mu R(x,y)=\mu \Rightarrow \mu R(y,x)=\mu$, Transitive relation $\forall\ (x,y),(y,z),(x,z) \in A \times A$ $\mu R(x,z) \geq$ Max [Min [$\mu R(x,y)$,$\mu R(y,z)$]].

B. Interval-Valued Intuitionistic Fuzzy Set

Interval values intuitionistic Fuzzy Sets (IVIES) are extensions of the theory of fuzzy sets and others are trying to cope with inaccuracy and uncertainty differently [10][11]. IVIFS can be expressed as follows:

$$A=\{x, (D(x), J(x), H(x))| \ x \in X\} \in [I] \qquad (1)$$

where define the symbols as follows:
D (x), J (x) and H (x): $X \rightarrow [I]$ represent the degree of membership and non-membership and the hesitation part (Error), of the element $x \rightarrow X$, respectively. Let [I] be the set of all closed subintervals of the interval [0, 1].

$$D(x) = [\mu 1^{a-}, \mu 1^{a+}] \in [I] \qquad (2)$$

$$J(x) = [\mu 2^{a-}, \mu 2^{a+}] \in [I] \qquad (3)$$

$0 \leq [\sup (D(x), \mu 1^{a+})] + [\sup (J(x), \mu 2^{a+})] \leq 1, \forall x \in X$. $\mu 1^{a-}$and $\mu 1^{a+}$ are the lower extreme, $\mu 2^{a-}$ and $\mu 2^{a+}$ the upper extreme, respectively. So A= ($\mu 1^{a-}$, $\mu 1^{a+}$], [$\mu 2^{a-}$, $\mu 2^{a+}$], [$\mu 1^{aH-}$, $\mu 1^{aH+}$]).

C. Intuitionistic Fuzzy Neural Network (IFNN)

Neural Network (NN) uses Intuitionistic fuzzy information and that is the reason for calling it the Intuitionistic Fuzzy Neural Network (IFNN) [12][13][14][15]. Single-input neuron Pij of an Intuitionistic Fuzzy Feed Forward Neural Network (IFFFNN) and Intuitionistic Fuzzy Weight (IFW) consists of ordered pairs of real numbers from set [0, 1]. The numbers of methods are extracted by Net Input, as depicted in Figure 1 and Table 1.

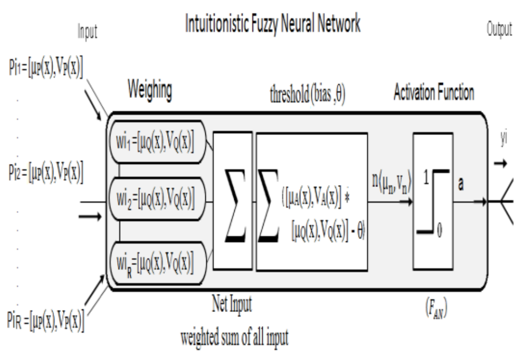
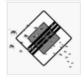
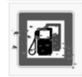
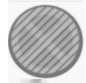
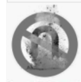


Figure 1: A single-input neuron at (IFNN)

Table 1
Road signs analysis in real time

N	Condition	Image One	Image Two
1	Daylight		
2	Night of Flash		
3	Insects		
4	Reflective		
5	Dirt		
6	Brightness		
7	Sunset		
8	Rainy		
9	Sunrise		
10	Foggy		

IV. USING GENETIC ALGORITHM TO TRAIN INTUITIONISTIC FUZZY NEURAL NETWORK (GA-IFNN)

We can use Evolutionary Algorithms like the Genetic Algorithms (GAs) to train Neural Networks during Directed Random Searches [15][16]. Genetic Algorithm-Neural Network (GA-IFNN) is able to find a solution quickly and faster than classic methods such as, The Back Propagation Network (BPN). It always heads towards a solution by lowering the error of the network. They search, starting from random points, and slowly converge to a resolution. All the weights in the network are joined to make one string (chromosome). And so this string is used in the GA as a member of the population. Each string represents the weights of a complete network. Neural networks method is used numerical analysis to derive weights for learning (training). BPN is one of the used methods which contain L, m, n where L is input, m is hidden layer and n is output neuron. Genetic Algorithm (GA) is the largest search and complex spaces to find the solution nearest to the perfection (flawless) [17]. Advantages of GA-NN algorithms which are likewise known as GANN are able to find the environment quicker than other strategies (NN) of the classical optimal solution. The drawbacks of GANN algorithms are: 1) Large amount of memory is required to handle and manipulate chromosomes. 2) Genetic Algorithms usually are not equally effective as training neural nets at Back Propagation (BP), as it is shown in Figure 2.

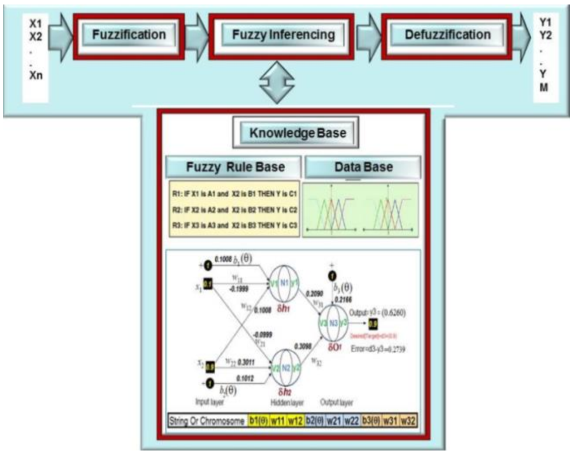


Figure 2: Inference with IFNN-GA

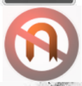
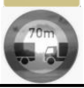
V. RESULTS

In order to overcome problems that challenge the drivers, such as dirt, insects, and different road conditions we use Fusion or Polygamy Technology with Fuzzy Logic, Neural Network, and Genetic Algorithm.

A. *The Perception Of The image road sign*

IFNN-GA receives the image of road sign and Convert it to black and white to simplify the color information, reduces the file size [12][18][19]. Training on images so it can be easily recognized, shows the primary key which refers to the image in the database, considering the time needed, performance, gradient, and matching as explored in Table 2.

Table 1
The Perception of The image of road sign

N	Image	Time	Performance	Gradient	Data Base	Matching
1		03	0.827/ 0.00131	4.47/ 0.00817	1	Suitable
2		03	0.810/ 0.00217	5.22/ 0.0103	2	Suitable
3		03	0.810/ 0.00360	5.76/ 0.0403	5	Wrong
4		04	0.816/ 0.00274	6.04/ 0.02150	4	Suitable
5		03	0.810/ 0.00212	4.46/ 0.00607	5	Suitable
6		04	0.802/ 0.00271	5.11/ 0.01650	6	Suitable
7		03	0.801/ 0.00194	4.73/ 0.01780	7	Suitable
8		03	0.815/ 0.00248	5.48/ 0.02860	8	Suitable
9		03	0.788/ 0.00141	4.48/ 0.00280	9	Suitable
10		03	0.823/ 0.00204	4.85/ 0.00228	1	Wrong

B. *Measure the effectiveness*

A total of 218 observations were obtained to measure the effectiveness of the study program, by comparing program efficiency in different road conditions compared to human eyes [20]. Observations were obtained in 13 road conditions. 4.9% were observed in daylight, 11.8% moonlight, 8.3% festive night, 16.7% observed with insects over road signs, 11.4% were obtained in reflective light, 6.9% dirt over signs, 7.9% brightness, 8.9% sunset, 7.78% rainy weather, 18.4% sunrise, 4.91% foggy weather, 8.6% mid-day light, and in 7.6 snowy weather, as shown in Figure 3.

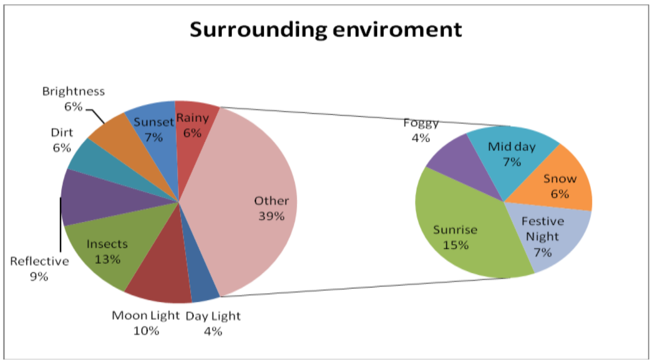


Figure 3: Comparing program efficiency in road condition.

The study program was tested for its effectiveness by comparing its efficiency in reading the road sign suitably in different road conditions compared to the efficiency of human eyes in reading road signs in same road conditions. The study found that the program was 65% able to read road signs suitably while human eyes were 32% able to read road signs in suitable way, as shown in Figure 4.

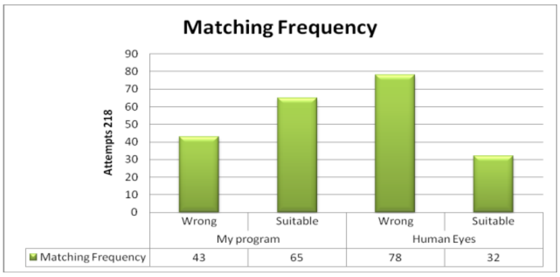


Figure 4: Comparing its efficiency in reading the road signs suitably in same road conditions.

In terms of the program ability to save time, statistical analysis found that the time needed by the program to read the sign range from 3 seconds to 5 seconds and the mean time was 3.49 seconds. However, the time needed by human eyes ranged from 3 seconds to 15 seconds, and the mean time needed was 9.08 seconds, which clearly indicate the efficiency of the study program in saving time compared to human eyes, as shown in Figure 5.

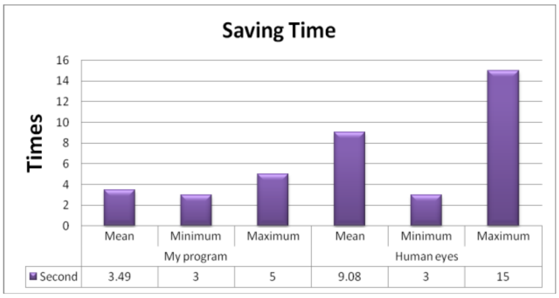


Figure 5: Comparing its efficiency in reading the road signs suitably in same road conditions

Statistical analysis was done to test the suitability of the study program in different road conditions in detailed way. The study program was 100% suitable in reading road signs in daylight compared to human eyes who scored only 13.7% suitable readings for signs. Moreover, this program scored 83.3% suitability in reading road signs in different road conditions including: Rainy weather, Foggy, Mid-day time , snowy weather, Festive night, while human eyes scores are not exceeding (0%- 35.2%) suitable scores in same road conditions. Furthermore, reading signs with insects covering the signs has scored better when utilizing the program compared to human eyes, as the study program scored 78.1% while human eyes scored only 15.1% suitability. Measuring suitability in sunrise, Sunset time and with dirt over the plate shows that the program was 84.3% suitable but human eyes didn't exceed (15.82-47%) in same conditions. Measuring suitability of the program compared to human eyes showed significant difference in the efficiency of detecting road signs by drivers as in reflective light the program scored =80.9 , while human eye scored 2.5.Measuring program efficiency in bright light scored 87.3 but with human eye the score was 2.1. Finally in Moon Light the suitability score was around =65 compared to only 10% suitability in human eyes, as shown in Figure 6.

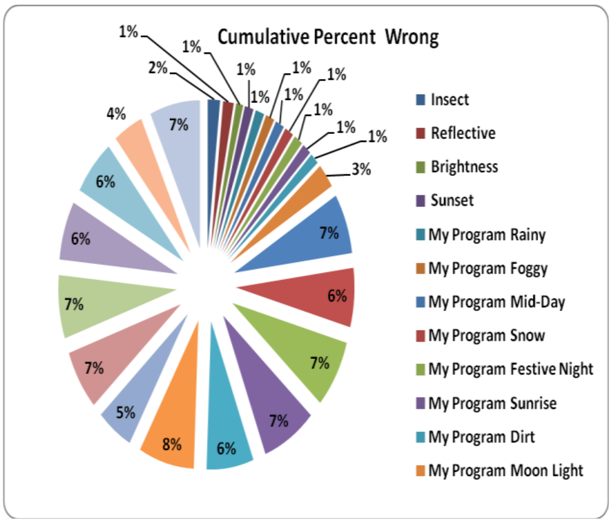


Figure 6: The suitability of the study program in road conditions

VI. CONCLUSIONS

This paper shows the study of Polygamy Technology to create system capable for learning, and not relying on the human eye. One model has been proposed to extract the best to recognize the road sign and it is shown that Intuitionistic Fuzzy Neural Network with Genetic algorithm (IFNN-GA) is adequate. Road signs analysis in real time has helped to give priority such as, ambulance, firefighter, and police to cross intersections and checkpoints and search for stolen vehicles in different climatic conditions. In future studies, we will develop a learning algorithm and apply to the Parked Vehicles by searching for vacant places without losing time to save fuel and prevent of stealing vehicles.

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